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

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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 be successful. This represents an example of the unanticipated consequences of purposive social action.

Uncertainty is a fact of life. The lack of knowledge about possible options and the outcomes of the choices associated with those options is a driving force in virtually all aspects of human decision making. From decisions on where to live, what school to attend, whom to marry (or whether to marry), and what occupation to pursue, social actors must almost always make their decision without knowledge of the consequences. We may seek control over the outcomes of our decisions, but we are never entirely successful in gaining this control. And as much as we bemoan the existence of uncertainty, life would be boring without it.

Uncertainty bedevils organizational life as well. Non-profit organizations struggle to gain information on ways to improve their funding base. Government agencies fear potential budget cuts in the legislature. And corporations merge in attempts to gain control of their markets so as to increase the predictability of their performance. 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. Whatever their line of business, banks' primary activity is to take risks. Banks are therefore an ideal laboratory to study how social actors manage uncertainty.

This paper is an examination of the means by which organizational actors, members of a major commercial bank, manage uncertainty. We argue that although actors in risk-taking organizations will rely heavily on formal assessment criteria in evaluating a potential transaction, these criteria will be insufficient under conditions of high uncertainty. When uncertainty is high, actors will rely on information obtained from their social relations with colleagues. The structures of the networks created by these social relations, we argue, will 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. 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.

THEORETICAL 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 theorizing about organizational decision making for several decades. Herbert Simon's classic work on satisficing (1947) was based on an explicit recognition of the role of uncertainty. Early rational actor models assumed that actors had complete information from which to optimize. Simon argued that there were cognitive and environmental limits to our ability to acquire complete information. Actors were therefore subject to bounded rationality. Within these limits, he suggested, actors chose the best satisfactory decision based on the information available.

In the past two decades, several prominent organizational models, including the transaction cost economics of Williamson (1975), the resource dependence model of Pfeffer and Salancik (1978), and the institutional theory of Meyer and Rowan (1977) and especially DiMaggio and Powell (1983), have drawn heavily on the concept of uncertainty. For Williamson, the bounded rationality experienced by firm actors created the potential for opportunism by suppliers and customers. The creation of internal hierarchies was viewed as a means of reducing the resulting transaction costs or, alternatively, as a means of reducing uncertainty. For Pfeffer and Salancik, the dependence of organizations on externally generated resources created a need to arrange for their smooth and predictable acquisition. The establishment of cooperative interorganizational arrangements, including joint ventures and director ties, was viewed as a means of reducing uncertainty. For DiMaggio and Powell, in highly uncertain environments, in which organizations have few clearly prescribed decision making criteria, organizations look to peers for clues regarding appropriate strategies and structures.

Implicit in these models is the notion that regularized social relations characterized by a high predicatability and reliability (what we might term "trust") can serve to mitigate the level of uncertainty among organizations and organizational actors. 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 compensate for a lack of knowledge, however. When knowledge about specific alters is available, the assumption is that actors will turn to those with whom they are closest. The consequences of uncertainty and the effects of social networks in reducing it play a central role in our study.

THE SETTING

In preparation for the study that we discuss in this paper, we conducted a preliminary study of the bank, which we refer to as "UniBank." Consistent with our above discussion, we framed our project as a comparison of decision making processes under conditions of relative certainty and uncertainty. Noting that several major financial institutions have attempted to rationalize and quantify their evaluation of customers in recent years (Altman and Haldeman 1995; McCoy, Frieder and Hedges 1994; McNamara and Bromiley 1997), we argued that in relatively clear-cut situations, in which a customer is either very strong or very weak, bank officers were likely to reach decisions using routine financial criteria. Under these conditions, we would expect to observe a high degree of consensus among a bank's officials. In less clear-cut situations, however, in which financial criteria are insufficient to determine whether or not the bank should extend credit, we expected officers to rely on their social networks, both within and outside the bank, to gauge their decisions.

Our preliminary study was designed to familiarize ourselves with corporate lending operations at UniBank and to examine the tenability of our initial hypothesis. The data for this study consisted of 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. All but two were taped.

The findings from our interviews were generally consistent with our original expectations. We found that the bank is attempting to rationalize the process of credit allocation by simplifying the approval of low risk decisions (such as situations in which customers draw on existing lines of credit). This new approach, although in its early stages at the time of our study, was designed to allow credit officers to focus more attention on the difficult and more high risk transactions. We found, as expected, that the bank is increasingly moving toward the use of quantitative evaluation criteria. Nevertheless, based on our interviews, the use of informal networks, both outside and inside the organization, continues to play a major role in decision making, especially in high risk transactions. As one banker explained, "for the deals that are risky, the models don't work. People still use word of mouth... There's the official procedures [sic] and the 'real way.' The 'real way' is old boys and buddies." We provide examples of the use of these networks in the following section.

Although our preliminary findings were intriguing, they were based on non-systematic data and analysis. Our sampling procedure was convenience-based rather than random and our interviews were only loosely-structured. In the present study, we identified a full sample of bankers to systematically address a series of questions about the nature of banker decision making under conditions of uncertainty.

