Getting Deals Done: The Use of Social Networks in Bank Decision Making *

Mark S. Mizruchi

University of Michigan

Linda Brewster Stearns

University of California, Riverside

Forthcoming in the *American Sociological Review*, October, 2001
Word count: 15,739, including footnotes, references, and tables

---

* Direct correspondence to Mark Mizruchi, Department of Sociology, University of Michigan, Ann Arbor, MI, 48109-1382 (mizruchi@umich.edu) or Linda Brewster Stearns, Department of Sociology, University of California, Riverside, Riverside, CA, 92521-0419 (linda.stearns@ucr.edu). Research for the paper was supported by the Citigroup Behavioral Sciences Research Council and the Russell Sage Foundation. We would like to thank Wayne Baker, Ron Burt, Daniel Byrd, William H. Greene, Mark Granovetter, Shin-Kap Han, Don Palmer, Yu Xie, the *ASR* editors and reviewers, and colloquium audiences at Carnegie Mellon, Cornell, Harvard, Michigan, Northwestern, and the 2001 Stanford Strategy Conference for their extremely helpful comments and suggestions.

Getting Deals Done: The Use of Social Networks

in Bank Decision Making

ABSTRACT

Economic actors confront various forms of uncertainty in their decision making, and the ways in which they deal with these obstacles may affect their success in accomplishing their goals. In this paper, we examine the means by which relationship managers in a major commercial bank attempt to close transactions with their corporate customers. We hypothesize that under conditions of high uncertainty, bankers will rely on colleagues with whom they are strongly tied for advice on and support of their deals. Drawing on recent network theory, we also hypothesize that transactions in which bankers use relatively sparse approval networks are more likely to successfully close than are transactions involving dense approval networks. We find support for both hypotheses. We conclude that bankers are faced with a strategic paradox: their tendency to rely on those they trust in dealing with uncertainty creates conditions that render deals less likely to successfully close. This represents an example of the unanticipated consequences of purposive social action.

A primary goal of sociologists has been to demonstrate that the structure of social relations, or networks, has consequences for behavior and/or outcomes. More recently, a number of researchers have described actors' personal networks in terms of social capital, which they see as a resource that helps actors achieve particular ends. Increasingly, social capital has been viewed not only as a resource that we possess by virtue of our position in a social structure, but also as something that, within limits, we can create, or tailor, to serve our goals. But even if we construct our own social networks, the structures that we create may not have the consequences that we anticipated. In some cases, what appears to be a perfectly reasonable use of social capital can have consequences that are exactly the opposite of those we intended.

This paper is an examination of the means by which organizational actors, members of a major commercial bank, use their social networks within the bank to close deals with their corporate customers. Our analysis consists of two stages. In the first stage, we propose hypotheses to account for the types of networks bankers construct. Building on a sizable literature in organizational sociology, we suggest that high levels of uncertainty will lead bankers to rely on their social ties within the bank. In the second stage, we argue that the structures of the networks created by these social relations affect the probability that a banker will successfully close a transaction. We show that the tendency of bankers to rely on those they trust in dealing with uncertainty leads them to create dense networks that actually reduce the probability of success. This strategic paradox, we argue, represents an example of the unanticipated consequences of purposive social action

(Merton, 1936).

The simultaneous focus on the causes and consequences of networks has been an ongoing concern in organizational research (Powell, Koput, and Smith-Doerr 1996; Gulati 1998), and a growing number of authors acknowledge that networks can have negative as well as positive outcomes (Baker and Faulkner 1993; Gargiulo and Benassi 2000; Labianca, Brass, and Gray 1998; Uzzi 1996). Most researchers who have focused on the *initiation* of network ties, however, have assumed that actors create networks to solve a problem, such as the need for skills or resources. The successful construction of these networks is then assumed to have positive, anticipated consequences for the actor. This view is well captured by Lin (2000:786), who defines social capital as "investment and use of embedded resources in social relations for expected returns." A considerable amount of research demonstrates the value of the strategic use of social networks (see Burt 2000 for a review). There are times, however, in which the returns from social ties are unanticipated by those who created them. Ties developed with the goal of achieving an outcome may have exactly the opposite effect. In the analyses described below, we show that the nature of the networks that bankers construct to solve a set of problems actually reduce the bankers' probability of being successful. This suggests that the process of network formation may yield unexpected as well as expected returns.

Our primary foci, then, are on two issues: first, the relation between the level of uncertainty and the use of social networks with one’s colleagues within the organization; and second, the extent to which the nature of bankers’ social networks affects the outcome of a transaction. We shall study this through an examination of account managers in a major U.S. commercial bank.

BACKGROUND

The concept of uncertainty, which March (1994:178) defines as "imprecision in estimates of future consequences conditional on present actions," has played a prominent role in organizational theory. From Herbert Simon's classic work on bounded rationality (1947) to a subsequent range of very different formulations (Williamson 1975; Meyer and Rowan 1977; Pfeffer and Salancik 1978; DiMaggio and Powell 1983), uncertainty reduction and management have been at the center of discussions of inter and intrafirm relations. Some organizations have as their primary basis of existence the management of uncertainty. Perhaps there is no better example of such an organization than a bank. Banking thus represents an especially good site for examining the way actors deal with uncertainty.

Uncertainty can have a number of dimensions. A deal may be risky because a customer is in a precarious financial situation or has experienced poor recent performance. The banker may have varying degrees of trust in his or her customer. The transaction may be highly complex as well, with a large number of unknowns. Bankers deal with these problems on a daily basis, and one means by which they manage them is by consulting their colleagues in the bank. A considerable literature suggests that social ties can serve to mitigate the uncertainties both among and within organizations. Long-term social relations between a firm's sales and purchasing agents and those of customer and supplier firms can serve to reduce the uncertainties and thus transaction costs associated with interfirm business (Granovetter 1985). Mechanisms such as director interlocks can reduce the uncertainties associated with resource dependencies (Pfeffer and Salancik 1978). The creation of specific structures can signal to the larger environment that an organization is a responsible actor, thus increasing its legitimacy and claim to societal resources (Meyer and Rowan 1977). And social relations among firms' officials can reduce the uncertainty associated with a range of organizational innovations and behaviors, from merger financing (Stearns and Allan 1996) and takeover defense strategies (Davis 1991) to contributions to nonprofit organizations (Galaskiewicz 1985) and political candidates (Mizruchi 1992).

Networks of social relations can account for responses to uncertainty within as well as between organizations. Kanter (1977), in her analysis of hiring practices in a large northeastern firm, found that managers, who tended to be white Protestant males educated in elite private institutions, tended to rely on these ascriptive criteria in making new appointments. Kanter's claim was that for managerial positions, in which qualifications and performance criteria are not clearly understood, managers dealt with this uncertainty by choosing those with attributes most like themselves. These signals (Spence 1974) are substitutes that are assumed to compensate for a lack of knowledge.

The networks that actors create on the basis of these uncertainties may have impacts of their own, however. A growing literature, stretching back to Granovetter's classic essay (1973), suggests that weak ties provide a wider range of information than do strong ties. More recently, Burt (1992) has suggested that actors whose social contacts are disconnected from one another have higher success rates than do actors with dense personal networks. Strong ties tend to be densely connected. Because, as noted above, actors may be likely to turn to those they trust under conditions of high uncertainty, it raises the possibility that the normal response to uncertainty may lead to deleterious consequences. If strong ties lead to dense networks with a limited range of information while weak ties lead to sparse networks with a broader range of information, then the counterintuitive decision to rely on weak ties under conditions of high uncertainty might actually lead to superior outcomes.

UNCERTAINTY, NETWORKS, AND DEAL MAKING

The site for our study was the corporate banking unit of a leading multinational commercial bank, which we refer to as UniBank. In preparation for the current study, we gathered information on UniBank policies gleaned through canvassing of annual reports over the past several years, internal documents, extensive discussions with two contact officials within the bank, and 14 in-depth, open-ended interviews with bank officials in three domestic locations (Chicago, Los Angeles, and New York). Interviews ranged from one to four hours each. These discussions allowed us to become familiar with the bank's deal making process.

Bankers pursue several forms of information when processing a transaction. First, they seek out the most complete and high quality information available on the customer's present and future financial condition, including formal credit information, both external (Standard and Poor's reports and ratings) and internal (the bank's own credit rating model). Second, bankers draw on information obtained through their own, and colleagues', experiences with the customer, including their knowledge and trust of the firm's management.

The bankers in our study are sales people. They sell by responding to clients' requests as well as by creating demand among these clients for the bank's many products. These products can be divided into four classifications (with examples in parentheses): lending (lines of credit and project finance), trading (derivatives and currency exchange), capital market services (syndication and securitzation), and transactional services (cash management and custody). The bankers' goal is to close deals. They are constrained, however, in the terms that they can offer their customers. Before a transaction at UniBank can close, the deal normally requires the approval of at least three officers within the bank. This system is the bank's formal mechanism for ensuring that the bankers sell to customers only those deals that meet the bank's targeted rate of return. This approval is no guarantee that the bank will achieve the estimated rate of return, only that the deal is expected to do so. Although the banker and the officers from whom he or she seeks approval are concerned with closing the deal and its rate of return, the banker's primary concern during the approval process is with the former while the officers' primary concern is with the latter. Once a transaction has reached approval status, their goals converge: both want the deal to close. It is therefore important to distinguish between a banker “successfully closing a deal,” that is, obtaining the business for the bank, and a “successful deal,” that is, a deal that upon completion provides the bank with the expected rate of return. Our concern in this paper is with the former.

To secure internal approval requires that the client be assigned a credit rating. The bank calculates the credit rating by combining Standard and Poor bond rating data with its own information. During the approval process, the transaction is evaluated along a two-dimensional table known as the approval grid. The grid consists of cells determined by a combination of the customer’s credit rating and the bank’s total and marginal (based on the size of the current deal) exposure to the customer. This grid determines how high in the bank's hierarchy the banker must go to secure approval for a deal.

