Getting a Bonus: Performance, Social Networks, and Reward among Commercial Bankers*

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ABSTRACT

Research on the effects of social networks on individual status attainment has exploded in recent years, but the results remain equivocal, varying across network structures, types of ties, and outcome variables. The focus in this literature has been on two primary outcomes—performance benefits and rewards (including promotion and compensation). These two types of outcomes have often been conflated, however, despite the fact that high levels of one do not guarantee high levels of the other. We examine the effects of job performance, network tie strength, and network structures on the size of the year-end bonuses received by 71 relationship officers in a major, multinational commercial bank. We find that performance has an effect on bonuses, but that several network variables have significant effects as well. In networks based on information acquisition, both strong ties and sparse networks are positively associated with high bonuses, as is the combination of the two. In networks based on approval and support for one's deals, neither tie strength nor density predicts bonus size, but the benefits of strong ties increase as network density increases. Our results demonstrate the importance of distinguishing networks based on collegial relations from those based on authority, as well as the importance of distinguishing the network factors that predict performance from those that predict rewards.

It is now a well-established finding that social network ties inside the workplace can lead to a range of advantages. The precise nature of these effects, as well as the types of network ties that contribute to them, have been the source of considerable debate. There is little doubt that the nature of informal linkages plays a significant role in organizational life, however. Among the benefits found to be associated with network ties, two broad types stand out. On one hand, networks have been shown to affect the rewards that actors receive, from promotions, to compensation, to being hired in the first place. On the other hand, there is increasing evidence that network ties also affect an actor's ability to perform his or her job. Network factors have been shown to have benefits for a range of performance outcomes, including successful completion of tasks, and increased sales to customers.

The fact that networks can influence both an achieved outcome—performance—as well as a potentially non-universalistic one—a reward—raises an interesting question: to what extent do networks simultaneously operate on both performance and reward? The existing literature has tended to treat performance and reward as either completely separate issues, or (usually implicitly) as interchangeable. Burt (1992), for example, refers to rapid promotion as an indicator of performance, when his own analysis raises the possibility that the network ties that facilitate promotion may do so for other, less universalistic, reasons. Podolny and Baron (1997) distinguish between performance and promotion, but do so implicitly, without discussing the relation between the two.

We believe that although reward and performance are likely to be related, they are not necessarily coupled. Even if a certain level of performance is necessary for any actor, it may be less important for some actors than for others. The questions we raise are twofold: First, what are the relative contributions of performance versus networks to the rewards that actors receive? And second, to what extent do the network factors that predict performance also predict reward? We argue that under conditions of ambiguity, in which performance is difficult to assess, networks take on an added importance. At the same time, we argue that certain kinds of networks may facilitate performance in a way that leads to increased rewards. We test these arguments using data on year-end bonuses among relationship managers in a large commercial bank. We show that

although the bank's evaluation criteria significantly predict a banker's bonus, the bankers' network ties are strongly associated with the bonuses they receive, net of performance. Moreover, the network ties and structures that account for strong performance differ from those that account for high bonuses. This suggests the importance of distinguishing between job performance and reward when examining the effects of intrafirm networks.

The paper proceeds in three stages. First, we situate our argument within the literature on intrafirm network effects on performance and rewards. Second, we examine the effects of two performance measures on banker bonuses. Finally, we develop and test a series of hypotheses on the effects of network ties and structures on bonuses. We show that both tie strength and network density play significant roles in the determination of rewards in networks used to extract information, but not in those used to generate approval for one's project. The effect of tie strength varies at different levels of density in both networks, however, in ways that are both consistent and inconsistent with the existing literature.

BACKGROUND

Over the past three decades, the study of social inequality has moved beyond its earlier focus on family background and human capital toward an emphasis on the role of social networks. In *Getting A Job*, Granovetter ([1974] 1995) showed that job seekers who found their employment through the use of social contacts had higher levels of job satisfaction and compensation than did those who found their jobs through formal means. He also found that it was one's casual acquaintances (termed "weak ties"), rather than close friends or relatives, who had the greatest impact on an actor's success in the job market. Several authors subsequently examined Granovetter's weak tie thesis (see, for example, Lin, Ensel, and Vaughan, 1981; Bridges and Villemez, 1986; and Marsden and Hurlbert, 1988), resulting in support to, and qualification of, the argument.

Most studies that examined the weak tie thesis were based on samples from general populations that included employees at a broad range of occupations. Some

researchers had begun to focus on the role of networks within a particular workplace, however. An early study by Brass (1984), for example, examined the ways in which networks contributed to interpersonal influence within a firm. An article by Krackhardt (1992) showed that the use of weak rather than strong ties during a union organizing campaign may have cost the union the election. The study of networks within the firm reached a major watershed with a publication by Burt (1992). It was not the existence of weak ties per se that conferred benefits, Burt argued. Rather, it was the fact, noted by Granovetter (1973), that a subject's weak ties were likely to be disconnected from one another, thus giving the subject access to broad and non-redundant sources of information. In a study of managers in a large corporation, Burt showed that those whose personal contacts were with individuals who were not connected with one another (that is, those who occupied what he called "structural holes") achieved more rapid promotion than did those whose ties were densely connected. The study by Burt led to a number of subsequent papers dealing with the effects of network ties within firms.

Burt's focus in *Structural Holes* was on two outcome variables. On one hand, he examined the extent to which industries that occupied structural holes in the network of inter-industry economic transactions had disproportionately high profit margins. On the other hand, he showed that individual managers within a high-tech firm who occupied structural holes experienced more rapid promotion than did managers who were in less advantageous positions. Throughout the book, Burt treats both outcome variables as indicators of performance. Podolny and Baron (1997), in their extension of Burt's model to different types of networks, also focus on promotion as a dependent variable. These authors treat promotion and performance as virtually identical, noting that various network structures will affect "performance, and hence mobility" (ibid: 676). The assumption that Burt is measuring performance is unarguable in the case of profits, the most commonly-used indicator of this variable at the firm (or, in this case industry) level. The same cannot be said of promotion, however. Although it is certainly true that rapid promotion may be a function of strong performance, there is no guarantee that it will be. Promotion could be more accurately treated as a reward rather than an indicator of performance. Even if they are highly correlated in practice, conceptually, performance and reward should be treated as distinct.

Although there have been other studies that have examined hiring (Fernandez and Weinberg (1997), promotion (Gabbay, 1997; Sparrowe and Popielarz, 2004), and compensation (Burt, 1997; 2000; Seibert, Kraimer, and Liden, 2001), most studies that have examined the effects of intrafirm networks on individual attainment have focused specifically on job performance. Burt (2000) has provided an exhaustive overview of this literature as of 2000. Several other studies (see, for example, Mehra, Kilduff, and Brass, 2001; Sparrowe, Liden, Wayne, and Kraimer, 2001; Ahuja, Galletta, and Carley, 2003; and Rodan and Galunic, 2004) have appeared since Burt's review.[1] What no one has done, to our knowledge, is to examine simultaneously the extent to which network ties affect both performance and reward.

In a study of 82 relationship managers in the corporate banking unit of a large commercial bank, Mizruchi and Stearns (2001) showed that bankers who constructed sparse networks to gain approval for their deals were more likely to successfully close a deal than were bankers who constructed more dense networks. In other words, they showed that network structure affected banker performance. Yet this study too left unanswered the relation between performance and reward. To what extent did the well-performing bankers receive compensation for their efforts? The data from the Mizruchi and Stearns study include information on the bankers' year-end bonuses, that is, they include data on the rewards the bankers received as well as on their performance. This allows for the examination of two additional issues that were not addressed by Mizruchi and Stearns: the extent to which the network structures that affected banker performance also affected their compensation, and the extent to which compensation was a function of performance as well as network ties.

In this paper we extend the Mizruchi and Stearns analysis of the relation between networks and performance. We begin with a discussion of the setting in which the study occurred. We then examine the extent to which the bankers' bonuses could be accounted for by their performance. We then consider the role of network ties in accounting for bonuses, including the bases for our contention that networks may affect rewards differently from the way they affect performance. Finally, we test a series of hypotheses about the effects of network ties and structures on the bankers' bonuses.