UNCERTAINTY, NETWORKS, AND DEAL MAKING

Bank officials pursue several forms of information when processing a transaction. First, the bankers 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 debt 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.

To close a deal, a banker must not only sell products to the customer but he or she must also secure internal approval. This process requires the assignment of a credit risk rating, similar to those used by Standard and Poor and other rating services. Once the risk rating is assigned, the transaction is evaluated along a two-dimensional table known as the credit transaction grid. The grid consists of cells determined by a combination of the customer's risk rating and the bank's total credit exposure to the customer. Each credit transaction requires the signatures 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, with 4 being the lowest level. Senior bankers are generally at levels 4 and 3, risk managers are generally at levels 3 and 2, and executive vice presidents are at level 1. The higher the total exposure and/or risk, the higher the level of senior credit officer required for approval of the transaction. For unusually large and/or high risk transactions, approval at even higher levels is necessary. Above the senior credit officers is a six-member credit policy committee. Above this committee there are "contact executives," key senior executives such as the vice chairman of the bank.

Bankers involved in transactions utilize 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 bank brings in specialists 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. The risk manager was working with a banker putting together an acquisition deal involving a major manufacturing firm. Because the company had a high risk rating, the deal required approval by a Level 1 credit officer plus the credit policy committee and a contact executive. Initially the appropriate Level 1 signator was "uncomfortable" with the deal. His reading of the information provided led him to conclude that the deal was too risky. 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.

MODEL AND HYPOTHESES

Banking has not been a widely-studied topic in sociology, but the amount of research has increased in recent years (see Mizruchi and Stearns 1994a for a review of this literature). In addition to the classic work by Mintz and Schwartz (1985), three recent studies have examined banking in explicitly network terms. Baker (1990) has examined the strategies that firms use to manage their relations with investment banks. He shows that most large firms tend to deal simultaneously with several such banks to avoid becoming overly dependent on a single one. Stearns and Mizruchi (1993a; 1993b; Mizruchi and Stearns 1994b) have studied the determinants of firms' use of various forms of debt financing. They have shown that both the level and type of financing used by large U.S. firms is associated with the existence and type of financial representation on the firms' boards of directors. Uzzi (1999) has examined the social relations between banks and nonfinancial firms and the extent to which these relations affect the firms' access to capital and the interest rates that they pay on their loans. Firms that have ongoing social relations with banks have both better access to capital and pay lower interest rates. Our study shares some properties with these earlier works, but our focus is on three distinct areas. First, we examine financial transactions from the perspective of the lender rather than the borrower. Second, we examine individual decision making at a micro level rather than firm-wide behavior at an aggregate level. And third, we directly examine the role of individual bankers' social networks in their decision making.

Our units of analysis are transactions handled by individual bankers. The 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 transaction is successfully closed. In the first stage, we suggest that high levels of uncertainty will lead bankers to rely on their social 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 social uncertainty. Economic uncertainty is defined as the degree of perceived risk to the bank’s capital. Social uncertainty is defined as a lack of familiarity with a customer’s management. Several bankers told us of judgment calls, difficult decisions that they made, based on "gut feelings" about a firm’s management.

Both models suggest that in cases of high uncertainty, bankers will consult with colleagues within the bank to gain more information about their 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 of the actors whom a banker 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 decisions under conditions of high uncertainty are likely to be more complex than those under conditions of low uncertainty. As situations become more complex, the possibility for multiple interpretations increases. We noted above that once bankers have made a decision to pursue a deal, they may be required to 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 of the actors from whom a banker seeks approval for a deal.

The dependent variable in the second stage of the model is whether a transaction closed. By closure, we mean that the bank secures the customer’s business according to the terms of the deal. 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 bank's ability to construct an agreement with which its officials are satisfied and that meets the needs of its customers is the primary determinant of whether a deal successfully closes, 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 and social uncertainty 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 risk will be less likely to close. There are two reasons for this. First, bankers will be more likely to decide that the deal is too risky to pursue. Second, in cases in which bankers do pursue such deals, under conditions of high uncertainty, 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. 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, and ultimately close, a deal, however, a different outcome is possible 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, a situation associated with low density networks. 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 the low-density groups will tend to have received more criticism and questioning, as well as 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 also be able to present a "better" deal, that is, a more persuasive case to the customer. 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.[1]

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 can be approximated by examining the level of inequality in his or her 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

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[1] In an important study, Podolny and Baron (1997) advance Burt's argument on the effects of structural holes (sparse networks among a person's alters) on social mobility. In their argument, structural holes are predicted to be more useful in networks defined by ties that involve the transmission of resources, while cohesive networks are expected to be more valuable in networks defined by ties that convey normative expectations and social identity. The approval networks in our study are best viewed as resource-based within Podolny and Baron's scheme, since the approval network on a particular deal is the result of a banker's strategic action. Equally important, though, is that our dependent variable in this analysis is not approval per se, but rather the success of the deal on the market external to the bank. Our argument is that the ability of a banker to respond to a broad range of criticism within the bank will increase the deal's probability of success outside of it. In that sense, we believe that a diverse network will constitute an advantage.

banker, the more likely the transaction will close.[2]

DATA AND VARIABLES

The units of analysis are specific transactions. These transactions may include cash management (handling the firm's accounts payable and receivable), trading (such as foreign exchange and hedging devices including swaps and options on commodities, securities, or currencies), and capital market services (such as the preparation and, outside the United States, underwriting of public offerings) as well as traditional lending. Over the past twenty years, the latter has played a decreasing role in the bank's operations.