As noted above, each credit transaction requires the signatures of a minimum of three officers, at least one of whom must be a senior credit officer at the level designated by the grid. These senior credit officers, of whom there are approximately 500, are required to have ten years of banking experience, at least two at UniBank. There are three types of senior credit officers-- senior bankers, risk managers, and executive vice presidents-- spanning four levels. Above the senior credit officers is a six-member credit policy committee. Above this committee are "contact executives," key senior executives such as the vice chairman of the bank.

Bankers involved in transactions use their social networks within the bank to ask advice from peers and superiors who have knowledge based on product expertise and/or past experiences with the customer. In the context of banker decision making it is useful to think in terms of two types of networks. On the one hand, there are what we shall term *information networks*. These are social relations that bankers use to secure knowledge about the status of particular firms or products, or appropriate ways to structure a transaction. On the other hand, there are what we shall term *approval networks*. These are social relations that bankers use to gain both confirmation and support for the transaction.

An example of the use of information networks appeared in one of our interviews with a senior banker. The banker recounted to us a hypothetical case involving a large client. In a typical case, the banker brings in a product specialist in the particular area, such as syndications, cash management, or foreign exchange. The teams vary based on the company involved and the type of transaction. "It could be a straight deal such as cash management or a never-before-done deal," he told us. Often it is a competitive situation with other banks, in which the bank must "make its deal appear 'prettier' than the others'." In these situations the banker will consult colleagues within the bank, often those whom he or she has consulted previously. As he noted, "That's where we get a lot of the network going." The banker will ask, "Gee, have you seen something like this before?... You talk to some people. One of the reasons they come to me is the exact same thing. They want to see what I think, because, maybe I've been doing it twice as long as they have." This example, typical of numerous ones we heard, suggests that networks are often used to reduce uncertainty.

An example of the use of approval networks was recounted to us by a risk manager. A banker was putting together an acquisition deal involving a major manufacturing firm. Because the company had a poor credit rating, the deal required approval by a Level 1 credit officer (the highest level) plus the credit policy committee and a contact executive. Initially the appropriate Level 1 signator was "uncomfortable" with the deal. The banker and risk manager then assembled a meeting with the Level 1 officer and the contact executive. The latter said he was "OK with the deal" (that is, he thought the deal was within acceptable risk) but he would not sign it unless the Level 1 officer signed. The banker and risk manager then approached a credit policy committee representative. They "got him comfortable with the deal" as well, but as with the contact executive, the credit policy person agreed to sign only if the Level 1 officer signed. Eventually, the Level 1 officer signed, thus securing the deal. In cases such as this, network ties often determine the specific persons whose support is solicited. In trying to get the required signatures, a senior credit officer told us, he will seek out those "higher-ups [he believes] will be favorable to the deal." Once bankers decide that a particular deal should go forward, they attempt to manage the disagreements surrounding the deal by using approval networks to obtain the necessary support.

How much discretion do the bankers have in constructing their networks? Clearly, they are constrained to some extent, in the same way that all actors are: one cannot develop network ties with actors who are unavailable. The formal organizational structure as well as the nature of the particular deal also play a role. Most deals require bankers to work with product specialists. There is, however, no formal means for assigning a product specialist to a deal. Although bankers are assigned to a customer’s account, product specialists are not. Rather, they are assigned to a product specialty area, such as lending or trading. The banker therefore has some discretion in selecting the product specialists with whom he or she will work on a given deal. The more complex the deal, the more likely the banker will consult several product specialists. In constructing their approval networks, most bankers are expected to seek support from their division head and, in many cases, the group's risk manager. As noted above, deals generally require three signatures, however, and most deals have more than three. There are few limits beyond those of time and knowledge as to whom can be consulted for information or support, although a banker's rank may affect his or her ability to secure them. One illustration of the variation in bankers' networks across deals is the fact that our results are virtually identical regardless of whether we control for within-banker variance. This suggests that there is as much variance among deals within bankers as there is across bankers. Our bankers may not make their networks exactly as they please. But they clearly do make them.

MODEL AND HYPOTHESES

Our analysis consists of two stages. In the first, we examine the extent to which uncertainty affects bankers' use of social networks. In the second, we examine the effects of these networks on whether a banker successfully closes a deal. In the first stage, we suggest that high levels of uncertainty will lead bankers to rely on their ties within the bank. We examine as endogenous variables the strength of the ties that bankers use in both their information and approval networks. In the second stage, we use as our dependent variable a dichotomous measure indicating whether a given deal was closed. Both our exogenous and intervening variables are expected to affect the outcome measure (closing a deal) in various ways.

Our primary exogenous variable is the level of uncertainty, which we divide into two components: economic uncertainty and lack of trust. Economic uncertainty is defined as the banker's perception of the degree of risk to the bank’s capital. Lack of trust is defined as the extent to which the banker has doubts about the individuals in the customer firm with whom he or she interacts

We have suggested that in cases of high uncertainty, bankers will consult with colleagues within the bank to gain more information about the customer or the type of transaction; that is, they will use their information networks. In situations in which a banker has not yet determined whether to support a deal, it is possible that his or her colleagues will provide negative as well as positive information about the company or the deal. The banker's primary concern in using information networks is thus to assemble additional information, not necessarily to gain support for a decision in which he or she already has a stake. It is in situations in which the banker lacks knowledge of the customer, or requires advice on the structuring of a deal, that he or she will be more likely to invoke internal information networks. In fact, most of the more senior bankers had long-term relations with their customers. For these bankers, the use of information networks typically involved questions about the deal rather than the customer.

There is a question of which colleagues a banker will consult. On the one hand, it is known from network theory (Granovetter 1973) and evidence (Granovetter 1974) that actors gain more information from those with whom they are relatively weakly tied. On the other hand, it is not clear that actors are consciously aware of the benefits of weak ties, and there is also evidence that under uncertain conditions, actors rely heavily on those they trust (Kanter 1977). The data from our preliminary interviews are consistent with this latter suggestion. To the extent that the benefits of weak ties are unknown while the value of strong ties is apparent, we believe that actors will be more likely to turn to those with whom they are strongly tied when faced with a difficult situation. This suggests the following hypothesis:

> H1: The higher the uncertainty in a transaction, the stronger the ties between the banker and those he or she consults for information.

High levels of uncertainty also increase the probability of ambiguous interpretations (March 1994: 175-219). When environments are highly uncertain, the number of potential variables affecting an outcome increases. This means that the possibility for multiple interpretations increases for decisions involving high uncertainty. Once bankers have made a decision to pursue a deal, they actively seek support for their position. This is done through the use of approval networks. We expect that bankers will seek out approval networks in much the same way that they seek out information networks. This means that under conditions of uncertainty, bankers will seek approval from those they trust. This suggests the following hypothesis:

H2: The higher the uncertainty in a transaction, the stronger the ties between the banker and those from whom he or she seeks approval for a deal.

A third possible source of uncertainty is the complexity of the deal. Complex deals, which are distinguishable from risky ones, necessarily require consultation with a relatively large number of colleagues. This suggests that in complex deals, even if bankers might prefer to rely for advice on those they trust, the nature of the deal may lead them to consult a larger network, which may involve a weaker set of ties. We therefore do not hypothesize a specific effect for deal complexity on the strength of a banker's ties. We do include this variable as a control, however.

The dependent variable in the second stage of the model is whether a transaction closed. As noted above, this was the primary goal of all of the bankers with whom we spoke. It is important to distinguish closure from approval. Situations in which bankers took a deal through the formal process but ultimately failed to gain in-house approval were quite rare in our study. We were able to document only two such cases. Our interviews suggested that self-censoring based on preliminary “testing of the waters” was the primary reason for this. Far more common are situations in which the banker gets his or her deal approved within the bank but fails to close on it. This can occur for a number of reasons. The customer may decide that the terms of the deal are unacceptable, and then choose to work with a bank that offers more favorable terms. In some cases, the bank and customer simply abandon the deal and consider an alternative approach. In other cases, a customer's situation changes in the midst of negotiations. The firm may be acquired by another or engage in an acquisition of its own. The banker's ability to construct an agreement with which his or her officers are satisfied and that is attractive to the customer is the primary determinant of whether a deal successfully closes, however.

Of what does such an attractive deal consist? Consider an example in which a customer requests a loan for an amount and/or rate that the bank finds unacceptable. Rather than reject the request, the bank's policy is to restructure the deal in a way that meets the customer's needs while simultaneously generating an acceptable rate of return for the bank. In this case, the customer may want to invest in its Asian facility. The banker, working with members of his or her approval network, may find that by restructuring the deal to draw the funds from the bank's local Asian branch, the customer benefits from the resulting currency and tax advantages. The customer receives the amount and price it wants, and the bank receives an acceptable interest rate and a larger up-front fee. There is no guarantee that restructuring will always produce a mutually beneficial outcome. This is the goal of the banker and the bank, however. Our concern is with the factors that predict a banker's ability to do this for a given deal.

Our argument suggests that to the extent that economic uncertainty and trust affect the closure of a deal, they would do so through their effects on the use of information and approval networks. At the same time, it is possible that uncertainty has a direct effect on closure. We expect that deals with higher levels of economic uncertainty will be less likely to close. There are two reasons for this. First, bankers may abandon a high risk deal early in the process because they believe they will experience difficulty gaining approval for the deal. Second, when bankers do pursue such deals, there is a greater chance that the deal will be restructured during the approval process in a way that makes it more difficult to sell to the customer, as, for example, in charging a higher interest rate or imposing additional restrictive covenants. We also expect that bankers will have a more difficult time closing deals with customers with whom there is less than complete trust. This suggests that the banker's trust of the customer will be positively associated with closure. And although we did not hypothesize a specific effect of complexity on the strength of a banker's ties, it is likely that bankers will have more difficulty closing highly complex deals, suggesting that we should observe a negative effect of deal complexity on closure. This discussion suggests the following hypothesis:

> H3: The higher the uncertainty in a transaction, the less likely the transaction will close.