[1] Reagans and Zuckerman (2001) focus on the effects of network ties on the performance of work teams.

SETTING

Between May 1997 and March 1999 we conducted semi-structured interviews with 91 of the 110 bankers in the global relationship banking unit of a major multinational financial corporation that we call "UniBank." The bankers in this unit dealt with the approximately 1,400 corporations that the bank had targeted as its customers. The bankers with whom we spoke represented 16 business units in two domestic locations. The units were divided by both industry and city. The Midwest office, located in Chicago, was considered one unit, for example, while within the New York location there were 14 separate industry groups—such as communications, electronics, and branded consumer goods—represented. In the twelve-month period prior to our interviews with the 91 bankers, we conducted 16 extended, open-ended, interviews with bank officers in three U.S. locations. We also pre-tested our interview instrument in a fourth location prior to beginning the formal interview process.

In an initial interview, we asked each banker to identify three deals on which she was currently working. We asked them to give us a range of deals, from simple to complex, that were in relatively early stages and for which the outcome was not known. We also collected detailed information on the nature of the deal and the banker's relationship with and views of the customer, as well as the banker's estimate of when he expected to know the outcome of the deals he had identified. Several months later we contacted each of the 91 bankers whom we interviewed at the first stage, and conducted a follow-up interview at which we learned the disposition of the deals. Because the outcomes of all of the deals were not always known at the first attempted follow-up interview, we in some cases conducted multiple follow-up interviews. At the follow-up stage we asked detailed information about the disposition of the deal. We also collected data on two types of networks (described below) for each of the deals in which the banker was involved. Because we requested information on three deals per banker, we collected data on six different networks for each of the bankers for whom we had three deals. We were able to successfully re-interview 82 of our original 91 bankers.

The earlier study was designed to examine the bankers' success rates in closing individual transactions, and our units of analysis were the deals rather than the bankers. We were able to collect individual-level as well as deal-level data, however. One important individual-level variable for which we have data is compensation, including the year-end bonuses that the bankers received. Just as the bankers were concerned with closing deals, they were also focused on the rewards associated with those deals. It nevertheless remains an open question whether the kinds of networks that facilitated success in closing deals were also those that resulted in high bonuses. In the following section we discuss these bonuses and their value as indicators of individual attainment. We then examine the extent to which the bonuses were associated with two different measures of banker performance.

HOW BONUSES WORK

The bankers we interviewed spanned five levels, from what were called "junior bankers" to senior vice presidents, but all had the same basic task: to sell to and close deals with the bank's corporate customers. All of the bankers received a fixed salary, which was pegged primarily to their rank: the correlation between the two variables in 1998 was .82. One of the interesting aspects of the bank's compensation system was the relatively low variation in salary levels among the bankers. The mean salary of $134,000 had a range from $76,000 to $210,000 but its standard deviation was only $25,000, and the distribution was surprisingly close to symmetric, with a skewness of only 0.227.

As in many corporate settings, the bankers' year-end bonuses made up a disproportionate share of their total compensation. The mean bonus in 1998 was $131,000, or virtually the same as the mean fixed salary. The variation among the bonuses was far greater than among the salaries, however. Bonuses ranged from a low of $5,000 to a high of $400,000, and the standard deviation among the bonuses was $102,000, or more than four times that of the salaries. The correlation between the bankers' salaries and bonuses was .68. Of the 81 bankers for whom we had data on both salary and bonus in 1998, 28 received bonuses that were higher than their salaries. In

many cases the differences were staggering. The two bankers who received the largest bonuses of $400,000 had salaries of $150,000 and $130,000 respectively. Meanwhile, two bankers with salaries of $138,000 received bonuses of only $75,000 and $60,000 respectively. It is evident from these data that the bonuses were the primary focus of attention for most of the bankers. As one of our key informants at the bank told us, bankers who receive several low bonuses in consecutive years "are usually shown the door."

How were the bonuses determined? We were able to interview four bank officials who were significantly involved in the process. It is clear from our interviews that the bankers' performance on the job was the primary criterion for the size of their bonus. Exactly how that performance was determined is less clear, and seemed to be as much art as science. In terms of formal evaluation criteria, the bank had only a single, three-category, performance rating: performed as expected, performed above expectations, and performed below expectations. Not a single one of our bankers was rated as performing "below expectations." Twenty of the 81 for whom we had data (24.7 percent) were rated as performing "above expectations."

Beyond the formal indicator of performance was a series of additional factors, some of which were quantifiable but others that were not. An important quantifiable criterion was a combination of the banker's ability to close deals, as indicated by the proportion of her deals that were successfully completed, and the size of those deals. In other words, bankers were rewarded to the extent that they were able to close on a series of large deals that promised significant revenue for the bank.

Regarding the non-quantifiable aspects, the primary basis for one's bonus appeared to be the perception of the banker's performance held by the senior managers who supervised him. This evaluation was usually made by comparing the banker to an identified peer group of those in similar positions. As one banker explained,

> "What would happen is that _____will put in a recommendation based on performance, and that includes revenue, net new revenue, teamwork, types of diversity of business done with different clients, and they will match that up against the peer group to see who did what and what level of net

> new revenue ought to be compensated for. But there is not a formula. It does not say for every dollar of net new revenue you will get X. It is subjective; there is no formula."

Part of the evaluation involves a general sense that the banker's activities are moving the bank in a positive direction, especially in terms of the bank's relations with its customers. As the same banker put it,

> "If I do the stuff I do and generate the business and the trend lines are good and everybody and all these external scores we use, in addition to revenue, that our clients like us, they are happy, we are being viewed as the top bank and all that kind of stuff, then good things happen at the end of the year."

Bringing in revenue and making customers happy are not the only factors that affect one's evaluation, however. It is also important that the banker establish a reputation as being willing to acknowledge his mistakes when one of his deals fails to perform.

> "Occasionally one is going to slip on you. Then they look really hard at how you handle it… Everyone's got a book around here. There is a book on me. You ask five people at the senior management… that know me, they will say this is what it is and that might be very different than is in my personnel file, but that is the book on me. Part of that is how I handle a deteriorating situation. Do I bring in the resources of the bank to minimize the damage? Or do I try to bowl through it and handle it myself and not tell anyone? You can actually be rewarded for doing it the first way. If you try to be a Texas Ranger, one ranger one ride, forget it; big takeaway difference. And everyone knows; I think everyone knows that."

Because there is no clear formula for assessing performance, the bankers' supervisors have a considerable degree of discretion. This means that particularistic factors, including the bankers' network ties to their supervisors and to other key players within the bank, as well as demographic characteristics that might be associated with these social connections, might conceivably play a role in the evaluations and subsequent rewards that the bankers receive. Before examining these factors, we shall examine the extent to which available indicators of banker performance account for their bonuses.

PERFORMANCE AND REWARD

Our units of analysis for the current study were the 82 bankers whom we were able to interview at both the initial and follow-up stages. This number was reduced to 80 due to missing data. All of the information pertaining to the bankers' deals with their customers, including the network data and the bankers' performance with their deals, were derived from our interviews. The remaining individual-level data were obtained from the bank's employee database. We had access to this database for the years 1997, 1998, and 1999. Because nearly all of our deals were resolved one way or another by the end of 1998, we used 1998 as our primary year, both in terms of our outcome variable and other individual-level data. Our dependent variable was the size of the bonus received by each banker at the end of the calendar year 1998.