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 has targeted as its corporate customers. The bankers with whom we spoke represent sixteen business units in two domestic locations.[3]

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

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[2] Burt (1992; 1997) found one exception to this relation. Managers who were newly appointed and/or women were found to benefit from becoming attached to a mentor, a single, powerful individual. This was not the case for either white or minority males in general. We plan to examine this contingency hypothesis in subsequent analyses.

[3] 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. Although three of these units, branded consumer, chemicals/pharmaceuticals, and electronics, have offices outside the United States, all three conduct business in the U.S.

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. All of the initial interviews and a majority of the follow-up interviews were conducted in person. We conducted some of the follow-up interviews, including several that were necessary because the outcome of deals was not always known at the first follow-up, by phone. We were able to secure at least some information on 253 deals at their initial stage. We collected outcome information on 194 deals. Of the 194 deals for which we know the outcome, 96, or slightly under 50 percent, were successfully closed. Missing data on particular variables reduced the number of usable observations to 175 for most analyses.

Our primary exogenous variables are our measures of uncertainty, which we have called economic and social uncertainty respectively. Economic uncertainty is based on the size of the deal (the bank's exposure, or capital at risk) and the risk rating of the customer. We operationalized economic uncertainty, or economic risk, as the product of these two variables. Social uncertainty is defined in terms of the nature of the relationship between the banker and the customer. We measured social uncertainty in terms of the proportion of turnover among the individuals at the company with whom the bankers work. We asked each banker to name the number of individuals at the customer firm with whom he or she currently works, and the proportion of them who have turned over during the banker's relation with the firm. When there is frequent shifting among those with whom the banker deals, it suggests the absence of a well-established, close relationship with the customer.[4] We also included three questions on a banker's relations with the firm's management. These included two on the degree of trust and one on the banker's opinion

[4] A related, alternative indicator of social uncertainty is the number of individuals at the customer firm with whom the banker interacts. The use of this variable in our equations yielded results virtually identical to the percent turnover variable.

of the firm management's financial capabilities. The first two measures yielded little variation, however. Several bankers responded to our question about the extent to which they trusted the customer by saying that "if we didn't trust them, we wouldn't be doing business with them." We did use the third measure, the banker's degree of confidence in the firm management's financial abilities, as a control (more on this below). But we chose to use the percent turnover as our indicator of social uncertainty. In addition to its greater variation, this variable also has the advantage of being a behavioral rather than a subjective indicator.

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). 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 personal friend (defined in terms of knowing one another's family and/or having entertained in one another's homes). 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 two separate density measures. 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 density measure, which we refer to simply as "density," is the density of the banker's full network. 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.

The use of different network measures as dependent variables in Hypotheses 1 and 2 from those used as independent variables in the analysis of closure is consistent with existing theory as well as the model we develop. It is also consistent with our interviews, which suggests that the bankers are conscious of their direct relations with colleagues when selecting their networks. 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 our first-stage analysis (Hypotheses 1 and 2), and ego network information and approval network strength as exogenous variables in our second-stage analysis (Hypothesis 4). The relevant findings are presented in Appendix B and can be viewed concurrently with those presented in Tables 2 and 3 below. We note here, however, that these findings led to no changes in our substantive conclusions.

Our final variable, 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. In addition to the hierarchy of the approval network, we also included the hierarchy of the information network as a control.

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 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.

TABLE 1a ABOUT HERE

TABLE 1b ABOUT HERE

None of the correlations among the predictors is large enough to suggest concern about collinearity. Although the differences are not enormous, it is also noteworthy that the associations between the two uncertainty variables (log economic risk and log percent turnover) and outcome are more strongly negative among the deals that survived to the approval stage than among all deals.

Turning to our analytic results, because we have examined more than one deal per banker, our observations are not statistically independent. In the analyses in Tables 2 and 3 as well as Appendix B, 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 the analyses that follow (with the exception of Equations 1b and 2b in Table 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 indicators of uncertainty (the product of exposure and company risk rating and percent turnover of personnel at the customer firm) on the strength of the bankers' relations with members of their information network. Because both of these variables were sharply right-skewed, we converted them to logarithms (base e). Along with the uncertainty measures, we included two additional variables as predictors: the respondent-reported degree of consensus within the bank on the deal and the respondent-reported complexity of the deal, both on 1-5 scales. The consensus variable would appear to be a viable indicator of the level of agreement surrounding the deal. Unfortunately, we are doubtful that this is the case, since bankers interpreted the question in multiple, and occasionally contradictory, ways. 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. Consensus did have a positive, albeit small (.14) bivariate association with deal closure, but its virtually zero correlations with the uncertainty variables raise further questions about its validity. Nevertheless, we include it as a control. The level of complexity of the deal is also included as a control. Although complexity might appear to be closely related to economic uncertainty, the two variables have a virtually zero correlation among all deals and a slight (although not significant) negative correlation among deals that reached the approval stage. Complexity does have a negative bivariate association with consensus, both for all deals (-.16) and those that reached the approval stage (-.13).