The effect of information networks on the closure of a deal is not necessarily straightforward. To the extent that these networks are large and non-redundant, the banker will have a wider range of data on which to both structure and evaluate a deal. Network size refers to the number of individuals consulted. Redundancy refers to the density of the actor's personal network, the extent to which those consulted by the actor are tied to one another. When personal networks are dense, actors are likely to receive the same or very similar information, because this information circulates among the same group of people. When personal networks are sparse, actors are likely to receive a greater range of information, since members of the network tend to be tied to a diverse set of alters (Granovetter 1973; Burt 1992). To the extent that more information from a range of sources is better than less information, we would expect this to benefit the course of a deal on which the banker is working. In deciding whether to pursue a deal, a different outcome is possible, however, because members of one's network may provide negative as well as positive information about the deal. If this is the case, then there would likely be no systematic association between the use and nature of information networks and the probability that a deal will be closed. Because of the potential crosscutting influences of members of one's information network, it is possible that a broad, sparse information network will increase the probability of closure, but it is also possible that there will be no association between the two variables. We therefore do not offer a specific hypothesis about the relation between the density of a banker's information network and the probability of closure, although we do include this variable in our model.

Approval networks, on the other hand, are used when a banker wants to gather confirmation for a deal that he or she already supports. As with information networks, approval networks will vary in both size and density. Whether a banker is able to secure support for a deal may depend on the range and breadth of the colleagues he or she enlists. Sparsely-connected groups are likely to contain a wider range of views and expertise than more densely-connected groups. This means that ideas supported by members of low-density groups will tend to have received more criticism and questioning and benefited from a greater range of insights. To the extent that a banker is able to gain support from a broad range of colleagues, he or she will be able to present a "better" deal, one that is attractive to both the customer and the bank. This suggests the following hypothesis:

> H4: The lower the density of the approval network consulted by a banker, the more likely the transaction will close.

Finally, related to the question of the redundancy of the network is the extent to which an actor is dependent on a single individual. Burt (1992) has argued, and provided evidence for the notion, that actors whose bases of information and social support are restricted by a strategically located individual are likely to be disadvantaged in the acquisition of organizational resources. A banker who is dependent on a single person in order to close a deal may have few others to whom to turn should this person fail to provide support. The extent to which an actor is highly dependent on a single individual, which Burt refers to as the degree of hierarchy, can be measured by examining the level of inequality in the actor's network. Hierarchical networks are dominated by one person, or a small number of persons. Non-hierarchical networks tend to give actors more alternative sources of support. Burt showed that corporate managers embedded in hierarchical networks had longer times to promotion than did those whose networks were less hierarchical. This suggests that bankers whose approval networks are hierarchical will, on average, have a more difficult time gaining support for, and closing, their deals. We propose the following hypothesis:

> H5: The lower the hierarchy of the approval network consulted by a

banker, the more likely the transaction will close.

DATA AND VARIABLES

Our units of analysis are specific transactions. These transactions may include any one, or combination of, the products mentioned above. From May, 1997 through March, 1999, we conducted semi-structured interviews with 91 of the 110 bankers in the bank's "global relationship banking" unit. This unit is responsible for handling the approximately 1,385 multi-national corporations that the bank had targeted as its corporate customers. The bankers with whom we spoke represented sixteen business units in two domestic locations.[1]

Our goal was to interview each banker twice. We were able to successfully re-interview 82 of our original 91 respondents. Most of the others were lost due to attrition (such as moving to another location in the bank, leaving the bank, or taking maternity leave). At the initial interview we asked each banker to describe three transactions in

[1] The business units consist of two regional offices (New York and Chicago) and 14 industry units. The industry units are automobiles, aviation, banks, branded consumer, chemicals/pharmaceuticals, communications, electronics, global energy, global power, insurance, investment banks/managed funds, retail, shipping, and technology.

which he or she was currently involved. Bankers were asked to provide us with a range of deals, from simple to complex, and encompassing a range of the kinds of activities in which they engage. We then asked bankers to provide specific information about the deals and their relations with the companies. At the follow-up interview we learned the outcome of the deals, and asked a number of questions, including the name generators that yielded the network variables.[2] All of the initial interviews and a majority of the follow-up interviews were conducted in person. Because the outcome of deals was not always known at the first follow-up, we conducted some of the follow-up interviews by phone. We were able to secure at least some information on 230 deals at their initial stage. We collected outcome information on 194 deals. The remainder were lost due to attrition. Based on their primary component, 27.3 percent involved loans to be held by the bank, 22.7 percent involved capital market services, 16.5 percent transactional services, 16.0 percent securitized loans (to be sold off by the bank), and 14.4 percent trading. The remainder involved a combination of products. Of these 194 deals, 96, or slightly under

[2] The bank maintained a "deal pipeline," a file in which bankers were expected to register all deals on which they were currently working. Our original goal was to use the deal pipeline to generate the deals for our study. This would have allowed us to collect a random sample of deals. In the course of our preliminary interviews, however, we learned that the deal pipeline was an invalid indicator of the banker's current portfolio. Because there was no apparent sanction for underreporting, most bankers neglected to register many of the deals in which they were involved. This was in part due to time pressures as well as concern for their success rate. The best alternative was to ask the bankers to generate the deals in a way designed to ensure sufficient variation. We do not claim that this produced a random sample of deals. We are confident that it provided a wide representation of the kinds of services that the bankers provide.

50 percent, were successfully closed. Loans were slightly more likely than the other types to close, but the difference was not statistically significant. Missing data on particular variables reduced the number of usable observations to 175 or fewer for most analyses.

Our primary exogenous variables are our measures of uncertainty, which include economic uncertainty, lack of trust in the customer, and the complexity of the deal. Economic uncertainty, as noted above, is defined in terms of the banker's perception of the financial risk of a deal. One possible indicator of risk is the approval grid, which views risk in terms of a combination of the bank's total exposure to the customer, the size of the deal, and the customer's credit rating (the bank uses a 1 to 6+ scale, with 6+ the highest risk, that corresponds roughly with Standard and Poor's ratings). There are two reasons that this is not a suitable measure for our purposes. First, the grid rating is normally assigned at a relatively late stage in the approval process. Because of its role in our model, as a predictor of the colleagues the banker consults, we wanted to gauge the banker's perception of risk in the early stages of the deal. This was especially important because in a significant number of cases, the approval level did not follow the formal scheme but varied as a result of negotiation by the banker and his or her colleagues. This meant that the actual approval level may have been as much a consequence of the banker's approval network as it was an indicator of risk. Second, although the bankers were aware of both the customer's credit rating and the bank's exposure in the particular deal, they were often unaware of the bank's current total exposure to the customer, especially if the bank was involved in other ongoing deals with the customer. Our goal was to identify a measure of risk that was specific to the particular deal and that reflected the banker's perception prior to reaching the approval stage. On the basis of its similarity to the approval grid, we operationalized economic uncertainty as the product of the bank's exposure in the deal and the customer's credit rating, converted to logarithms (base e) to adjust for skewness.[3]

Lack of trust is defined as the extent to which the banker has doubts about the individuals in the customer firm with whom he or she interacts. We asked bankers to tell us, on a 4 point scale, with 4 being high, the extent to which they "trust the individuals at the customer firm to do what they say they're going to do." The bankers' trust of their customers tended to be high. Nearly 50 percent of all trust relations were given the highest score of 4, and more than 80 percent of the remainder received scores of 3. We determined on the basis of this finding that the most important distinction was between a score of 4 and all others. We therefore combined scores of 1 through 3 into a single category and treated customer trust as a dichotomous variable, with 1 indicating high trust (no doubt) and 0 indicating low trust (at least some doubt). Complexity of the deal was determined by asking bankers to rate the deal, relative to those on which they generally

[3] An analysis of the approval grid indicated that the level of exposure in the deal and the bank's total exposure to the customer at given approval levels were correlated .993. In other words, in using the grid to predict the required approval level, the deal-specific and total exposure were interchangeable. We operationalized risk as the product of the customer's risk rating and the bank's exposure in the particular deal because the outcome cells of the grid resembled a product of the customer's risk rating and exposure. This indicator had a .917 correlation with the approval level on the grid, indicating that it was a good approximation of the bank's conception of risk.

work, on a 1 to 5 scale, with 1 being very simple and routine and 5 being highly complex .

The network variables were generated by asking respondents to provide the first names or initials of up to eight individuals whom they consulted for information (information networks) or support (approval networks). Each banker had separate information and approval networks for each of his or her deals. We asked bankers to rate the strength of each relation, both between them and each alter and among the alters themselves, on a 1 to 4 scale, with 1 being an infrequent work colleague, 2 a moderately frequent work colleague, 3 a frequent work colleague, and 4 a frequent work colleague who is also a personal friend (defined in terms of knowing one another's family and/or having entertained in one another's homes; there were no cases in which bankers mentioned personal friends who were not also frequent work contacts). Zeros were occasionally used by bankers to identify cases in which alters had no contact or were unaware of one another's existence. We computed three separate measures based on this scale. The first, the strength of the banker's ego network, was computed for the banker's direct relations with members of his or her information and approval networks. It was computed by the formula

$$E_i = (\Sigma S_{ij}) / 4N$$

where E_i equals the strength of actor i's ego network, S_{ij} equals the strength (on the 1-4 scale) of the actor's relations with each alter j, and N equals the number of alters. The sum of the values for each of the banker's direct relations is divided by the number of ties times four, since 4N is the highest possible sum.