In our initial analysis, we examined the effects of the bankers' performance on their bonuses, in the absence of controls. We examined two variables as indicators of the banker's performance. First, despite its lack of specificity, we used the bank's formal three-level performance measure, in which bankers were rated as performing below, at, or above expectations. As we noted earlier, none of our bankers was cited as performing below expectations, and about 75 percent were viewed as performing as expected. We therefore treated formal performance as a dummy variable, with 1 indicating that the banker performed above expectations. For our second measure of performance we considered the most important issues cited in our interviews: the ability to close a high proportion of one's deals, and in particular, to close deals that generated significant

revenue for the bank. These discussions suggested that it was the combination of a high closure rate along with large-sized deals that would have figured prominently in a banker receiving a high bonus. To measure this variable, we computed an interaction term reflecting the product between the proportion of the bankers' deals in our data that they successfully closed and the average level of dollar exposure to the bank for those deals (where exposure refers to the amount of the bank's capital that would be at risk during the course of the deal). This interaction represented the combination of a high success rate with large deals. Because the exposure level was highly skewed, we converted it to logarithms (base e) prior to computing the interaction term. The size of a banker's bonus was closely, although not perfectly, pegged to her salary (as noted earlier, the two had a correlation of .68). We therefore controlled for the bankers' salary in all of our models, except our first baseline model using performance as a predictor.[2]

Equation 1 of Table 1 contains the results of a regression equation with the bank's performance measure and our measure of performance (based on the bankers having successfully closed large deals), along with the main effects for deal size (the log exposure) and the banker's deal success rate. Because we predict that performance will be positively associated with bonuses, we use one-tailed statistical tests for both coefficients. As Equation 1 indicates, both performance measures are positively and significantly associated with bonus size. The equation indicates that being rated as performing above expectations corresponded to a predicted increase of nearly $66,000 of additional bonus. The effect of the interaction term for closure rate and deal size indicates that for a banker who closed all three of her sampled deals, the effect of log deal size on bonus size was 41.491, versus -1.653 for a banker who closed none of his deals. The two performance measures (along with the main effects for the interaction) combine to account for about 15 percent of the variation in the bonus.

[2] The distribution of bonuses is slightly right-skewed, and the results from the analysis using log bonus were similar to those using the non-logged version, except that the effects of performance were weaker in the logged version. All but one of our equations using the raw measure of bonus exhibited significant heteroskedasticity, as indicated by a Breusch-Pagan test. We recomputed these models using Huber-White robust standard errors. In no case did the use of robust standard errors result in a change in the substantive interpretation of our results. Given the increased interpretability of the coefficients, and the fact that

TABLE 1 ABOUT HERE

In Equation 2 we introduce the control for the bankers' salary. Not surprisingly, salary is a strong positive predictor of bonus size. The inclusion of this variable has a depressive effect on the coefficients for the two performance measures, but both remain statistically significant in the predicted (positive) direction. In fact, the T-statistic for the bank's performance measure actually increases when we control for salary. Being rated as performing above expectations corresponds to a predicted increase in one's bonus of more than $57,000 in this model. As is evident from the coefficients of determination, the insertion of salary into the equation allows the model to account for a considerably greater proportion of the variation in bonuses than do the two performance measures. The coefficient for salary indicates that a $1,000 increase in a banker's salary leads to a predicted increase of $2,671 in his bonus. The addition of the two performance measures (along with the main effects) to a model containing only salary raises the coefficient of determination by .079 (from .466 to .545).

As noted earlier, the correlation between salary and rank is .82. Not surprisingly, when we inserted rank into the equation, the effect of salary dropped sharply, but, as shown in Equation 3, the effects of the two performance variables were barely affected. An examination of the residuals indicated that the analyses in Equations 2 and 3 had significant levels of heteroskedasticity (Breusch-Pagan $\chi 2 = 20.8$ and 17.8 respectively, each with 1 degree of freedom, p in both cases < .001). We recomputed both equations using Huber-White robust standard errors. The results using the robust standard errors were virtually identical to those based on the raw standard errors in both cases.[3]

The results in Table 1 demonstrate that the bonuses that bankers receive are at least partially affected by formal measures of performance. The two performance measures that we used together account for only about 15 percent of the variation in bonus size. It would be misleading to suggest that this is a small level of explained variance, however, because bonus size is first and foremost a function of the banker's

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heteroskedasticity does not affect our results, we have decided to report the findings based on the raw bonus as our endogenous variable.

[3] These results are available on request.

rank and base salary, two variables that together account for more than 51 percent of the variation in bonuses. At the same time, the performance measures add only .074 to the coefficient of determination once salary and rank are controlled. This represents approximately 15 percent of the remaining variation.

The results of this analysis indicate that we can account for some portion of the bankers' bonuses based on formal measures of performance, but they also indicate that there are other factors, either alternative variables or alternative aspects of performance, that account for a sizable component of the bonuses. The quotes from our interviews suggest that performance is the primary determinant of one's bonus. Our findings suggest, however, that the variables that determine how performance is evaluated may depend on other factors, including those associated with the bankers' social networks.

We know from the study by Mizruchi and Stearns (2001) that the character of the bankers' networks affects their ability to close deals. It may be that the bankers' network ties affect their performance in ways that are not captured by either the bank's performance indicator or by the closing of large deals per se. In the following section we develop a series of hypotheses to account for the ways in which the bankers' network ties affect their bonuses. We shall argue that the kinds of network structures that lead to high rewards are not necessarily the same as those that contribute to outstanding performance.

HYPOTHESES

We have conducted a preliminary analysis of the effects of the bankers' performance on their bonuses. Except for the controls for salary and rank, we have not thus far considered any other potential predictors. Among the factors that might affect the size of the bankers' bonuses are a range of demographic factors, including race, gender, and marital status. We consider the effects of these variables in our subsequent analyses. Our primary theoretical interest, however, is with the effects of the bankers' social networks. In this section we introduce a series of hypotheses relevant this issue.

Given the predictions of the structural hole approach (Burt, 1992), as well as the predictions and findings generated by Mizruchi and Stearns (2001), our hypotheses

involving the effect of network structures on bonuses would appear to be straightforward: bankers with sparse networks should presumably earn higher bonuses than those with dense networks. There are two aspects of the research site for this study that complicate matters. First, as in the Mizruchi and Stearns study, we have data on two different types of networks, each of which may affect the bankers' bonuses in different ways. Podolny and Baron (1997) showed that the effects of network structures on promotion differed depending whether the ties constituting the network were based on instrumental or expressive relations. We argue that the effect of network structures may vary depending on whether one's ties are collegial in nature or based on relations of authority. Second, there are aspects of bonuses themselves that may lead to a set of network effects distinct from those predicted in earlier studies. We have suggested the importance of distinguishing between performance and reward, and we have argued that each might be predicted by different types of network ties and structures. While the study by Mizruchi and Stearns focused on predictors of one aspect of performance—deal closure—in this paper we focus on the predictors of a reward, in this case bonuses. At the same time, we suggest that the network ties that contribute to high bonuses may do so in part because they allow for stronger performance.

Two Types of Networks

In the process of putting together a deal, the bankers in our study made use of two types of networks. On one hand, they turned to colleagues for information and advice about constructing the deal. We refer to these ties as *information networks*. On the other hand, the bankers turned to a set of superiors to gain support for a deal once they had constructed it. We refer to these ties as *approval networks*. Those in the information network were a combination of a banker's peers and superiors. Those in the approval network were almost exclusively a banker's superiors. Because the two networks were used to accomplish different tasks, they had distinct criteria for selection. Even when the same individuals were involved in a banker's information and approval networks, the nature of the relations with those individuals differed.

Information networks consisted primarily of two groups. On one hand, they were product specialists, who had detailed knowledge of either the client with whom the banker was working or the specific financial product the banker was attempting to sell. On the other hand, they consisted of the banker's superiors, on whom the bankers called for similar kinds of advice. The information network served three functions: to determine the feasibility of a deal; to create a deal that would be more attractive to the customer; and to successfully implement a deal once it had closed. Because information networks contributed to both the quality and outcome of a deal, the character of these networks was a factor in the banker's performance of her job.

Approval networks consisted primarily of a banker's immediate superior as well as others above him in the hierarchy, whose support was required to allow him to offer a particular deal to the client. The function of the approval network was to gain confirmation that the deal would be a profitable one for the bank. Approval networks were therefore a factor in the way that a banker was evaluated by his superiors. Although a banker's superiors were often involved in his information network as well as his approval network, the nature of the relations with those superiors differed in the two cases. In the information network, the relations were collegial: the banker approached the superior as a colleague, to gain knowledge about task-related issues. In the approval network, the relations were hierarchical: the banker approached the superior as an authority figure, whose support she required in order to close a deal.[4]

The different character and functions of the two networks lead us to suggest a different set of hypotheses for each one. Our focus is on the effects of three separate network variables: the strength of the bankers' direct ties; the density of the networks formed by the ties among the bankers' alters; and the degree of hierarchy in the bankers' networks. We are also interested in the combined effect of tie strength and density—that is, whether the effect of a banker's network density varies depending on the strength of

[4] An analogue to this distinction occurs in the academic world. In some cases, a faculty member might approach his department chair to discuss a research issue, or a joint project. In other cases, the same professor might approach the chair in her role as department chair, to request support for a particular initiative. In the former case, the relation involves a transfer of information, and the chair is treated as a colleague. In the latter case, the relation involves a quest for support, and the chair is treated as a superior.

her individual ties. We suggest specific hypotheses for each variable across the two types of network.