TABLE 2 ABOUT HERE

As is evident in Equation 1, the level of economic uncertainty (the level of exposure weighted by the customer's risk rating) 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 social uncertainty variable; the level of turnover of personnel at the customer firm was not associated with the strength of a banker's information network ties. Complexity of the deal 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. The fact that this effect is not negative indicates that in some complex deals bankers still approach their strong ties. Moreover, the fact that the economic uncertainty effect 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. Consensus is marginally positively associated with strong information network ties. Although we did not present a specific hypothesis for this variable, this positive correlation is not what we would have expected. Given the negative correlation between consensus and complexity of a deal, we believe that this effect is tapping a similar process as that captured by the effect of complexity: high consensus deals are relatively straightforward, and therefore involve relatively routine consultation. The latter is more likely to occur with one's strong ties.[5]

The equations predicting the strength of ties with members of a banker's approval network (represented in Equations 2 through 4 of Table 2) require some discussion. Our model predicting the determinants of closure is based on the assumption that bankers make use of an information and approval network in every deal (or virtually every deal) on which they are working. In conducting our interviews, however, we discovered that a sizable number of unsuccessful deals terminate before they reach the approval process. This means two things. First, these deals do not have an approval network. More importantly, however, it means that the deals for which we do have data on approval networks may constitute a biased sample of the total number of transactions. We cannot examine the determinants of the nature of a banker's approval network nor can we examine the effect of the structure of this network on the outcome of a deal without taking into account the fact that a sizable number of failed deals have no approval network.

This phenomenon, known as sample selection bias, is a common problem in the analysis of social science data (Berk 1983). 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 instantaneous 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

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[5] The banker is probably more likely to agree with those with whom he or she is strongly tied. This would also account for the positive association between consensus and tie strength.

variable into the substantive equation. Because the disturbances in the substantive equation are likely to be heteroskedastic (Greene 1997:977), we use White's (1978) consistent estimator of the covariance matrix (available in LIMDEP) to correct for heteroskedasticity prior to computing the clustered standard errors in Equation 3 of Table 2. The results are substantively identical regardless of whether we apply White's correction, however.

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.[6] For our predictors of a deal reaching the approval process, we selected five variables: the four that served as predictors of strength of ties in the information network (economic uncertainty, percent turnover, complexity of the deal, and consensus) 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 four 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. The fifth variable was selected as the instrument (to be excluded in the substantive equation).

Equation 2 of Table 2 presents the selection equation predicting the existence of an approval network. Interestingly, only one of the five predictors in the selection equation, economic uncertainty, is significantly associated with the presence of an approval network. Contrary to what we might expect, high levels of uncertainty make it *more* likely that a deal will reach the approval process. Although this finding appears counterintuitive, our interviews suggest a straightforward explanation. As we noted above, UniBank has made significant attempts to rationalize the process of credit allocation. One means by which the bank has done this is by simplifying the approval of low risk decisions. For high risk

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

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.

The non-significant effects of turnover, complexity, and consensus, are at least in part explainable. On the one hand, the positive, albeit non-significant, effect of turnover may represent bankers' efforts to shepherd relatively high uncertainty deals through the approval process. On the other hand, deals with low complexity and high consensus would be expected to proceed further due to the greater ease with which they can be handled. The non-significant effects of these variables may reflect the presence of counteracting forces, such as the greater difficulty of doing business with a high-turnover customer and the tendency to withhold seeking approval on relatively simple and high consensus deals.

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 five 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. Some observers (Winship and Mare 1992:339-342) have expressed caution about the maximum likelihood procedure because it requires assumptions about bivariate normality of the disturbances that can be difficult to meet. If the maximum likelihood results are in question, then this reduces the reliability of the OLS equation as well. As a check on our results, we report both the Heckman and OLS results. The maximum likelihood equation is available on request.

Equations 3 and 4 present the substantive equations predicting the density of the banker's approval network alters. Equation 3 contains the Heckman model results, while Equation 4 includes the OLS estimates. The findings in these models, although different in some respects from those in Equation 1, are broadly consistent with the first equation's finding on information networks: In deals with high levels of uncertainty, bankers are more likely to turn to colleagues with whom they are close. Although the effect of social uncertainty in the Heckman model (Equation 3) is only marginally significant, both economic and social uncertainty are positively associated with the use of strong tie approval networks. In deals involving a combination of high exposure and high risk firms and in those with customers that have experienced a high level of personnel turnover, bankers are more likely to turn for approval to colleagues with whom they are close. In the OLS model (Equation 4), the positive effect of economic uncertainty on approval tie strength is considerably stronger than its effect in Equations 1 and 3. As in the information network model, the effect of turnover is not significant in the OLS model. Although we did not issue explicit hypotheses for the effects of complexity and consensus, we note that these variables are not significantly associated with the strength of ties in a banker's approval network, although the coefficient for complexity approaches statistical significance (for a two-tailed test) in the Heckman model. As in the equation predicting strength of information network ties, the effect of consensus is positive, albeit not significant, in the Heckman model. The effect is close to zero in the OLS model. Unlike the information network case, the non-significant effect of complexity runs in a negative direction in both models. In other words, there is also a slight, although not statistically significant, tendency for bankers to use strong tie approval networks for relatively simple, high consensus deals. This may result from the fact that less complex deals involve fewer participants so that bankers can turn easily to their close colleagues in such situations.