The second measure, which we refer to as alter network density, or simply density, is the level of connectivity among those in the banker's network for the particular deal. It consists of the weighted strength of relations among those with whom the banker is tied. This is computed by the formula

$$D_i = (\Sigma S_{jk}) / [2 (N^2 – N)]$$

where D_i equals the density of banker i's network, S_{jk} equals the strength (on the 1-4 scale) of each of actor i's direct ties j with i's other ties (k), and $2(N^2 - N)$ equals the number of possible ties among banker i's direct ties $[(N^2 - N)/2]$ multiplied by 4, since 4 is the maximum strength of a given relation. The first of these measures, strength of the banker's ego network, was used to test Hypotheses 1 (for the information network) and 2 (for the approval network). The second measure, the density of the banker's network, was used to test Hypothesis 4, as well as to measure the density of the bankers' information networks.[4]

The use of different network measures as dependent variables in Hypotheses 1 and

[4] This measure is equivalent to the standard measure of network density (the number of actual ties divided by the number of possible ties) weighted by the strength of tie. The conventional measure assumes a binary network, in which relations are either present or absent. In our networks the overwhelming majority of actors had at least some connection. The primary source of variation is the relative frequency of their interaction.

2 from those used as independent variables in the analysis of closure is consistent with existing theory as well as the model we develop. As Burt (1992, chapter 1) has suggested, however, strong tie networks are not necessarily dense nor are weak tie networks necessarily sparse. Still, actors who seek out relations with strongly-tied alters will tend to have more dense alter networks than will those who seek out relations with more weakly-tied alters. The correlations in our data between information network direct tie strength and density were .472 for all deals and .583 for the deals that reached the approval process. The correlation between approval network direct tie strength and density was .701. Although we doubt that they were consciously attempting to construct specific types of alter networks, there were occasions in which bankers approached colleagues whose support was necessary to gain the support of other important colleagues. To ensure the tenability of our two-stage model, we computed additional equations that treat alter network density in the information and approval networks as endogenous variables in the first stage of our analysis (Hypotheses 1 and 2), and ego network information and approval network strength as exogenous variables in the second stage (Hypothesis 4). The relevant findings are discussed below. Although the two variables are highly correlated, we also inserted ego network strength into some of our equations simultaneously with alter network density. We present these equations below.

The hierarchy of a banker's network was operationalized as the coefficient of variation of the strength of the banker's direct ties. This is slightly different from the definition used by Burt (1992), but the coefficient of variation was identified by Allison (1978) as a well-behaved measure of inequality. Although we did not develop a specific hypothesis about the effect of the hierarchy of the information network, we did include this variable as a control.

In addition to the variables described above, we also controlled for three variables that might affect the outcome of a deal independent of our hypothesized factors: the banker's rank, whether UniBank was the primary bank for the customer firm, and the respondent-reported degree of consensus within the bank on the deal. The bankers in our study occupied five different levels within the firm, from assistant vice president to managing director. A banker's rank within the bank may affect not only the kinds of deals on which she works, but also the kinds of networks he is able to construct. One lower-ranked banker, for example, complained to us about the difficulty of having his phone calls to colleagues returned, presumably due to his low status. There was little indication from our interviews that highly ranked bankers were either more or less likely to work on deals that had a high probability of success. It is appropriate to include this variable as a control, however.[5] Similarly, whether UniBank is the customer's primary bank may affect

[5] In addition to the banker's rank, we examined two person-specific variables, gender (29 percent of our deals were handled by women) and the banker's length of service dealing with the customer. The latter is a useful proxy for length of service with the bank, but has the advantage of being deal-specific. Gender was not significantly associated with either the strength of information or approval network ties or deal outcome in any of the equations, nor did its presence in the model affect the significance of the other coefficients. Length of service with the customer had a significant effect on the strength of information and approval network ties, but its inclusion did not alter the strength of the other coefficients. This variable was also not significant in any of the equations involving outcome, and its presence either had no impact on the effects of our hypothesized predictors or (in three cases) increased them.

whether the bank gains the customer's business on a particular deal. It is therefore important to control for this variable as well. Our indicator for lead bank was a three-level ordinal variable, with 0 indicating that UniBank was not the customer's lead bank, 1 indicating that UniBank was one of the customer's lead banks, and 2 indicating that UniBank was the customer's sole lead bank. The consensus variable, which we measured on a 1 to 5 scale, with 5 indicating unanimity, was designed to examine the extent to which the banker's peers were "on the same wavelength" regarding the deal. Finally, because the definition of network density includes $N^2 - N$ in its denominator, density is in part a function of size; larger networks tend to be relatively sparse. It is therefore possible that any effect we find for density is simply a function of the number of alters in a banker's network. Even if this is the case, our interpretation of the network effect could be similar, in that the larger the number of bankers from whom the banker gains support for a deal, the greater the likelihood that he or she received a broad range of feedback. But a large approval network could also be viewed as an additional indicator of risk, in that superiors may be more willing to support a high-risk deal when a substantial number of others have already signed on (as in our example from our interview referred to above). Considering size and density simultaneously will therefore allow us to examine the effect of the network structure independent of the previously unexplained factors that lead to large networks. We therefore include the size of the banker's networks as controls, where size is simply the number of alters named by the banker for the particular deal-network.[6]

---

[6] It is possible that bankers might have entered into a deal with the idea that the deal was either

RESULTS: The Use of Social Networks

Tables 1a and 1b present means, standard deviations, and correlations among the variables in our analysis. We have presented these in two separate tables because only a

---

particularly "strong" or "weak," and this notion might have affected the character of the networks the bankers constructed. If this were the case, then an observed association between network structure and deal closure might be a spurious consequence of the banker's initial view of the deal. There are two reasons that this possibility is unlikely to affect our findings. First, based on our interviews, this process appears to be relatively rare. We observed three deals (among more than 200) that were from the start viewed as "blockbusters," in which a large number of bankers sought to give their support. Except for these three cases, bankers did not speak of deals in terms of their strength, but rather in terms of their degree of complexity or risk. Second, in each of the three "blockbuster" cases, the most prominent outcome was the presence of a large approval network. By controlling for network size, we increase the likelihood that this process did not distort the effect of network density. It is also possible that the character of competing deals from other banks might have affected whether UniBank successfully closed a deal. Our interviews suggest that the bank faced competition from other banks in most of its deals, including those involving its long-term customers. We saw little evidence from our interviews to indicate that competition was systematically associated with any of our predictors, however. We also asked bankers, in response to failed deals, an open-ended question regarding why they thought the deal failed. Losing out to a competitor was mentioned in about 20 percent of the cases (the most common responses were "customer's needs changed" and "customer's situation changed"). There was no discernable pattern between reason for failure and any of our predictors of closure.

subset of our cases include approval networks. Among the 194 deals for which we have outcome information, only 151 (77.8 percent) proceeded far enough to include an approval network. The remaining 43 deals failed prior to reaching the approval process. Of the 151 deals that reached the approval process, 96 (63.6 percent) were successfully closed. Table 1a includes descriptive statistics and correlations among the 173 deals for which we had data on all of our substantive variables, regardless of whether they reached the approval stage. Table 1b includes the same information for the 137 deals on which we have all variables that reached the approval stage.[7]

TABLE 1a ABOUT HERE

TABLE 1b ABOUT HERE

Except for the correlations between alter network density and the controls for network size and ego network strength, none of the correlations among the predictors is large enough to suggest concern about multicollinearity. It is of note that the level of economic uncertainty and the complexity of the deal have a virtually zero correlation, both among all

---

[7] The effect of size of the information network was virtually zero and had no effect on the strength of the other coefficients. Because of the null result and the fact that we did not develop an explicit hypothesis for the effect of information network structure on closure, we omit this variable from the correlation matrices and the equations we present below.

deals and among deals that reached the approval stage. This suggests that these two variables are measuring very different dimensions of uncertainty. The positive (albeit small) association between complexity and customer trust suggests, not surprisingly, that bankers were more willing to pursue a complex deal when they had had positive prior relations with the customer.

Because we have examined more than one deal per banker, our observations are not statistically independent. In the analyses that follow we use a technique to compute robust variance estimates for clustered observations, in which we transform the variance-covariance matrix of the regression coefficients to take into account the non-independence of deals within individual bankers. The standard errors in Tables 2 and 3 are based on these estimates. A description of the model is presented in Appendix A.

Table 2 presents the tests of Hypotheses 1 and 2. In Equation 1, we examine the effects of our two hypothesized indicators of uncertainty-- the natural logarithm of the product of exposure and company credit rating (economic uncertainty) and degree of trust of the customer firm-- on the strength of the bankers' relations with members of their information network.

TABLE 2 ABOUT HERE

As is evident in Equation 1, the level of economic uncertainty has a statistically significant positive association with the strength of the banker's ties with those whom he or she consults for information related to a deal. This finding is consistent with

Hypothesis 1. When uncertainty is high, bankers tend to turn to those with whom they are close. This effect did not hold for the trust variable; the level of trust of the customer firm was not associated with the strength of a banker's information network ties, a finding inconsistent with Hypothesis 1. And, although we did not hypothesize a specific effect of complexity in Hypothesis 1, this variable was also not associated with strength of ties. One possible reason for this is that in some complicated deals, bankers may be forced by the nature of the deal to interact with a wide range of others. Support for this notion is found in a separate analysis (available on request) in which we used size, rather than tie strength, of the information network as the dependent variable. Complexity of the deal is the only significant predictor in the equation; its T-statistic of 2.556 is strongly positive (one-tailed $p < .01$), suggesting that in complex deals bankers will consult with a relatively large number of colleagues. Economic uncertainty has no effect on the size of the information network ($T=0.153$). This suggests, consistent with our argument, that bankers turn to their strong ties, rather than to a large number of colleagues, for information in high-risk deals.[8] The fact that the economic uncertainty effect on tie strength holds even when we control for the complexity of the deal supports our contention that under conditions of high risk, bankers will turn for advice to those they trust.