Networks of Colleagues: Hypotheses Involving the Information Network

Network density. As we noted above, a banker's information network has value to the extent that it contributes positively to the performance of her job. One primary source of this value consists of high quality advice and feedback from one's colleagues. The question is what kind of network is most conducive to this high quality information. Most work within the network literature has focused on the value of weak ties. In the classic study of this process, Granovetter ([1974] 1995) found that job seekers who used weak ties had greater success in finding employment than did those who relied on strong ties. The primary reason for this, according to Granovetter, was that weak ties provide access to a broader range of information than do strong ties. One's strong ties tend to be densely connected to one another, so that the strong tie alter has access to the same sources of information as does the focal actor. The value of weak ties is that they tend to be disconnected from one another. The information one hears from a weak tie is therefore more likely to come from sources otherwise unknown to the focal actor.

Although strong ties tend to be connected to one another while weak ties tend to be disconnected, this is not always the case. It is possible for an actor to have strong ties with a set of disconnected alters. Burt (1992) expanded on this point by suggesting that it was the existence of non-redundant ties per se that provided sources of new information. In other words, a network of disconnected alters, regardless of whether the ties were weak or strong, was the source of "good ideas" (Burt, 2004). From the perspective of an actor, a network of non-redundant ties is sparse, in that one's direct ties are not tied to one another.

The bankers in our study relied heavily on the information provided by their colleagues. Because the quality of this information was likely to have had a direct effect on the quality of their performance, then to the extent that strong performance was associated with high bonuses, we would expect bankers with high quality information to

receive higher bonuses. Based on the above discussion, bankers with sparsely connected information networks were likely to have received higher quality information than did those with densely connected information networks. This suggests the following:

> H1: The lower the level of density in a banker's information network, the higher the bonus the banker receives.

Strength of Ties. Although sparse networks and weak ties do not necessarily correspond, empirically the two are likely to be highly correlated. The correlation between density and tie strength is .79 in our approval networks and .64 in our information networks. Given these correlations, it seems logical that if the effect of network density on bonuses is negative, then the effect of tie strength on bonuses should be similarly negative. At the same time, the correlation of .64 in the information networks indicates that there is a considerable amount of independent variation between the two variables. We argue that in the case of information network tie strength, a dynamic occurs that is entirely different from that involving network density. A primary reason for this has to do with the complexity of the financial instruments with which our bankers are dealing. Hansen (1999) found, in a study of project completion rates among 41 divisions of a large electronics and computer firm, that in dealing with complex (non-codified) information, strong ties were more valuable than weak ties. This finding confirmed the widely-held notion that while weak ties are valuable for information search, strong ties are more useful for information transfer.

The deals on which the bankers in our study worked had two components. On one hand, the banker constructs a deal and attempts to sell it to her corporate customer. On the other hand, once a banker closes a deal, the deal still has to "perform." That is, it has to be carried through, to ensure that the agreed upon terms are fulfilled by both parties. To accomplish this, the banker depends on those in her information network, especially the product specialists who advised her in the course of constructing the deal. The question is, which kinds of peers will be most willing to assist the banker in implementing the deal? This issue differs from the provision of information, which, as Granovetter showed in his study of the transmission of job information ([1974] 1995), is

often relatively cost free. It is closer to the transfer problem discussed by Hansen. To assist in implementing a deal requires considerably greater effort and commitment to the banker than does the provision of information. We suggest that it is those with whom a banker is close who will be most likely to provide this high level of commitment. To the extent that the securing of this assistance in implementing a deal contributes to improved performance, it suggests that ceteris paribus, an information network characterized by strong ties will contribute favorably to a banker's bonus. This suggests that:

> H2: The stronger a banker's ties with those in his or her information network, the higher the bonus the banker receives.[5] [6]

Tie strength and density. As we have seen, the primary basis of Burt's extension of Granovetter involves the notion that while tie strength might correlate with network structure, it does not determine it. By picking up on the fact that the important variable in Granovetter's model was density rather than tie strength, Burt noted that

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[5] In the previous section we examined two indicators of performance: the bank's formal evaluation criterion and an interaction term involving the product of deal size and deal completion rate, a measure that corresponded to what the bankers we interviewed told us were significant criteria that the bank used in determining one's bonus. Our discussion of deal implementation suggests that there is a third possible indicator of performance: the performance of the deal once it is successfully closed. Mizruchi and Stearns (2001) showed that neither density nor tie strength in the information network was associated with deal closure. This suggests that to the extent that information network density and tie strength affect a banker's performance, they may be more likely to do so at the (post-closure) deal implementation stage. Unfortunately, the bank does not keep records of the performance of individual deals. Instead, it records the aggregate performance of all deals for each of the bank's customers. This made it impossible for us to include a measure of deal-level performance. This means that although we can use information network tie strength and density to predict a banker's bonus, we cannot measure the extent to which these variables affect post-closure deal performance. We believe that to the extent that strong information network ties and sparse information networks are positively associated with the size of a banker's bonus, it is a result of their value for improving the performance of the banker's closed deals. The absence of data on this latter variable therefore requires us to treat the mediating link of deal performance as a black box.

[6] The suggestion that deal performance could serve as a mediating variable raises the possibility that a path model might best capture our hypothesized network effects for information network density and tie strength (as well as two of our subsequent hypothesized effects). Because, as noted above, we lack data on the component of performance that we believe is affected by information network density and tie strength, we cannot directly test the argument that information network density and tie strength affect bonus size through their effects on performance. We have therefore chosen not to present a path model in the analysis that follows. Instead, to examine whether the network effects on performance differ from those on reward, we shall compare Mizruchi and Stearns's findings on the determinants of performance with our results on

ceteris paribus, weak ties might actually be less beneficial than strong ties. This suggestion informs Hypothesis 2, above, but it also raises an additional issue: To what extent would an information network that combined strong direct ties with disconnected alters—that is, both high tie strength and low density—provide benefits above and beyond those resulting from either variable by itself? There is reason, based on our earlier argument as well as Burt's logic, to expect to observe a tie strength-density interaction. As Hansen (1999) notes, sparse networks may provide more information than do dense networks, but there is always the danger that the information one receives will be unreliable. Other things being equal, we would expect information from diverse sources to be of more use to the extent that it comes from alters whom the actor trusts. Such strong tie alters may also have a greater incentive than weak tie alters to provide accurate and detailed information, in part because of the level of commitment in the relationship, but also because these alters may themselves depend on ego for various favors (Pfeffer and Salancik, [1978] 2003). This discussion suggests that a combination of strong ties and sparseness within a banker's information network would yield benefits that would contribute to the banker's performance. To the extent that these performance benefits are reflected in the banker's bonus, we can suggest the following:

> H3: The stronger a banker's direct ties with the alters in his or her information network, the greater the effect of sparse networks on the size of the actor's bonus.

Hierarchy. One additional element of the structural hole hypothesis involves the extent to which actors are dependent on a single alter. Burt (1992) suggested that individuals whose bases of information and advice are monopolized by a strategically located individual are likely to experience disadvantages relative to those who have access to alternative sources of information and advice. An actor who is dependent on a single alter may have few others to whom he can turn if he fails to receive useful information or support from this person. This dependence on a single person, which Burt

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the determinants of bonuses. This is facilitated by the fact that we were able to replicate Mizruchi and Stearns's findings on the effects of both approval and information network density on deal closure.

refers to as network "hierarchy," is both conceptually and empirically independent of density. Our data indicate a small, and negative, association between hierarchy and density, -.29 in the information network and -.24 in the approval network. Although hierarchy and density are not positively correlated, we suggest that the two affect bankers' bonuses in similar ways. A hierarchical information network may restrict a banker's access to information just as a dense network does. This suggests the following:

> H4: The less hierarchical a banker's information network, the higher the bonus the banker receives.