Regardless of the reason, these non-significant effects do not alter the fact that bankers turn to their strong tie colleagues for support in high risk situations, even when complexity is controlled. Despite the differences among Equations 1, 3, and 4, the findings in Table 2 are consistent with Hypotheses 1 and 2.

RESULTS: Determinants of Closure

As in our analysis of the determinants of approval network tie strength, our analysis of deal closure requires the use 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. The two models yielded virtually identical results in all but one case. We report both sets of results in the analyses that follow.[7]

Because we are using the selection equation for the existence of the approval

[7] The algorithm to compute robust standard errors with clustering, written for us by William Greene (see Appendix A), was not available for the bivariate probit model. As a result, the T-statistics that we report from these analyses are based on conventional standard errors. Because the conventional standard errors from the two-stage models were higher than those from the cluster models, the differences in the T-statistics between the two-stage and bivariate probit models reported in Table 3 are larger than what they

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 very similar. We have included the associated bivariate probit selection equations in Appendix C (Table C1). 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.[8] The two uncertainty variables, the log of the quantity exposure times the customer risk rating (economic uncertainty) and the log of the proportion of turnover of personnel with whom the banker deals at the customer firm (social uncertainty) are both negatively associated with the likelihood of a deal closing in the two-stage equation, consistent with Hypothesis 3. Although the two effects remain negative in the bivariate probit model, they are below the threshold for statistical significance. This is the only instance in our deal outcome models in which the results of the two-stage procedure deviate from those in the bivariate probit. We interpret this finding as indicating qualified support for Hypothesis 3. Once a deal reaches the approval process, high levels of both economic and social uncertainty have a tendency to reduce its likelihood of closure. The banker's report of the degree of consensus within the bank around the deal was not associated with closure in either of the two models. It is possible on the basis of this finding to conclude that the level of agreement among bankers about the viability of a deal does not affect the probability of closure. We believe that it may also reflect the lack of validity of our indicator.

would be had we reported the conventional standard errors for the former. This suggests that the T-statistics from the bivariate probit models are likely to be conservative estimates.

[8] In addition to these variables, we also considered the banker's rank as a control. Inclusion of this variable had no effect on closure, nor did it affect the strength of the remaining coefficients. Results of these analyses are available on request.

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. Although this finding is not contrary to our expectations, we did not predict it either. One possible explanation for this finding, 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. That an especially strong relationship with a single product specialist is sufficient to produce a successful deal is consistent with our finding that a hierarchical information network will increase the likelihood of closure.

The effects of approval network density and hierarchy are strongly negative in both models, providing support for Hypotheses 4 and 5. These effects were consistently the strongest in our models. The broader the range of colleagues whose support is enlisted, the more likely a deal is to close. Even when we 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 and even qualified support for Hypothesis 3, however, we must address one remaining issue: the complexity of the deal. We included this variable as a control in our analyses of the use of information and approval networks, as well as in our selection model equation for whether a deal reached the approval process stage. Because this variable was not a significant predictor in any of these three equations, we did not include it in our analyses of deal outcomes. As Table 1b indicates, however, deal complexity is negatively correlated with closure at approximately the same level as is economic uncertainty. Among all deals (Table 1a), complexity is more strongly correlated with closure than is either of the uncertainty variables. In Equations 2a and 2b of Table 3, we insert deal complexity into the substantive equation predicting deal closure. Although we include this variable primarily as a control, we predict that it will be negatively associated with closure. The insertion of complexity into the substantive equation is permissible because we still have one variable, the banker's confidence in the firm's management, from the selection equation that is not included in the substantive equation. Examining the coefficients in Equations 2a and 2b, we see that our two key predictors, density and hierarchy of the approval network, remain strongly negative, at about the same level as in Equations 1a and 1b. Hierarchy of the information network remains significantly positive, and consensus and information network density remain non-significant. The effect of complexity is negative, as expected. But the insertion of complexity into the equation causes the significant negative effects of our two uncertainty variables, economic risk and customer personnel turnover, to disappear in the two-stage model and weaken considerably in the bivariate probit. In fact, three of the four uncertainty coefficients change from negative to positive (albeit non-significant) signs. This calls into question our support for Hypothesis 3. High economic uncertainty remains a significant predictor of the use of strong tie information and approval networks. But, controlling for deal complexity, it is no longer a significant negative predictor of deal closure. Before we completely reject Hypothesis 3 on substantive grounds, it is possible that complexity itself represents a form of uncertainty. A deal might succeed or fail for reasons having to do with its structure, independent of the level of economic risk or the banker's social relations with the customer. If we think of perceived financial risk as economic uncertainty and unstable social relations with the customer as social uncertainty, then we might conceive of the complexity of a deal as technical uncertainty, or a lack of predictability created by the structure of the transaction, independent of its size, the company's financial condition, and the banker's social relations with the customer. These findings suggest that uncertainty may be a multidimensional concept that can be captured by a range of separate, and not necessarily correlated, indicators.