The equation predicting the strength of ties with members of a banker's approval

[8] To further examine this view, we inserted size of the information network as a control into the equation predicting tie strength. This variable was not significantly associated with tie strength ($T=-0.996$) nor did its presence have any effect on the strength of the economic uncertainty coefficient.

network (Equation 3 of Table 2) requires some discussion. As noted above, approximately 22 percent of our deals failed before reaching the approval process. This means that the deals for which we have data on approval networks may constitute a biased sample of the total number of transactions. This phenomenon, known as sample selection bias, is a common problem in the analysis of social science data (Berk 1983; Winship and Mare 1992). The most widely-used approach to handling problems of sample selection bias is a two-stage model developed by Heckman (1979). In the standard Heckman model, the investigator first computes a probit model predicting factors that affect the probability of being selected into the outcome condition (in our case, the probability of having an approval network). From the selection equation, the researcher then uses the probit coefficients to estimate, for each observation, a value, λ, which represents a hazard rate, the probability that a deal will disappear from the sample (that is, fail to reach the approval process), conditional on being at risk of disappearing (Berk 1983:390-391; Greene 1995:638-640). The λ is then inserted as a variable into the substantive equation.

In order to compute this model, we must identify a set of predictors for the selection variable (existence of an approval network). Although it is not absolutely necessary, estimation is facilitated if we ensure that there is at least one variable in the selection equation that does not appear in the substantive equation.[9] For our predictors of a deal reaching the approval process, we selected seven variables: the six that served as

[9] Identical selection and substantive equations increase the likelihood of multicollinearity between λ and the predictors in the substantive equation (Berk 1983:396-397).

predictors of strength of ties in the information network and the banker's reported confidence in the customer firm management's ability to keep the firm on a strong financial footing (on a 1-4 scale). The six variables from Equation 1 of Table 2 were chosen to render the analysis of the strength of approval network ties as close as possible to the analysis of the strength of information network ties.

Equation 2 of Table 2 presents the selection equation predicting the existence of an approval network. Interestingly, only two of the seven predictors in the selection equation are significantly associated with the presence of an approval network. Consistent with what we might expect, trust of the customer is positively associated with the presence of an approval network. Contrary to what we might expect, high levels of economic uncertainty make it *more* likely that a deal will reach the approval process. Although this finding appears counterintuitive, our interviews suggest a straightforward explanation. For high risk deals, several bankers told us, it is important to begin securing approval as soon as possible. For low risk deals, in which the securing of approval is unproblematic, bankers will often refrain from seeking approval until they believe the deal has a good chance of closing. This means that a significant number of low risk deals will fall apart before the banker has established an approval network. As a consequence, high risk deals have a higher probability of reaching the approval process.

Moving to the substantive analysis, because the Heckman model produces inefficient estimates, some authors (Berk and Ray 1982:382; Breen 1996:40) have recommended the use of an alternative, maximum likelihood, estimator. Breen (1996:70-71) describes a test for whether the maximum likelihood estimator, as opposed to OLS, should be used. This involves regressing the hazard rate (λ) on the variables in the substantive equation. If the coefficient of determination from this equation is close to zero, Breen recommends the use of OLS. We conducted this test and found that the estimated R^2 was zero, rounded to six places. All seven regression coefficients, plus the constant, had T-statistics of virtually zero. Consistent with Breen's suggestion, the results of the equations using OLS and maximum likelihood estimators were virtually identical. This finding suggests that OLS estimates are appropriate.

Equation 3 presents the OLS equation predicting the strength of the banker's relations with members of their approval networks. The findings in this model are consistent with the first equation's finding on information networks: In deals with high levels of economic uncertainty, bankers are more likely to turn to colleagues with whom they are close. As in the information network model, the effect of trust of the customer is not significant. Although we did not issue an explicit hypothesis for the effect of complexity, we note that this effect approaches statistical significance in a two-tailed test ($p=.08$). This finding raises the possibility that bankers are using larger networks for complex deals. A separate analysis (not shown here) provides support for this notion. Complexity has a significant positive effect on the size of the banker's approval network ($T=2.508$, $p < .01$). As with the information network, the use of larger networks occurs in complex deals but not in risky ones. Economic uncertainty does not increase the size of bankers' approval networks; in fact, the effect is negative ($T=-1.928$, two-tailed $p=.054$). The findings in Table 2 thus indicate that bankers turn to their strong tie colleagues for support in high risk situations but the level of economic uncertainty has no effect on the size of the approval network.[10] In contrast, complexity leads to the creation of larger networks but does not affect the strength of the bankers' ties.. The banker's trust of the customer firm, does not predict the nature of the ties the banker consults. But the findings on the role of economic uncertainty are consistent with Hypotheses 1 and 2.[11]

---

[10] As with our analysis of information network tie strength, we inserted size of the approval network into the model in Equation 3. In this case, the effect was significantly negative (T=-3.785, p< .001): larger networks were associated with weaker ties. The presence of this variable had no impact on the size or strength of the economic uncertainty coefficient, however.

[11] As noted above, our two-stage model treats ego network strength as endogenous in the first stage and alter network density as exogenous in the second stage. To what extent does uncertainty predict the structure of bankers' alter networks? To examine this, we substituted alter network density for ego network strength as our dependent variables and recomputed the equations in Table 2. None of our predictors was significantly associated with information network density. This means that although bankers turned to their strong direct ties for information in high-risk deals, they did not appear to strategically construct either a dense or a sparse alter network. With approval network density, on the other hand, the results were almost identical to those predicting approval ego network strength. High levels of economic uncertainty were associated with high levels of alter network density. This is in part an artifact of the high correlation between tie strength and density; when we control for tie strength, the economic uncertainty effect disappears. Another possible explanation is that bankers may sometimes be more successful in gaining support from a superior if they have already enlisted the support of another colleague whom the superior trusts. This is consistent with the example of the approval network from our interviews, described above. The fact that the finding disappears once we control for tie strength suggests caution with this interpretation, however. These findings, along with data from our interviews, provide

RESULTS: Determinants of Closure

As in our analysis of the determinants of approval network tie strength, our analysis of deal closure requires the consideration of a sample selection model. An approach similar to the Heckman model is available for situations in which both the selection and substantive equations contain binary dependent variables. In this case, the substantive equation is a second probit equation, with closure as the dependent variable. An alternative approach also exists under these conditions, however. If both dependent variables are dichotomous, it is possible to compute the sample selection model with a bivariate probit design (Greene 1995:465). In this model, the two probit equations are computed simultaneously through an iterative procedure. The error terms for the two equations are correlated, creating an autocorrelation estimate, rho (ρ), which is then included in the model.

Although Greene (1995:646) recommends the bivariate probit model, when we applied this model to our data, our log likelihood function did not converge to a clear solution. We therefore decided to examine Hypotheses 3-5 using both the two-stage and bivariate probit approaches. With a few exceptions, the two models yielded virtually identical results. Because there were differences and because we lack a clear basis on

---

little systematic evidence that bankers were strategically tailoring their networks to take into account relations among their alters.

which to choose, we report both sets of results in the analyses that follow.[12]

Because we are using the selection equation for the existence of the approval network (Equation 2 of Table 2), we report only the substantive equations for closure in Table 3. Selection equations in the bivariate probit analysis vary across models, although they tend to be similar. We have included the associated bivariate probit selection equations in Appendix B (Table B1). Equations 1a and 1b present our basic model that tests Hypotheses 3-5 as well as the effects of the density and hierarchy of the bankers' information networks. Equation 1a provides the two-step estimates, while Equation 1b provides the bivariate probit estimates.

Hypotheses 3 through 5 deal with three broad predictors of the likelihood of a deal successfully closing: uncertainty; density of the approval network; and hierarchy of the approval network. All three are predicted to be negatively associated with closure. The first uncertainty variable, the log of the quantity exposure times the customer credit rating (economic uncertainty), is not significantly associated with the probability of closure in Equations 1a or 1b. This variable was significantly negatively associated with closure in the two-stage model when complexity was removed from the equation (not shown here). The effect disappears when we control for the complexity of the deal. The second uncertainty variable, the banker's trust of the customer firm, is not statistically significant in the two-stage model in Equation 1a but it does reach statistical significance in the

[12] Unlike the analysis of approval network tie strength in Table 2, a regression of λ on the predictors in the outcome equation indicated the need to include λ in all of the two-stage equations in Table 3.

bivariate probit model (Equation 1b). The effect of deal complexity is strongly significantly negative in both equations. As we would expect, the more complex the deal, the less likely it is to close. These findings provide mixed support for Hypothesis 3. Complexity has a strongly negative effect on closure. The level of economic uncertainty is not associated with closure once we control for complexity; and trust is significantly associated with closure in the bivariate probit model but not in the two-stage model.

The fact that economic uncertainty fails to predict closure seems counterintuitive. As we hypothesized, we initially expected risky deals to be more difficult to accomplish. One possible explanation for this finding may be the restructuring of deals that occurs during the approval process. We learned during our interviews that it is the bank's policy not to turn deals away but to restructure them until the bank believes it will secure an acceptable rate of return. Such a reconfiguration might involve securing an initial fee, charging a higher interest rate, or selling off parts of a loan. In such situations the banker benefits from the networks that produce creatively restructured deals, ones that can satisfy both the customer and the bank.

Among the remaining variables, the banker's report of the degree of consensus within the bank around the deal was not associated with success of the deal in either of the models.[13] Although the coefficients for banker rank and having UniBank as a lead bank are positive, neither effect reaches statistical significance. The fact that rank is not

[13] One possible reason for this may be a lack of validity of our indicator. Some bankers assumed, for example, that once a deal was agreed upon by all parties in the bank, it had a high degree of consensus, even if there had been considerable controversy at earlier stages.

significantly associated with closure may be in part because higher-ranked bankers tend to work on more complex deals.