Networks of Superiors: Hypotheses Involving the Approval Network

Network density. As we noted earlier, the approval network was a means by which a banker gained support from her superiors for a deal on which she was working. While members of one's information network were chosen primarily on the basis of their expertise, members of one's approval network were selected primarily on the basis of their authority. Just as a banker's information network could improve her job performance, the banker's approval network could have performance benefits as well. As Mizruchi and Stearns (2001) showed, bankers with sparse approval networks, in which their deals received confirmation from a disconnected group of superiors, were more likely to successfully close deals with their corporate customers than were bankers with more dense approval networks. Assuming that the improved performance that results from the use of sparse approval networks had a positive effect on the bankers' bonuses, we would predict a negative association between approval network density and bonus size.

There is one factor that might raise a question about this association, however. The approval network in our study, although not identical to what Podolny and Baron (1997) call their "buy-in" network, has similarities to it. Podolny and Baron define the buy-in network as "a network composed of those individuals whose support an actor needs in order to pursue initiatives successfully within the organization" (ibid: 676). The

buy-in network is defined in broader terms than our approval network. For Podolny and Baron, members of the buy-in network "have normative expectations for how ego should allocate time and what goals ego should pursue" (ibid). Our approval networks represented strategic connections used to construct a deal. In that sense, the approval network is directed more specifically to the completion of a particular task, rather than representing a more general conception of how one should go about one's work. Both networks involve an element of support, however. To the extent that a banker's approval networks stabilize over time, we might expect them to operate in a way similar to Podolny and Baron's buy-in networks. Because performance evaluation often contains an element of subjectivity, the same level of objective accomplishment may be evaluated differently depending on the evaluator's relation with the subordinate. The ties in a banker's approval network represent superiors who have indicated a level of support for the banker's deals. If these superiors are themselves densely-connected to one another, it suggests the possibility that they will provide a consistent basis of normative support. In other words, the support a banker receives from one superior may be reinforced by the close relations the superior has with other members of the banker's approval network, just as such reinforcement may fail to occur when such networks are sparsely-connected (Krackhardt, 1992). The consistent basis of support associated with dense networks of superiors may translate into favorable evaluations of the banker's performance. If this were the case, then we might expect a dense approval network to contribute to a high bonus.

There are reasons, therefore, to believe that approval network density could be either negatively or positively associated with the size of a banker's bonus. These two possibilities lead us to present two competing hypotheses:

H5a: The lower the level of density in a banker's approval network, the higher the bonus the banker receives.

H5b: The higher the level of density in a banker's approval network, the higher the bonus the banker receives.

Strength of Ties. In our discussion of the effects of information networks, we noted that ceteris paribus, strong ties would be positively associated with high bonuses, due to the significant role of one's information network partners in helping to implement a deal once it had closed. Unlike the information network, the primary benefits of one's ties in the approval network occur with respect to the closure of the deal, prior to its implementation. Mizruchi and Stearns (2001) showed that deals in which bankers used sparse approval networks were more likely to successfully close than were deals involving dense approval networks. Given that sparse networks are likely to consist primarily of weak ties, it would follow that approval networks with a preponderance of weak ties would be associated with greater success than would approval networks based primarily on strong ties. The question is whether the benefits of weak ties exist net of their association with low network density. Mizruchi and Stearns (2001) found that deals with weak tie approval networks were disproportionately likely to successfully close, even when network density was included in the equation. One possible reason for this, mentioned by the authors, was that the tie strength variable was accounting for a portion of a latent variable, alter diversity, that was not accounted for by network density. In other words, the independent effect of weak ties on deal closure may have been a consequence of measurement error.

Although weak ties in one's approval network may have been beneficial in the closure of a deal—a component of performance—we argue that they have a different effect on the distribution of one's bonus—which constitutes a reward. As with information network ties, in which we hypothesize that bankers will benefit from strong ties to product specialists who are willing to assist them in implementing a deal, we believe that for securing a bonus, bankers benefit to the extent that they have strong ties to their superiors. The disbursement of a reward reflects a degree of commitment, and it may incur (as well as result from) a sense of obligation. It is one thing to casually pass information, as appeared to have occurred to job seekers in Granovetter's ([1974] 1995) study. The payment of a bonus involves a far greater investment, however. Given a choice between rewarding someone who is a close colleague or friend versus one who is a casual acquaintance, most decision makers, we argue, would reward the close colleague or friend. This does not mean that there are never occasions in which one might

strategically choose to reward a more casual acquaintance over a close colleague. Friends' support may be taken for granted, and an actor may view it as useful to cultivate an alter with whom one is not close. Other things being equal, however, we believe that in the disbursement of rewards, a supervisor is more likely to reward those with whom she is close than those with whom she is distant. We therefore hypothesize that

> H6: The stronger a banker's ties with those in his or her approval network, the higher the bonus the banker receives.

Tie strength and density. In our discussion of the effects of bankers' information networks on their bonuses, we noted that the benefits of information networks resulted in part from their effect on the bankers' performance. Networks that were sparse, non-hierarchical, and characterized by strong ties were presumed to improve the bankers' performance, which in turn was predicted to have a positive effect on the size of their bonuses. In our discussion of the role of density in bankers' approval networks, we similarly suggested a link between performance and reward (although we suggested this possibility only for the effect of sparse networks on bonuses). In all of these cases, one could argue that networks benefit bankers because they facilitate the bankers' performance. In that sense, one could interpret support for Hypotheses 1-5a as evidence for a universalistic system, in which achievement rather than connections is the primary basis of one's rewards. From Granovetter through Burt, however, the effect of social networks on individual outcomes has often been viewed as less benign. Even if actors receive rewards based on their performance, network ties may give some actors advantages that make it easier for them to achieve high performance levels. Moreover, as we saw in our discussion of approval network tie strength, it is possible that a strong connection to a superior may positively affect one's reward, independent of his performance. Yet it is not only that strong ties to one's superiors lead to the possibility of a higher bonus. We argue that the extent to which strong approval network ties affect one's bonus may vary depending on the density of one's network.

One important aspect of the benefits of one's networks is the extent to which the banker is a member of, or has ties to, a relatively small, cohesive "inner circle" within the

bank. This inner circle, to the extent that it exists, is likely to consist of a relatively dense network of the banker's superiors. Sullivan, Haunschild, and Page (2007) found, for example, that firms with director interlocks with high status firms tended to have dense networks, since the high status firms tended to be connected to one another. It follows from this that if the superiors from whom a banker receives support are themselves densely connected, then the banker is connected to this inner circle. Note that the combination of strong ties to densely-connected alters would not indicate a connection to the inner circle in a network of peers, since highly-clustered peer networks may simply indicate relative isolation. Given their smaller numbers, however, a highly-dense network of superiors is likely to be centrally located in the organization's overall network.[7] In other words, dense networks among high-status actors are likely to be indicative of inner circle membership, or at least proximity to the inner circle. If this is the case, then a banker will receive benefits from a dense network to the extent that she has strong ties to her alters. This suggests that in the approval network—based on the support of one's superiors—we should observe a positive interaction effect between tie strength and density. This suggests the following:

> H7: The stronger a banker's direct ties with those in his or her approval network, the greater the effect of dense networks on the size of the actor's bonus.

Hierarchy. Mizruchi and Stearns (2001) found that bankers whose approval networks were non-hierarchical had a greater likelihood of successfully closing deals than did bankers with hierarchical approval networks. Even if, following Podolny and Baron, a dense approval network is beneficial in that it leads actors to experience a consensus of normative support, it is still preferable for a banker not to be heavily

[7] This can be illustrated by considering the most widely-used indicator of network centrality: the eigenvector approach developed by Bonacich (1972). In this measure, an actor is central to the extent that she is tied to other actors who are themselves central. If we assume that a banker's superiors are relatively central in the bank's network, then by definition they are disproportionately likely to be involved in densely-connected networks with other highly central actors. Brass (1984) relied on a similar assumption, defining a "dominant coalition" as a densely-connected group of high-level officials. He found that employees with close connections to this group experienced relatively high rates of promotion.

dependent on a single alter. This is especially true given that bonus decisions involve more than just the banker's immediate superior. To the extent that support from a plurality of alters is preferable to dependence on a single one, we can suggest that

> H8: The less hierarchical a banker's approval network, the higher the bonus the banker receives.