DISCUSSION

The results provide considerable support for our hypotheses. Bankers are more likely to deal with strong tie associates, for either information or support, under conditions of high uncertainty. And low levels of complexity, as well as 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 whom they trust, with whom they are closely tied. On the other hand, embeddedness in strong-tie 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 sociological issues. First, they support the contention from much organizational analysis (Granovetter 1974; Kanter 1977; DiMaggio and Powell 1983) that actors will use trusted individuals or symbols to deal with uncertainty. Granovetter's analysis suggested that employers rely on the recommendations of those they trust when dealing with the uncertainty involved in hiring. Kanter reiterated this claim, but also suggested that in the absence of personal references, decision makers would rely on symbolic information, such as physcial attributes or place of education (Spence 1974, makes a similar argument). DiMaggio and Powell also argued that under conditions of uncertainty, organizational actors would mimic those whom they viewed as worthy of respect. In all of these cases, actors are viewed as making use of actual or imputed social relations in their decision making. Galaskiewicz and Wasserman (1989) found that corporations in the Twin Cities area tended to mimic those with whom their leaders had social relationships when making contributions to local nonprofit organizations. Social networks have been found to be important 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 audience. 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. An 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. Conversely, March (1991) has discussed the value of a combination of "fast" and "slow" learners in an organization, suggesting the importance of a diversity of perspectives for solving problems. 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.

At the same time, unlike the actors in most network studies, in which the networks are taken as exogenous, our bankers actively constructed their networks, based on the nature of the deal on which they were working. These networks were not entirely endogenous. Bankers had limits on those whose support they could seek, and their choices were more constrained on some deals than on others. Yet within these limits, the bankers did have discretion. That their choices might have led to undesirable outcomes is an idea with clear practical implications.

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). Even what appear to be perfectly rational decisions may have consequences the opposite of what we 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 either 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 the 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. Deals often fail for reasons that have little to do with the actions of particular bankers. Customer needs may change. Their circumstances may be altered, by an acquisition attempt, for example. And a competitor may come through with a superior bid. We believe that we may 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. With one exception (the bivariate probit equations in Table 3 and in the appendices), we report the robust standard errors in our analyses. In every case, however, the standard errors based on the two approaches were very similar, and the substantive conclusions derived from them were identical. Results of the analyses with the conventional standard errors are available on request.

APPENDIX B: Models With Alternative Indicators of Density

We argue in the text that under conditions of high uncertainty, bankers will rely, for both information and approval, on colleagues with whom they are strongly tied (Hypotheses 1 and 2). We also suggest that deals in which bankers use low-density approval networks will have a greater probability of successfully closing (Hypothesis 4). We consider this a two-stage process that creates a paradoxical result: the outcome of a banker's attempt to reduce uncertainty becomes an impediment to successful closure of a deal. As noted in the text, however, our measure of the strong ties to whom bankers turn to reduce uncertainty, the strength of the actor's direct ties to alters, is not the same as our measure of the density of the network that we hypothesize to reduce the probability of closure, which is based on the density of ties among the alters themselves. Since strong-tie networks are not necessarily dense nor are weak-tie networks necessarily sparse, our argument contains a potential logical leap. Based on both theory and our interviews, we stipulate that bankers will be looking to specific peers rather than attempting to construct sparse or dense alter networks. There are occasions, however, in which bankers are conscious of inter-alter relations as they approach specific colleagues, as in cases in which one colleague's support is necessary to gain the support of another. To ensure that our findings are robust across measures, we present two tables, based on Tables 2 and 3 in the text. In Table B1, we present the equivalents of Equations 1, 3, and 4 in Table 2, but with alter network density for the information and approval networks as our dependent variables. In Table B2, we present the equivalents of Equations 1a, 1b, 2a, and 2b in Table 3, but with ego network density for the information and approval networks as independent variables. As in the Heckman models in the text, Equation 2 of Table 2 is the selection equation for Equation 2 of Table B1. The selection equations for the bivariate probit models are presented in Table C2 (Appendix C).

Turning first to Table B2, in which the results are straightforward, it is evident that the substitution of the strength of direct ties in the information and approval network leads to conclusions identical to those reached in Table 3. This suggests that the outcome of bankers' attempts to reduce uncertainty has a direct effect on the likelihood of deal closure. The use of strong-tie approval networks is associated with a lower probability of a deal successfully closing. Theoretically, we believe that the process by which this occurs is best captured by the multiple lens hypothesis discussed in the text. But this finding gives us confidence that the two-stage process we describe in the text is empirically accurate.