TABLE 3 ABOUT HERE

Consistent with our earlier discussion, the density of the bankers' information networks was not significantly associated with the likelihood of closure. As we noted above, the information that bankers receive from colleagues may suggest that the deal is not worth pursuing, or that it should be handled differently (which may lead to the banker abandoning the deal and starting anew). The hierarchy of the bankers' information networks was positively associated with the likelihood of closure in the two-step model but was not significant (in a two-tailed test) in the bivariate probit equation. To the extent that this effect is positive, one possible explanation, supported by our interviews, is that bankers often reported that it was important to have good relations with product specialists when putting together a deal. Several bankers suggested that a strong relationship with a single product specialist may be sufficient to produce a successful deal.

The effects of approval network density and hierarchy are strongly negative in both models of Equation 1, providing support for Hypotheses 4 and 5. The broader the range of colleagues whose support is enlisted, the more likely a deal is to close.[14] Even when we

---

[14] One possible implication of our argument, suggested by an anonymous reviewer, is that sparse networks might be especially valuable in high-uncertainty deals. If so, this would suggest the presence of interaction effects between density and uncertainty. To examine this, we created interactions combining

control for the density of the approval network, the level of hierarchy is still strongly associated with closure. Bankers whose approval networks are dominated by one or a small number of alters are less likely to successfully close their deals.

The findings in Equations 1a and 1b of Table 3 thus suggest strong support for Hypotheses 4 and 5 and partial support for Hypothesis 3. Before we assume unambiguous support for Hypotheses 4 and 5, however, we must address two remaining issues: the size of the approval network and the strength of the banker's direct relations. Both of these variables, especially ego network strength, are highly correlated with approval network density, and the presence of all three variables in the same equation raises concerns about multicollinearity (the coefficient of determination of density regressed on the remaining independent variables is .695). Our solution to this is to enter each of the two controls separately and examine whether their presence affects the strength of the density effect. In Equations 2a and 2b we include network size. In Equations 3a and 3b we remove size and insert ego network strength. The insertion of approval network size has several interesting consequences. The effect of customer trust becomes more strongly significant in the bivariate probit model (Equation 2b) and approaches significance (p=.063) in the two-stage model (Equation 2a). The effect of information network hierarchy drops below

---

approval network density with economic uncertainty and complexity, both of which, if the reviewer is correct, we would expect to be negative. We did observe negative coefficients for these interactions, but none were statistically significant. We also examined interactions involving density and trust, all of which we also found to be non-significant. The effect of density appears to hold regardless of the level of uncertainty.

significance in the two-stage model. And the effect of complexity increases slightly in both models. If our earlier argument about the value of a broad range of support is accurate, then we would expect a large approval network to be consistent with success of the deal. We find a positive effect of approval network size in both models. Even when we take this variable into account, however, the effect of network density remains strongly negative, as does the effect of hierarchy. Clearly the effect of density is not an artifact of network size. A similar finding arises when we control for ego network strength (Equations 3a and 3b). Although the presence of this variable does reduce the effect of density, especially in the bivariate probit model, both effects remain significant, in the predicted negative direction, despite the possible presence of multicollinearity (the squared multiple correlation of alter density on the remaining regressors, including ego network strength but excluding network size, is .620). The strong, negative effect of approval network hierarchy holds in both equations, as does the negative effect of complexity. The positive effect of customer trust drops barely below statistical significance ($p=.0505$) in the bivariate probit model and remains non-significant in the two-stage model. The important findings in these two sets of equations, however, are that the effects of approval network density and hierarchy remain significantly negative in all four equations, even after we control for the effects of network size and ego network strength. This provides strong support for Hypotheses 4 and 5.

Despite the likely presence of multicollinearity, we also examined models with approval network size, strength, and density included simultaneously. These are presented in Equations 4a and 4b of Table 3. As is evident from the table, the simultaneous inclusion of network size and strength depresses the density effect below the boundary of statistical significance. The coefficients for strength and size remain significant in the expected direction, as does the effect of network hierarchy, although the effect of strength drops just below significance ($p=.070$) in the bivariate probit model (the simultaneous insertion of network density and tie strength into Equation 4b reduces the log likelihood function by 9.94, which is equivalent to an improvement χ^2 of 19.88 w. 2 df, $p < .001$). We believe that this finding on approval network density does not damage the support for Hypothesis 4, for two reasons. First, although multicollinearity among network size, strength, and density may lead to inflated standard errors for all three coefficients, this is especially likely to be the case for the density coefficient because the correlation between size and strength is only -.301, while that between size and density is -.512 and that between strength and density is .701. Second, even without a significant density effect, the combined findings for the size and strength variables are consistent with our argument. Network theory suggests that a large number of weak ties will create a diverse network, which is precisely the basis for our hypothesized effect of low density. It is true, as we noted above, that strong ties do not necessarily form a dense alter network nor do weak ties necessarily form a sparse one. Existing theory, and our own findings, indicate that this is very likely to be the case, however. Given the imperfect nature of our measures, the combination of large size and weak ties in a banker's network would seem to be a reasonable alternative indicator of the concept-- diversity of perspectives-- that our network density measure is designed to tap.[15] The findings in Equations 4a and 4b, along with those from the other equations in Table 3, are thus consistent with our argument in Hypothesis 4.

DISCUSSION

The results provide considerable support for four of our five hypotheses, and mixed support for the fifth. Bankers are more likely to deal with strong tie associates, for either information or support, under conditions of high economic uncertainty, supporting an important component of Hypotheses 1 and 2. Economic uncertainty does not have a significant partial effect on the closure of a deal, as we suggested in Hypothesis 3, but our finding that low levels of complexity are associated with closure is consistent with the hypothesis, and our findings on customer trust indicate that in at least some of our models, trust is associated with closure. Most significantly, we find strong support for Hypotheses 4 and 5. Relatively sparse and non-hierarchical approval networks are conducive to successful closure of a deal.

These findings suggest a paradox, however. On the one hand, when uncertainty is high, bankers cling to those they trust, with whom they are closely tied. On the other

[15] This holds, we believe, even if we make allowances for the possibility that some of the size effect could be capturing the degree of risk in the deal. Note, for example, that neither economic uncertainty nor trust is associated with network size.

hand, embeddedness in strongly-connected networks is precisely the condition that makes it more difficult to close deals. Uncertainty creates conditions that trigger a desire for the familiar, and bankers respond to this by turning to those with whom they are close. Yet it is these very actions that make it more difficult for the banker to be successful. Not only is this an illustration of the simultaneous weakness of strong ties and the strength of weak ones, but it is also a commentary on how our social instincts can run counter to our best interests.

Our findings touch on a number of issues. First, they support the contention from much organizational analysis that actors will use trusted individuals or symbols to deal with uncertainty, a finding consistent with a range of classic (Granovetter 1974; Spence 1974; Kanter 1977) and more recent (Podolny 1994; Stuart, Hoang, and Hybels 1999; Galaskiewicz, Dowell, and Bielefeld 2000) studies. Social networks have been found to be important means of managing uncertainty in other organizational contexts. We find that they are significant in the banking world as well.

But it is not only the presence or use of networks but also their specific character that is important. Granovetter's strength of weak ties hypothesis (1973) and Burt's concept of structural holes (1992) are both relevant to our study, and both emphasize the importance of distinguishing among types of ties and/or networks. In Granovetter's model, an actor is likely to receive a greater volume of information from weak ties. In Burt's model, an occupant of a structural hole is able to control the flow of information between different groups. The mechanism created by sparse approval networks among our bankers differs slightly from both of these formulations. We suggest that what a sparse approval network creates is a diversity of views, and potential criticisms, that compel the banker to create a higher-quality product. Consider as an analogy a scholar presenting an argument to a group of like-minded peers. Although the peers might be very knowledgeable about the topic, and therefore able to provide many helpful criticisms, they are also likely to share many broad assumptions with the presenter and one another. If the scholar then presents her material to a very different audience, to whose criticisms she has not been previously exposed, she may have a more difficult time convincing her listeners. On the other hand, had the scholar originally presented her work to an audience of unconnected alters (a group that is likely to have a more diverse set of views), she may be better prepared to anticipate the criticisms of a wider range of audiences in the future. We argue that a similar process occurs among our bankers. A deal that receives support from a tightly-connected group of alters may receive less probing criticism (or at least a less broad set of criticisms) from the banker's colleagues. We believe that ceteris paribus, these deals will be less attractive to the customer than will a deal that has been subjected to feedback from a more diverse group of colleagues. Another example of this phenomenon is illustrated in David Halberstam's *The Best and the Brightest* ([1972] 1992), in which a group of brilliant, but like-minded, Presidential advisors uncritically ushered the United States into full-scale military involvement in Vietnam. In addition to the acquisition of information (the weak tie hypothesis) and the ability to manage the flow of information (the structural hole hypothesis), then, our analysis suggests a third potential benefit of sparse social networks: criticisms that allow an actor to anticipate a variety of contingencies, or what we might call the *multiple lens* hypothesis.

Our finding also provides an example of one of the most venerable concepts in the social sciences: the unanticipated consequences of purposive social action (Merton 1936). Sociologists since Durkheim have focused on the non-rational elements of economic behavior, emphasizing the role of symbols, rituals, and trust. Our focus has been on bankers operating in a high-stakes arena in which there are strong incentives and measurable levels of success, exactly the conditions that even sociologists would concede lend themselves to rational behavior. We have strong reason to believe that our bankers are intendedly rational. They certainly have a clear set of goals and a set of strategies to accomplish them. The bankers are constrained by bounded rationality, however, in that they operate with a lack of clear information. Thus, even when they engage in purposive, intendedly rational behavior, their decisions may have consequences the opposite of what they expect. We have uncovered one such strategic paradox: the use of strong ties seems to be a rational strategy for managing uncertainty. Yet if bankers' ultimate goal is to close deals, then the use of strong ties appears counterproductive. It is the sparsely-connected, diverse approval networks that are most closely associated with the successful closure of deals.