DATA AND MEASURES

As we noted earlier, the study from which this paper is drawn originated as a study of transactions, that is, the deals in which the bankers were involved. Our goal was to collect data on three deals for each of the bankers we interviewed. We were successful in most cases, but for some bankers we were able to glean complete data on only two or, in a few cases, only one deal. In the current study our units of analysis are the bankers rather than their deals. To develop individual-level network measures, we operated with the assumption that the network structures that characterized the bankers' multiple deals constituted a representative sample of the bankers' overall networks within the bank. Given the range of deal types for which we collected network data, we believe that this is a valid assumption. Consistent with this assumption, we were able to reproduce at the individual level of analysis findings equivalent to those that Mizruchi and Stearns (2001) generated at the deal level of analysis. The remainder of the data, both from our interviews with the bankers and from the bank's records, are either individual-level or can be easily adapted to the individual level.

For each of the networks, both information and approval, for each deal, we asked the bankers to name up to eight people whom they consulted for either information about the customer or the deal (information networks) or to whom they went to gain either support or confirmation for the deal (approval networks). To make it easier for the bankers to respond, we asked them to provide either first names or initials (Podolny and Baron, 1997: 680). For each of the alters with whom the banker had a relation, we asked the banker to rate the strength of the relation on a 1 to 4 scale, with 1 being an infrequent

work colleague (in terms of the amount of time spent interacting in work-related activities), 2 a moderately frequent work colleague, 3 a frequent work colleague, and 4 a frequent work colleague who was also a personal friend, in that the banker knew the person's family and/or they had socialized in one another's homes. A tie strength of 4 was thus based on an additional criterion—personal relationship—that was absent from the criteria in values 1 through 3. There were no cases in which bankers mentioned alters as personal friends where they were not also frequent work colleagues. We therefore view relation 4 as a higher point on a rough continuum. Once the bankers had identified their direct ties and the strength of the ties, we asked them to rate, to the best of their ability, the relations among each of the alters, on the same 1 to 4 scale. In some instances bankers suggested a rating of zero for the alter ties, on the ground that the alters did not know or were unaware of one another.[8]

To compute the average tie strength of a banker's network, we summed the values on the 1 to 4 scale for each alter (as well as the few cases in which the ties were defined as 0) and divided by 4N, where N was the number of alters (4N was the highest possible value, which would be achieved if every one of the banker's direct ties had a strength of 4). To compute the density of the banker's alter network, we used the formula $D_i = (\Sigma S_{jk}) / 2 (N^2 - N)$, where S_{jk} equals the strength of each of the alter-to-alter ties. The denominator represents the highest possible density, which would occur if every alter tie had a value of 4.[9]

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[8] This system for identifying alter networks, in which respondents are asked to estimate the relations among their alters, is the same as that originally devised by Burt (1984) for the General Social Survey of the National Opinion Research Center. It is the most widely-used approach for computing ego-centric network density. A question could be raised regarding the accuracy of the responses in which actors are requested to provide information on the relations among the alters in their networks. In the vast majority of cases, our respondents had little difficulty answering these questions. Given the widespread use of this measure by other researchers, as well as the ease with which the bankers responded to this task, we have a high level of confidence in the validity of these data.

[9] The number of possible ties in a network is $(N^2 – N) / 2$. Because 4 was the highest possible score for a given tie, the denominator in our measure of density was the quantity $(N^2 – N) / 2$, multiplied by 4. Most networks of person-to-person relations are binary, with a 1 representing the existence of a tie and a 0 representing non-existence. Because we were dealing with a relatively small group of actors inside a single organization, virtually every alter was at least acquainted with every other alter (except for the small number of cases in which alters, usually at remote locations, were unaware of one another). Had we coded the alter-to-alter ties as binary, we would have had little variation in network density; the vast majority of networks would have had a density of 1. Varying the strength of ties among the alters allowed us to gain a clearer sense of the degree of cohesiveness within each actor's network.

The hierarchy of a banker's personal network was operationalized as the coefficient of variation of the strength of the bankers' direct ties. This measure—the ratio of the standard deviation to the mean—is designed to represent the level of inequality in the bankers' personal relations. The greater the variation in strength among the banker's ties, the more likely she is to be dependent on a single alter. The coefficient of variation is slightly different from the measure used by Burt (1992) to capture hierarchy. Allison (1978: 877), however, has suggested that the coefficient of variation is a valid measure of inequality for variables of this type.[10]

Approximately 60 percent of our bankers had three deals for which we had complete information. Another 30 percent had two such deals, and the remaining 10 percent had one deal. For each of the bankers we computed the mean tie strength, alter network density, and hierarchy for each of their deals and then took the means of the three variables for both their information and approval networks. This left each banker with six individual-level variables: tie strength, density, and hierarchy, for each of the two types of network.[11]

In addition to the network variables, we examined several demographic and other individual-level measures. These included a series of dummy variables: the banker's gender (coded 1 for male), marital status (coded 1 for married), race (coded 1 for white), and whether the banker had earned a bachelor's, business, or law degree from a list of elite schools identified by Useem and Karabel (1986) (coded 1 for elite school graduate).[12] As in our earlier analysis of the effects of performance on bonuses, we controlled for both the banker's rank (based on the five levels the bankers spanned) and base salary. We also examined control variables for the banker's age (in years) and

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[10] Burt (personal communication) has conveyed to us that this measure provides a reasonable indicator of hierarchy. It is the same measure used by Mizruchi and Stearns (2001).

[11] In *Structural Holes*, Burt (1992) bases structural hole occupancy on three criteria: network size, density, and hierarchy. In tests of the structural hole thesis, most researchers have used network density—defined as we do here (except for the binary nature of the network ties)—as their primary indicator of structural hole occupancy (see Podolny and Baron, 1997). We examine hierarchy and network size (discussed below) as distinct variables in our analyses.

[12] Twenty-seven of the 82 bankers (33 percent) were women, 28 (34 percent) were unmarried, and 17 (21 percent) were non-white. Fourteen of the 17 non-whites were Asian, two were Hispanic, and one was African-American. Eight of the 14 bankers coded as Asian were U.S. citizens. Seventeen (21 percent) of

experience. We measured experience both in the number of years the banker had worked at UniBank, as well as the number of years since the banker's first appointment at the bank. The latter distinction was necessary because some bankers had worked at UniBank in earlier years, left, and then subsequently returned. Because the effects of network density may be artifacts of the size of the networks (given the way density is calculated, there is a built-in tendency for density to decline with network size), we controlled for the number of alters in both the information and approval networks.

Given our focus on the effects of the bankers' network ties and structures, we do not offer formal hypotheses for any of the demographic and performance variables that we include in our analyses. We do have predicted effects for several of these variables, however. We expect, following our findings in Table 1, to find that bankers with high performance levels on the two measures, and those at higher ranks and with higher salaries, will earn higher bonuses than those at lower levels of these variables. We also expect that bankers who are older and who have more experience will earn greater bonuses than those who are younger and have less experience, and that bankers with degrees from elite institutions will receive higher bonuses than those from non-elite schools, although this latter effect, if operative, could indicate either the use of particularistic criteria or the possibility that bankers with elite educations have higher levels of human capital that are reflected in their performance. As for the effects of gender, marital status, and race, we have no reason to believe that members of any of these groups experienced systematic discrimination within the bank. The possibility remains, however, that some form of disadvantage occurs. For this reason, we control for these variables.