TABLE B1 ABOUT HERE

TABLE B2 ABOUT HERE

The findings in Table B1 are a bit more complicated, although they do nothing to alter our substantive conclusions. Equations 2 and 3 show that when economic uncertainty is high, bankers are likely to use dense approval networks. This finding is consistent with the one, reported in Table 2, in which bankers turn to those with whom they are close under conditions of high uncertainty. If bankers were aware that sparse alter networks increased the probability of closure, then we would expect them to construct sparse alter networks under uncertain conditions. Instead, they do the opposite. This does not necessarily mean that the bankers are never concerned about alter-alter relations. If eliciting support from one colleague is helpful in gaining the support of another, then bankers may actively construct relatively dense approval networks. This is consistent with our findings. Regardless of the bankers' consciousness of their inter-alter ties, the findings in Equations 2 and 3 add further support to our discussion of the strategic paradox that the bankers face. In the analysis of information networks (Equation 1), we find no effect of uncertainty on alter network density. This null effect raises the possibility that the bankers were seeking information from unconnected alters: On the one hand, high uncertainty leads bankers to turn to their strong ties. On the other hand, the alter networks among these strongly-tied peers are generally less dense than we would expect. It is possible that this finding reflects attempts by bankers to turn, for information, to strongly-tied alters who are themselves not densely connected. The null character of the effect leads us to be cautious about this interpretation, however.

Most important for our purposes, though, is the general conclusion from these two tables: The finding described in the text, that the networks bankers use under conditions of high uncertainty are precisely those that reduce the probability of a deal successfully closing, receives further confirmation here.

APPENDIX C: Selection Equations for Bivariate Probit Models

TABLE C1 ABOUT HERE

TABLE C2 ABOUT HERE

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Table 1A

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

	Mean	SD	2	3	4	5	6
1. Outcome of the Deal (1=closed)	.495	.501	531	022	-014	138	-139
2. Approval Network (1=yes)	.778	.416		190	103	091	-088
3. Log Economic Risk	11.179	3.667			024	056	005
4. Log Percent Turnover	1.433	1.719				079	010
5. Consensus	3.849	1.060					-159
6. Complexity of Deal	3.399	1.143					
7. Confidence in Management	3.577	.569					
8. Information Network Strength	.672	.166					
9. Information Network Density	.570	.222					
10. Information Network Hierarchy	.351	.280					

Decimal points are omitted from the correlation coefficients to conserve spa

Table 1B

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

	Mean	SD	2	3	4	5	6	7	8	
1. Outcome of the Deal 1=closed)	.636	.483	-122	-091	124	-125	018	-135	–153	
2. Log Economic Risk	11.549	3.161		-048	-015	-057	-030	235	044	-
3. Log Percent Turnover	1.516	1.742			019	051	025	031	083	-
4. Consensus	3.885	1.011				-131	083	183	018	-
5. Complexity of Deal	3.363	1.107					120	-104	-010	
6. Confidence in Management	3.570	.579						007	-000	
7. Information Network Strength	.677	.161							583	-
8. Information Network Density	.577	.207								-
9. Information Network Hierarchy	.324	.253								
10. Approval Network Strength	.702	.171								
11. Approval Network Density	.656	.209								
12. 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 (Heckman) (3)	Approval Network (OLS) (4)
Constant	0.501****	0.133	-0.277	0.618****
	(6.534)	(0.141)	(-0.459)	(6.603)
Log Economic Risk	0.008**	0.062***	0.049**	0.010***
	(1.953)	(2.439)	(1.835)	(2.506)
Log Turnover	0.004	0.061	0.037*	0.006
	(0.559)	(1.000)	(1.527)	(0.701)
Consensus	0.020*	0.061	0.030	-0.000
	(1.819)	(0.572)	(1.146)	(-0.032)
Complexity of Deal	0.001	-0.087	-0.061	-0.014
	(0.055)	(-0.811)	(-1.572)	(-1.014)
Confidence in Management		-0.010		
		(-0.045)		
Lambda (λ)			1.250	
			(1.544)	
R^2	.050		.058	.048
χ^2		8.197		
Log likelihood				
N	173	175	137	137

*p < .10; **p < .05; ***p < .01; ****p < .001. Probabilities of the substantive variables are one-tailed. Those of the constant and control variables are two-tailed. Equation 1 is an OLS regression model. Equation 2 is a probit model. Equation 3 is an OLS model with correction for heteroskedasticity. Equation 4 is an uncorrected OLS 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 four equations are strength of information network ties, whether the deal reached the approval stage, and, for the last two, strength of approval network ties.

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	7.793***	3.729****	-2.946	2.672**
	(2.917)	(3.433)	(-0.465)	(2.450)
Log Economic Risk	-0.185**	-0.051	0.286	0.010
	(-1.931)	(-1.108)	(1.029)	(0.277)
Log Turnover	-0.180**	-0.076	0.209	-0.031
	(-1.807)	(-1.159)	(0.956)	(-0.005)
Consensus	-0.075	0.046	0.293	0.039
	(-0.485)	(0.407)	(1.154)	(0.359)
Information Network Density	-0.358	-0.302	-0.309	-0.291
	(-0.540)	(-0.411)	(-0.473)	(-0.436)
Information Network Hierarchy	1.262**	1.094*	1.340**	0.989*
	(2.163)	(1.717)	(2.245)	(1.777)
Approval Network Density	-3.576****	-3.142****	-3.778****	-2.600****
	(-4.943)	(-3.846)	(-5.062)	(-3.666)
Approval Network Hierarchy	-2.052****	-1.755****	-2.025****	-1.581***
	(-4.268)	(-3.108)	(-4.151)	(-2.979)
Complexity of Deal			-0.646**	-0.229**
			(-1.740)	(-2.123)
Lambda (λ)	-4.839*		10.650	
	(-1.828)		(1.199)	
Rho (ρ)		-0.993		0.996****
		(-0.489)		(6.352)
N	136	136	136	136
χ^2	45.308****		47.606****	
df	8		9	
Log likelihood		-150.994		-149.592