This finding raises a series of questions that will require further work to address: How aware are these bankers of the rationale behind their use of approval networks and the consequences of their choices? Several bankers with whom we spoke after the completion of our formal interviews noted that our argument about the value of sparse approval networks "rang true." They did not appear to be aware of the negative association between the strength of their individual ties and the sparseness of their network, however. We also do not know the extent to which the use of strong ties actually reduced bankers' uncertainty. Nor do we know the extent to which bankers are aware of the potentially contradictory consequences of their decisions. And although we know that bankers have discretion in their use of approval networks, we lack information on the variation in the amount of choice that bankers had across deals. All of these issues could be addressed in follow-up interviews. They would provide a unique opportunity to examine the creation, and strategic use, of social networks.

Certainly these are preliminary results, and there are unique characteristics of deals that cannot be fully understood in the aggregate form presented here. We believe that we have uncovered a genuine strategic paradox, however, one that could have real consequences for the success of organizations and the individuals within them.

APPENDIX A: Analytic Model

Because we have examined more than one transaction per banker, our 194 deals are potentially non-independent. There are several means of handling this problem. One is to reduce the degrees of freedom in our statistical tests to reflect the number of independent observations. Another approach is to scale values on transactions to the person-means, a variant of what is called least squares with dummy variables (LSDV). Hannan and Young (1977) have shown that LSDV estimates are superior to OLS estimates in terms of both consistency and efficiency. Because none of our bankers had more than three deals, and for many we have information on only one or two, the LSDV approach is infeasible. An alternative is to compute robust estimates of the variance-covariance matrix, adjusted for clustered observations. This approach is well-suited to situations such as ours, in which the number of "groups" relative to observations within the groups is large (Rogers 1993). The use of robust standard errors was developed by Huber (1967) and White (1978). The adjustment for clustering was developed by Rogers (1993). The computer program STATA has a module to compute robust standard errors with clustering. Because we were conducting our data analysis with LIMDEP, Professor William Greene, the author of the program, generously wrote an algorithm for us to perform the computation within LIMDEP. This algorithm is based on the same principles as those described in the STATA manual (Greene, private communication; Stata 1999, pp. 256-260). The cluster estimate of the asymptotic variance-covariance matrix can be written as

$$\nu = V \; (G'G) \; V$$

where V is the standard variance-covariance matrix of the regression coefficients $[\sigma^2 (X'X)^{-1}]$ and G is an n x k matrix of sums of the individual scores (the first derivatives of the log likelihood) for the observations in each cluster, where n equals the number of clusters (in our case, the number of individual bankers) and k the number of exogenous variables plus one (the constant). For OLS regression, the elements in G are

$$g_i = \Sigma \; [(e_{it}/\sigma^2) \; x_{it}]$$

where e_{it} is the OLS residual of the observation t of group i and x_{it} is the value of the independent variable for the particular observation. For the probit model, the matrix equation is the same, but the elements of G are

$$g_i = \Sigma\,[\lambda_{it}\, x_{it}]$$

where λ_{it} is the inverse Mills ratio from the probit model for the particular observation (Greene, private communication; Greene 1995, p. 640).

Greene's LIMDEP algorithm operates by first computing a standard OLS or probit model, assuming independence, and then storing the residuals or inverse Mills ratios as input for the computation. The regression coefficients of the standard and clustering models are identical. Only the standard errors are different. The standard errors from our robust cluster analyses were in every case very similar to the conventional standard errors, and the substantive conclusions derived from them were identical. Results of the analyses with the conventional standard errors are available on request.

APPENDIX B: Selection Equations for Bivariate Probit Models

TABLE B1 ABOUT HERE

References

Allison, Paul D. 1978. "Measures of Inequality." *American Sociological Review* 43:865-880.

Baker, Wayne E. and Robert R. Faulkner 1993. "The Social Organization of Conspiracy: Illegal Networks in the Heavy Electrical Equipment Industry." *American Sociological Review* 58:837-860.

Berk, Richard A. 1983. "An Introduction to Sample Selection Bias in Sociological Data." *American Sociological Review* 48:386-398.

Berk, Richard A. and Subhash C. Ray. 1982. "Selection Biases in Sociological Data." *Social Science Research* 11:352-398.

Breen, Richard. 1996. *Regression Models: Censored, Sample Selected, or Truncated Data*. Thousand Oaks, CA: Sage Publications.

Burt, Ronald S. 1992. *Structural Holes*. Cambridge: Harvard University Press.

------. 2000. "The Network Structure of Social Capital" *Research in Organizational Behavior* 22:345-423.

Davis, Gerald F. 1991. "Agents without Principles? The Spread of the Poison Pill through the Intercorporate Network." *Administrative Science Quarterly* 36:583-613.

DiMaggio, Paul J. and Walter W. Powell. 1983. "The Iron Cage Revisited: Institutional Isomorphism and Collective Rationality in Organizational Fields." *American Sociological Review* 48:147-160.

Galaskiewicz, Joseph. 1985. *Social Organization of an Urban Grants Economy*. Orlando, FL: Academic Press.

Galaskiewicz, Joseph, Myron Dowell, and Wolfgang Bielefeld. 2000. "Testing Ecological and Social Capital Theories of Organizational Growth." Unpublished manuscript, Department of Sociology, University of Minnesota.

Gargiulo, Martin and Mario Benassi. 2000. "Trapped in Your Own Net? Network Cohesion, Structural Holes, and the Adaptation of Social Capital." *Organization Science* 11:183-196.

Granovetter, Mark. 1973. "The Strength of Weak Ties." *American Journal of Sociology* 78:1360-1380.

------. 1974. *Getting A Job*. Cambridge: Harvard University Press.

------. 1985. "Economic Action and Social Structure: The Problem of Embeddedness." *American Journal of Sociology* 91:481-510.

Greene, William H. 1995. *LIMDEP*. Version 7.0. Bellport, NY: Econometric Software.

Gulati, Ranjay. 1998. "Alliances and Networks." *Strategic Management Journal* 19:293-317.

Halberstam, David. [1972] 1992. *The Best and the Brightest*. New York: Random House.

Hannan, Michael T. and Alice A. Young. 1977. "Estimation in Panel Models: Results on Pooling Cross-sections and Time-series." *Sociological Methodology* 7:52-83.

Heckman, James J. 1979. "Sample Selection Bias as a Specification Error." *Econometrica* 45:153-161.

Huber, Peter J. 1967. "The Behavior of Maximum Likelihood Estimates under Non-standard Conditions." *Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability* 1:221-233.

Kanter, Rosabeth Moss. 1977. *Men and Women of the Corporation*. New York: Basic.

Labianca, Giuseppe L., Daniel J. Brass, and Barbara Gray. 1998. "Social Networks and Perceptions of Intergroup Conflict: The Role of Negative Relationships and Third Parties." *Academy of Management Journal* 41:55-67.

Lin, Nan. 2000. "Inequality in Social Capital." *Contemporary Sociology* 29:785-795

March, James G. 1994. *A Primer on Decision Making*. New York: Free Press.

Merton, Robert K. 1936. “The Unanticipated Consequences of Purposive Social Action.” *American Sociological Review* 1:894-904.

Meyer, John W. and Brian Rowan. 1977. "Institutionalized Organizations: Formal Structure as Myth and Ceremony." *American Journal of Sociology* 83:440-463.

Mizruchi, Mark S. 1992. *The Structure of Corporate Political Action*. Cambridge: Harvard University Press.

Pfeffer, Jeffrey and Gerald R. Salancik. 1978. *The External Control of Organizations*. New York: Harper & Row.

Podolny, Joel M. 1994. "*Market Uncertainty and the Social Character of Economic Exchange*." Administrative Science Quarterly 39:458-483.

Powell, Walter W., Kenneth W. Koput, and Laurel Smith-Doerr. 1996. "Interorganizational Collaboration and the Locus of Innovation: Networks of Learning in Biotechnology." *Administrative Science Quarterly* 41:116-145.

Rogers, William H. 1993. "Regression Standard Errors in Clustered Samples." *Stata Technical Bulletin* 13:19-23.

Simon, Herbert A. 1947. *Administrative Behavior*. New York: Macmillan.

Spence, A. Michael. 1974. *Market Signaling*. Cambridge: Harvard University Press.

Stata. 1999. *Stata User's Guide*. Release 6. College Station, Texas: Stata Press.

Stearns, Linda Brewster and Kenneth D. Allan. 1996. "Economic Behavior in Institutional Environments: The Merger Wave of the 1980s." *American Sociological Review* 61:699-718.

Stuart, Toby E., Ha Hoang, and Ralph C. Hybels. 1999. "Interorganizational Endorsements and the Performance of Entrepreneurial Values." *Administrative*

Science Quarterly 44:315-349.

Uzzi, Brian D. 1996. “The Sources and Consequences of Embeddedness for the Economic Performance of Organizations: The Network Effect." *American Sociological Review* 61:674-698.

White, Halbert. 1978. “A Heteroskedasticity Consistent Covariance Matrix and a Direct Test for Heteroskedasticity.” *Econometrica* 46:817-838.

Williamson, Oliver E. 1975. *Markets and Hierarchies*. New York: Free Press.

Winship, Christopher and Robert D. Mare. 1992. “Models for Sample Selection Bias.” *Annual Review of Sociology* 18:327-350.