Finally, one perpetually difficult issue in the identification of social network effects has been the problem of endogeneity. Even if we find that bankers with seemingly favorable network structures receive higher bonuses than those without such structures, the possibility exists that the networks are a consequence rather than a cause of these outcomes. In our case, it is possible that well-performing bankers (those who had earned high bonuses in the past) were highly sought after for both information and

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the bankers held college or professional school degrees from schools defined as "elite" by Useem and Karabel (1986).

support (or that their requests for information and support were more easily met), and that the associations that we observe between various network variables and bonuses could be a result of this form of selection. Our data include information on the bonuses the bankers received in the previous year. Including this lagged endogenous variable in our equations can help ensure that any effects we observe will not be spurious consequences of the previous year's performance. We conducted our analysis both with and without the lagged dependent variable. There were two differences in the results using the latter, neither of which affected the evaluation of our hypotheses, except in one case in which a network effect that was non-significant in the model without the lagged dependent variable became significant when the lag was included. For reasons that we discuss in the following section, we shall focus on the equation without the lagged dependent variable, and then introduce models with the lagged dependent variable.

RESULTS

Table 2 presents the means, standard deviations, and correlations among the variables.[13] Although we were able to assemble complete data for all 82 bankers on most

[13] Due to space considerations, as well as the fact that they did not affect our results, we have excluded age and the two experience variables from the analysis. One of the experience variables—the number of years in one's most recent tenure at the bank—had a significantly positive effect on bonus size, but its inclusion in the model had no impact on the coefficients or significance levels of the other variables. The effect of age in the full model was actually negative. Age was, not surprisingly, positively correlated with bonus size ($r = .347$) but the variable was so highly correlated with rank, salary, and years in tenure ($r = .699$, .653, and .700 respectively) that there was little independent variation left for it to explain. One possible interpretation of this negative coefficient is that it represents a "dead wood" effect. That is, perhaps the benefits of age are positive in one's early years but decline over time, to the point that an increase in age actually leads to a decline in one's bonus. To test this hypothesis, we created a quadratic term for age. If our conjecture is correct, we would expect to see a decreasing effect of age as age increases; in other words, a positive first-order effect and a negative second-order effect. When we inserted the quadratic term for age into the full model, both the first and second-order coefficients were negative, and both had T-statistics close to zero. When we examined a simple model with only age and age^2 as our independent variables, however, we did observe coefficients in the predicted direction: the coefficient for age was 27.36 ($T = 1.89$, $p < .05$) while that for age^2 was -.26 ($T = -1.56$, $p < .10$). These coefficients indicate that the effect of age on bonus size would hit zero (and begin to turn negative) at an age of 52.4 (where the inflection point is computed by setting the second derivative of the original regression equation equal to zero, which yields $-b_1 / 2b_1^2$); we reiterate that this model includes only age and age^2, with no controls. As with the experience variable, the inclusion of age in our model had no effect on the size or significance of

variables, missing data on some of our network variables reduced the number of observations in our regression models to 70. The correlations indicate that men and married persons earn significantly higher bonuses than do women and single persons ($p < .05$ in both cases). The correlations for "white" and elite education are also positive, indicating that whites and those with one or more degrees from elite institutions receive higher bonuses than do minorities and those without a degree from an elite school. Neither of these correlations is statistically significant, however. Moreover, the effects of gender and marital status disappear once controls are introduced.

TABLE 2 ABOUT HERE

TABLE 3 ABOUT HERE

Table 3 includes four regression equations, with various combinations of predictors. Because we hypothesize specific directions for all but one of our network variables, and because we have clear expectations for the directions of salary, rank, and the two performance measures, we use one-tailed statistical tests for all of these coefficients, except that involving approval network density, for which we test two competing hypotheses. We use two-tailed tests for all of the remaining variables, including the four demographic variables and information and approval network size. We do not test hypotheses for the main effects of variables that are components of interaction effects.

Equation 1 of Table 3 presents the full model, excluding the network interaction terms. Several things are of note in this equation. First, as we would expect, both rank and salary are positively associated with bonus size. Interestingly, these effects remain statistically significant despite the fact that the two variables have a correlation of .827. Second, even with salary, rank, and the demographic and network variables included in the model, the effects of the two performance measures remain positive and statistically significant. Bankers who were evaluated as performing above expectations received a

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the remaining coefficients. Detailed results of the models computed with age and the two experience variables are available on request.

predicted bonus nearly $48,000 higher than those who were evaluated as performing according to expectations. Third, none of the four demographic variables—race, gender, marital status, or elite education—was significantly associated with bonus size. In fact, not one of these variables had a T statistic even approaching statistical significance. The higher bonuses that men and married persons receive thus appear to be due primarily to differences in rank.

In terms of the network effects, we hypothesized that bankers with information networks consisting of relatively strong ties and sparse networks would earn higher bonuses than bankers with relatively weak ties and dense networks. Both of these hypotheses received support in our findings. An increase in average tie strength of .1 leads to a predicted increase in one's bonus of more than $24,000. By the same token, an increase in network density of .1 leads to a predicted decrease in one's bonus of nearly $21,000. These findings hold even when we take the size of the information network into account. They lend support to Hypotheses 1 and 2.

The other hypotheses tested in Equation 1 fare less well. Information network hierarchy has virtually no effect on bonus size (the coefficient is positive, contrary to prediction, but is close to zero). None of the coefficients involving the approval network are statistically significant. The strongest effect involves approval network tie strength, which, contrary to Hypothesis 6, is negatively associated with bonus size.[14] This negative effect may be due to the possibility that the weak ties variable is in part tapping characteristics of a sparse approval network. On the other hand, the approval network density coefficient is positive, albeit very small. Because we derived two competing hypotheses for approval network density, the fact that the effect is not significantly different from zero may reflect the possibility that both low and high density networks could, in different circumstances, have positive effects on bonus size. Another possibility is that the null effect of both variables is due to multicollinearity (the correlation between mean tie strength and density in the approval network is .793). To consider this possibility, we examined two separate equations, one with approval network

[14] The coefficient is not statistically significant (T = -1.11), but given that we are employing one-tailed tests for all of our hypothesized effects except those in Hypotheses 5a and 5b, we cannot reject a null hypothesis

tie strength only and the other with approval network density only. The coefficient for tie strength actually declined, from -111.56 to -85.55, while the T statistic remained virtually identical (-1.11 versus -1.14). The coefficient for density moved from positive (37.3, T = 0.39) to negative (-31.97, T = -0.45), but it remained close to zero, and nowhere near statistically significant. The null results for approval network tie strength and density are thus not due to multicollinearity. The approval network hierarchy coefficient was negative, as predicted by Hypothesis 8, but this effect also does not approach statistical significance.

Equation 2 of Table 3 includes the same model as Equation 1, except that we insert the interaction effects between tie strength and density for both the information and approval networks. In Hypothesis 3 we suggested that bankers would benefit from a combination of strong ties and sparseness in their information networks, so that the interaction effect would be negative. In Hypothesis 7 we suggested that bankers would benefit from a combination of strong ties and high density in their approval networks, so that the interaction effect would be positive. The coefficients for these two interaction effects are both significant in the hypothesized direction, and the addition of these two variables significantly improves the fit of the model (incremental F = 5.57 w. 2 & 49 d.f., $p < .01$). The interaction effect of -998.05 for the information network indicates that at an average tie strength of zero (the minimum), the effect of a one-unit increase in density on bonus size is 396.8, while at an average tie strength of 1 (the maximum), the effect of a one-unit increase in density on bonus size is -601.2. The inflection point (at which the effect of density changes from positive to negative) occurs at a mean tie strength of .397. The interaction effect of 729.51 for the approval network indicates that at an average tie strength of zero, the effect of a one-unit increase in density on bonus size is -481.5, while at an average tie strength of 1, the effect of a one-unit increase in density on bonus size is 248.0. The effect of approval network density on bonus size changes from negative to positive at an average tie strength of .660.[15] All of the other effects in the model remain

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for Hypothesis 6 on the basis of a negative coefficient regardless of how large (in absolute terms) its T statistic is.

[15] Conversely, the effect of information network tie strength on bonus size changes from positive to negative at a density of .853, while the effect of approval network tie strength changes from negative to positive at a density of .565.

substantively identical in Equation 2, with the exception of approval network hierarchy. In Hypothesis 8 we suggested that bankers with less hierarchical approval networks would receive higher bonuses than would bankers with more hierarchical approval networks. The coefficient for approval network hierarchy was -21.5 (T = -0.57, p = .285) in Equation 1. In Equation 2 the coefficient increased in strength to -65.9 (T = -1.78, p = .04), consistent with the hypothesis. This indicates that an increase in hierarchy from 0 to 1 (the approximate range of the variable) would lead to a predicted decline in one's bonus of nearly $66,000.