*p < .10; **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 the two-stage models, in parentheses. Equations 1a and 2a are two-stage (TS) selection models. Equations 1b and 2b are bivariate probit (BP) substantive equations.

Table B1

Effects of Uncertainty on Density of Bankers' Alter Networks

Independent Variables	Information Network (1)	Approval Network Heckman) (2)	Approval Network (OLS) (3)
Constant	0.612****	-0.600	0.759****
	(5.352)	(-0.888)	(6.845)
Log Economic Risk	-0.122	0.069**	0.011***
	(-0.386)	(2.248)	(2.834)
Log Turnover	0.006	0.053*	0.005
	(0.554)	(1.551)	(0.461)
Consensus	-0.001	0.005	-0.042***
	(-0.029)	(0.171)	(-2.779)
Complexity of Deal	-0.013	-0.094*	-0.022
	(-0.787)	(-1.745)	(-1.138)
Lambda (λ)		1.898**	
		(1.985)	
R^2	.007	.090	.075
N	173	137	137

*p < .10; **p < .05; ***p < .01; ****p < .001. Probabilities of the substantive variables are one-tailed. Those of the constant and control variables are two-tailed. Equation 1 is an OLS regression model. Equation 2 is an OLS model with correction for heteroskedasticity (with the sample selection term based on the model in Equation 2 of Table 2). Equation 3 is an uncorrected OLS model. Regression coefficients are reported on the first line, with T statistics, based on robust variance estimates with clustering, in parentheses. Dependent variables are density of the information network for Equation 1 and density of the approval network for Equations 2 and 3.

Table B2

Effects of Uncertainty and Ego 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	9.283***	3.606****	0.864	2.753**
	(3.223)	(3.476)	(0.125)	(2.500)
Log Economic Risk	-0.249***	-0.061	0.125	0.004
	(-2.371)	(-1.277)	(0.405)	(0.101)
Log Turnover	-0.213**	-0.060	0.092	0.004
	(-2.218)	(-0.913)	(0.375)	(0.072)
Consensus	-0.013	0.123	0.286	0.129
	(-0.080)	(1.063)	(1.035)	(1.172)
Information Tie Strength	1.537	1.249	1.364	1.401
	(1.414)	(1.263)	(1.204)	(1.481)
Information Network Hierarchy	1.571**	1.181*	1.608**	1.264**
	(2.275)	(1.860)	(2.357)	(2.462)
Approval Tie Strength	-5.517****	-4.477****	-5.596****	-4.245****
	(-4.801)	(-3.784)	(-4.704)	(-3.934)
Approval Network Hierarchy	-2.515****	-1.979****	-2.507****	-1.917****
	(-4.445)	(-3.155)	(-4.488)	(-3.143)
Complexity of Deal			-0.515	-0.280***
			(-1.233)	(-2.496)
Lambda (λ)	-6.487**		5.750	
	(-2.332)		(0.596)	
Rho (ρ)		-0.993		0.998****
		(-0.861)		(6.731)
N	136	136	136	136
χ^2	45.215****		46.716****	
df	8		9	
Log likelihood		-151.337		-148.458

*p < .10; **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 the two-stage models, in parentheses. Equations 1a and 2a are two-stage (TS) selection models.

Equations 1b and 2b are bivariate probit (BP) substantive equations.

Table C1

Selection Equation Coefficients for
Bivariate Probit Models in Table 3

Independent Variables	(1)	(2)
Constant	0.072	0.273
	(0.075)	(0.310)
Log Economic Risk	0.060**	0.070**
	(2.314)	(2.514)
Log Turnover	0.083	0.062
	(1.225)	(0.909)
Consensus	0.071	0.093
	(0.689)	(0.920)
Complexity of Deal	-0.132	-0.113
	(-1.495)	(-1.201)
Confidence in Management	0.036	-0.081
	(0.180)	(-0.468)
N	173	173

*p < .10; **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.

Table C2

Selection Equation Coefficients for
Bivariate Probit Models in Table B2

Independent Variables	(1)	(2)
Constant	0.021 (0.021)	0.371 (0.417)
Log Economic Risk	0.063** (2.430)	0.064** (2.363)
Log Turnover	0.092 (1.360)	0.084 (1.235)
Consensus	0.067 (0.641)	0.063 (0.621)
Complexity of Deal	-0.140 (-1.595)	-0.107 (-1.136)
Confidence in Management	0.050 (0.252)	-0.073 (-0.407)
N	173	173

*p < .10; **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 B2. The dependent variable in the above equations is whether the deal reached the approval stage.