Table 1A

Means, Standard Deviations, and Correlations
Among Variables, All Deals (N=173)

	Mean	SD	2	3	4	5	6	7	8	9
1. Outcome of the Deal (1=closed)	.495	.501	531	022	133	052	069	137	-139	019
2. Approval Network (1=yes)	.778	.416		190	118	055	092	091	-088	011
3. Log Economic Uncertainty	11.179	3.667			-089	-005	075	056	004	-017
4. Customer Trust	0.490	.501				123	114	131	141	301
5. Banker Rank	2.314	1.007					-002	056	209	134
6. Lead Bank	0.959	0.774						066	132	079
7. Consensus	3.849	1.060							-159	095
8. Complexity of Deal	3.399	1.143								059
9. Confidence in Management	3.577	.569								
10. Information Network Strength	.672	.166								
11. Information Network Density	.570	.222								
12. Information Network Hierarchy	.351	.280								

Decimal points are omitted from the correlation coefficients to conserve space.

Table 1B

Means, Standard Deviations, and Correlations
Among Variables, Deals with Approval Networks (N=137)

	Mean	SD	2	3	4	5	6	7	8	9	10	11	1
1. Outcome of the Deal 1=closed)	.636	.483	-122	094	031	027	124	-125	017	-135	–153	076	4
2. Log Economic Uncertainty	11.549	3.161		-060	-073	039	-015	-057	-030	235	044	-084	–0
3. Customer Trust	0.510	.502			182	124	243	125	337	012	-048	012	0
4. Banker Rank	2.338	1.006				006	006	269	120	236	104	–123	1
5. Lead Bank	0.987	.792					059	117	052	024	002	061	0
6. Consensus	3.885	1.011						-131	083	183	018	-054	1
7. Complexity of Deal	3.363	1.107							120	-104	-010	045	1
8. Confidence in Management	3.570	.579								007	-000	035	-0
9. Information Network Strength	.677	.161									583	–232	–1
10. Information Network Density	.577	.207										-134	–1
11. Information Network Hierarchy	.324	.253											0
12. Approval Network Size	3.662	2.094											
13. Approval Network Strength	.702	.171											
14. Approval Network Density	.656	.209											
15. Approval Network Hierarchy	.375	.314											

Decimal points are omitted from the correlation coefficients to conserve space.

Table 2

Effects of Uncertainty on Strength of Banker's Ego Networks

Independent Variables	Information Network (1)	Selection Equation (2)	Approval Network (3)
Constant	0.466***	-0.030	0.556***
	(5.412)	(-0.031)	(5.675)
Log Economic Uncertainty	0.007*	0.069**	0.011**
	(1.819)	(2.772)	(2.463)
Customer Trust	-0.007	0.430*	-0.006
	(-0.244)	(1.707)	(-0.162)
Banker Rank	0.031*	0.059	0.043**
	(2.093)	(0.444)	(2.596)
Lead Bank	0.014	0.116	0.015
	(0.793)	(0.790)	(0.778)
Consensus	0.018	0.043	-0.002
	(1.627)	(0.394)	(-0.137)
Complexity of Deal	-0.006	-0.143	-0.025
	(-0.526)	(-1.265)	(-1.706)
Confidence in Management		-0.135	
		(-0.543)	
R^2	.082		.104
χ^2		11.704	
df		7	
N	173	175	137

*p < .05; **p < .01; ***p < .001. Probabilities of the substantive variables are one-tailed. Those of the constant and control variables are two-tailed. Equations 1 and 3 are OLS models. Equation 2 is a probit model. Regression or probit coefficients are reported on the first line, with T statistics, based on robust variance estimates with clustering, in parentheses. Dependent variables for the three equations are strength of information network ties, whether the deal reached the approval stage, and strength of approval network ties respectively.

Table 3

Effects of Uncertainty and Network Characteristics on Likelihood of Deal Closure (Two-Stage Sample Selection and Bivariate Probit Models)

Independent Variables	(TS) (1a)	(BP) (1b)	(TS) (2a)	(BP) (2b)
Constant	1.949	2.347*	-0.819	1.845
	(0.595)	(2.191)	(-0.239)	(1.776)
Log Economic Uncertainty	0.057	0.012	0.115	0.011
	(0.442)	(0.326)	(0.860)	(0.340)
Customer Trust	0.579	0.349*	0.872	0.392*
	(1.061)	(1.682)	(1.533)	(1.857)
Banker Rank	0.055	0.045	0.072	0.035
	(0.392)	(0.376)	(0.551)	(0.268)
Lead Bank	0.260	0.158	0.328	0.163
	(1.102)	(1.207)	(1.356)	(1.194)
Consensus	0.052	-0.003	0.070	-0.030
	(0.395)	(-0.027)	(0.512)	(-0.289)
Complexity of Deal	-0.439*	-0.294**	-0.587**	-0.327**
	(-2.054)	(-2.569)	(-2.803)	(-2.788)
Information Network Density	-0.329	-0.265	-0.465	-0.469
	(-0.502)	(-0.415)	(-0.678)	(-0.706)
Information Network Hierarchy	1.243*	0.942	0.990	0.874
	(2.077)	(1.485)	(1.599)	(1.456)
Approval Network Density	-3.913***	-2.732***	-2.992***	-2.366***
	(-4.954)	(-3.961)	(-3.218)	(-3.087)
Approval Network Hierarchy	-2.076***	-1.542**	-1.684***	-1.411**
	(-4.274)	(-2.651)	(-3.218)	(-2.440)
Approval Network Size			0.231**	0.148*
			(2.748)	(2.016)
Approval Network Strength				
Lambda (λ)	2.825		4.415	
	(0.814)		(1.274)	
Rho (ρ)		0.999***		0.999***
		(6.647)		(11.915)
χ^2	47.747***		55.396***	
df	11		12	
Log likelihood		-146.137		-142.106

*p < .05; **p < .01; ***p < .001; probabilities for substantive variables are one-tailed; those for control variables are two-tailed. Probit coefficients are presented, with T-statistics, based on robust variance estimates with clustering, in parentheses. Equations 1a and 2a are two-stage (TS) selection models. Equations 1b and 2b are bivariate probit (BP) substantive equations. N=136 in all models.

Table 3 (continued)

Effects of Uncertainty and Network Characteristics on Likelihood of Deal Closure (Two-Stage Sample Selection and Bivariate Probit Models)

Independent Variables	(TS) (3a)	(BP) (3b)	(TS) (4a)	(BP) (4b)
Constant	2.877	3.087*	0.153	2.280
	(0.811)	(2.481)	(0.042)	(1.938)
Log Economic Uncertainty	0.066	0.141	0.119	0.016
	(0.473)	(0.366)	(0.825)	(0.451)
Customer Trust	0.608	0.349	0.883	0.406*
	(1.023)	(1.639)	(1.447)	(1.817)
Banker Rank	0.139	0.074	0.161	0.079
	(0.945)	(0.590)	(1.195)	(0.596)
Lead Bank	0.292	0.170	0.365	0.186
	(1.237)	(1.290)	(1.497)	(1.360)
Consensus	0.126	0.053	0.148	0.028
	(0.914)	(0.462)	(1.068)	(0.237)
Complexity of Deal	-0.537**	-0.340**	-0.674**	-0.361**
	(-2.380)	(-2.934)	(-2.966)	(-3.078)
Information Network Density	-0.322	-0.317	-0.479	-0.469
	(-0.475)	(-0.484)	(-0.649)	(-0.677)
Information Network Hierarchy	1.427*	0.962	1.158	0.825
	(2.229)	(1.710)	(1.740)	(1.517)
Approval Network Density	-2.289**	-1.614*	-1.347	-1.174
	(-2.478)	(-1.743)	(-1.260)	(-1.071)
Approval Network Hierarchy	-2.624***	-1.908**	-2.237***	-1.757**
	(-4.779)	(-2.828)	(-3.919)	(-2.829)
Approval Network Size			0.225**	0.151*
			(2.877)	(1.913)
Approval Network Strength	-3.199**	-2.134*	-3.192**	-2.052
	(-2.736)	(-1.712)	(-2.706)	(-1.475)
Lambda (λ)	2.978		4.502	
	(0.811)		(1.225)	
Rho (ρ)		0.998***		0.999***
		(5.532)		(7.338)
χ^2	53.670***		60.987***	
df	12		13	
Log likelihood		-143.526		-140.192

*p < .05; **p < .01; ***p < .001; probabilities for substantive variables are one-tailed; those for control variables are two-tailed. Probit coefficients are presented, with T-statistics, based on robust variance estimates with clustering, in parentheses. Equations 1a and 2a are two-stage (TS) selection models. Equations 1b and 2b are bivariate probit (BP) substantive equations. N=136 in all models.

Table B1

Selection Equation Coefficients for
Bivariate Probit Models in Table 3

Independent Variables	(1)	(2)	3	4
Constant	-0.232	-0.043	-0.302	0.135
	(-0.223)	(-0.043)	(-0.296)	(0.135)
Log Economic Uncertainty	0.074**	0.074**	0.074**	0.072**
	(2.661)	(2.640)	(2.768)	(2.582)
Customer Trust	0.439	0.433	0.421	0.411
	(1.566)	(1.556)	(1.538)	(1.498)
Banker Rank	0.102	0.100	0.122	0.116
	(0.746)	(0.717)	(0.911)	(0.848)
Lead Bank	0.190	0.179	0.210	0.178
	(0.971)	(0.897)	(1.009)	(0.870)
Consensus	0.062	0.081	0.066	0.080
	(0.582)	(0.722)	(0.615)	(0.726)
Complexity of Deal	-0.203*	-0.210*	-0.203*	-0.207*
	(-1.998)	(-2.018)	(-1.988)	(-1.981)
Confidence in Management	-0.098	-0.161	-0.090	-0.203
	(-0.407)	(-0.655)	(-0.405)	(-0.855)
N	173	173	173	173

*p < .05; **p < .01; ***p < .001. All probabilities are two-tailed. Each equation contains probit coefficients (with T statistics in parentheses) corresponding to the bivariate probit model of the corresponding number presented in Table 3. The dependent variable in the above equations is whether the deal reached the approval stage.