Given our relatively high ratio of regression to residual degrees of freedom, as well as the fact that none of the four demographic variables approached statistical significance, we recomputed Equations 1 and 2 without these variables. The results are presented in Equations 3 and 4. Because of missing data on one of the variables that is no longer in these equations, the number of observations in these models increased from 70 to 71. As is evident from the table, the findings in these two equations are substantively identical to those in Equations 1 and 2. As in Equation 2, the addition of the two interaction terms (in Equation 4) provided a significant improvement in the fit of the model (incremental F = 5.88 w. 2 & 54 d.f., $p < .01$). The only difference between the models in Equations 3 and 4 and those in Equations 1 and 2 is that the T statistics for the substantive and some of the control variables are larger in Equations 3 and 4. Together, these equations provide further support for Hypotheses 1, 2, 3, and 7, and partial support for Hypothesis 8.

There is one additional point that we have to consider. In the previous section we noted that given the potential endogeneity of our network effects, we considered the use of a lagged dependent variable—the bankers' previous year (1997) bonus—in order to rule out the possibility that our network effects were consequences of the bankers' prior compensation. One problem with conducting this analysis is the sheer difficulty of identifying independent effects once we control for this variable. First, we lose seven additional cases due to missing data, reducing our sample size to 63. Second, not only is the bankers' bonus from the previous year correlated .898 with the current year's bonus, but it is also correlated .828 with the current year's salary and .820 with the bankers' rank. The use of this variable thus poses substantial multicollinearity problems. Indeed,

a regression of the current year's bonus on the previous year's bonus, current salary, and rank yields a coefficient of determination of .759, yet the coefficients for salary and rank are not even statistically significant, and the coefficient for rank is negative (the T statistics are 0.81 and -0.67 respectively). It is therefore unclear what the inclusion of the lagged dependent variable will add to the controls that we have already included.

To consider all possibilities, however, and to be as conservative as possible, we computed the fully specified models from Table 3 (Equations 1 and 2) with the lagged dependent variable. The results of these models are presented in Table 4. In Equation 1, we see that the effect of the previous year's bonus is, not surprisingly, strongly positive. The inclusion of this variable sharply reduces the effects of salary and rank. The coefficient for salary drops from 1.554 to .875, and its one-tailed probability increases from .01 to .08. The coefficient for rank drops from 36.558 (T = 2.42, p = .009) to -9.122 (T = -0.74), that is, it becomes non-significant, and negative. Moreover, the coefficients for the two performance measures decline as well. The effect of the bank's formal performance evaluation declines from 47.87 in Equation 1 of Table 3 (T = 2.38) to 6.57 in this equation and is no longer statistically significant (T = 0.44), while the effect of the combination of closure rate and deal size declines from 24.29 (T = 1.80, p = .038) to 15.94 (T = 1.55, p = .064).

TABLE 4 ABOUT HERE

On the other hand, the coefficients for the two network variables that were significant in Table 3—tie strength and density in the information network—remain statistically significant in the predicted direction. The coefficients do decline in magnitude (that of tie strength drops from 245.1 to 144.6 while that of density drops from -208.5 to -157.5), but both coefficients remain significant at the .05 level. In other words, despite the inclusion of a lagged dependent variable with the resulting multicollinearity, the network effects that we identified in the model without the lagged variable continue to hold. Interestingly, the coefficient for approval network tie strength becomes more strongly negative (b = -142.1 vs. -111.6 in Table 3, with a T statistic of -1.90). This runs counter to Hypothesis 6, in which we predicted a positive effect of

approval network tie strength on bonus size, but because we used a one-tailed hypothesis with a positive prediction, we cannot treat this coefficient as statistically significant. It may be, as we suggested above, that our measure of weak ties is in part capturing the effects of disconnected alters. The fact that the effect of approval network density remains positive and is not statistically significant runs counter to this interpretation, however.

In Equation 2 of Table 4 we insert the interaction terms for information and approval network tie strength and density. As in Equation 1, the bank's formal performance measure is not statistically significant, and neither salary nor rank is significant either, although the performance measure based on closure rate and deal size is significantly positive.[16] In Hypotheses 3 and 7 we predicted a negative interaction effect for the information network and a positive interaction effect for the approval network. As in Equation 2 of Table 3, these network effects remain significantly negative and positive respectively, as predicted. The magnitudes of the effects decline—from -998.05 to -749.69 for the information network interaction and from 729.51 to 396.34 for the approval network interaction. Both coefficients remain statistically significant, however, T = -2.33 (p = .012) for the information network and T = 1.65 (p = .053) for the approval network. Although the approval network interaction T statistic is slightly above that required to reject the null hypothesis at the .05 level, when we computed the equation using Huber-White robust standard errors, the T statistic for this coefficient increased to 2.10 (p = .021).[17] In addition, as in Table 3, the effect of approval network hierarchy is statistically significant in this equation, albeit only at a .10

[16] The coefficient for gender becomes marginally significant in this equation. Interestingly, the effect of being a male is negative, meaning that controlling for the other variables in the model, women earn higher bonuses than do men. This coefficient was also negative (although not significant) in the equation in Table 3 that included the interaction effect between tie strength and density, as well as in Equation 1 of Table 4, and it was positive (but not significant) in Equation 1 of Table 3. Given the instability of this coefficient across different model specifications, as well as the fact that its probability level in Equation 2 of Table 4 exceeds .05, there does not appear to be a strong basis for concluding that women receive higher bonuses than men.

[17] The incremental F test between Equations 2 and 1 yields an F of 2.80 (w. 2 & 41 d.f., p = .072), or just below the threshold for significance at the .05 level. In addition to the slightly weaker interaction effects in this equation (compared to those in Table 3), one possible reason for this lack of significance is the already very high R^2 from the first equation, due primarily to the inclusion of the lagged dependent variable.

level (T = -1.41). The T statistic based on the robust standard error is -1.73, however, which exceeds the level for significance at the .05 level (p = .046).

DISCUSSION

Overall, these results demonstrate strong and consistent support for four of our hypotheses—those involving tie strength and density in the information network and the tie strength * density interaction effects for both the information and approval networks—and partial support for a fifth: the effect of approval network hierarchy is significantly negative in the equations that include the interaction effects. Table 5 presents a list of the results of each of our hypotheses for both the information and approval networks. As the table indicates, the information network hypotheses received support in three of the four cases, compared with only one of the four for the approval networks, although we also received partial support for a second hypothesis involving the approval networks. In terms of information acquisition, which is essential for strong job performance, bankers benefited to the extent that they had strong ties to their colleagues, but with relatively low-density relations among those colleagues. Consistent with earlier work (Hansen, 1999), this suggests that actors benefit from a broad range of information (as indicated by low density networks), but that it is important that the information come from trusted sources (as indicated by strong ties), especially if the information is complex, as it is in the case of the bankers in this study. We found, in addition, that the value of a sparse network increases to the extent that the banker has strong direct information network ties. The degree to which a banker's information network was non-hierarchical, meaning that she was not dependent on a single alter, was not associated with bonus size.

The hypotheses involving the approval network fared less well. For the approval network, we hypothesized that bankers would receive higher bonuses to the extent that their network consisted of strong ties and was non-hierarchical. We posited two competing hypotheses regarding the role of network density, suggesting that density could have either a negative or a positive effect on bonus size. None of these three

hypotheses received consistent support, although we did observe the predicted negative effect of network hierarchy in the models that included the interaction effects (Equations 2 and 4 of Table 3 and Equation 2 of Table 4). We did find, however, consistent with Hypothesis 7, that the benefits of strong ties with one's superiors were disproportionately large when those alters were densely-connected with one another, that is, when the banker's approval network was dense. Our argument here was that a banker with strong ties to his superiors would have the resulting positive evaluations reinforced to the extent that the superiors themselves were close, creating a positive normative consensus among them. This hypothesis received support in all of the models in which it was tested.

TABLE 5 ABOUT HERE

The null effect of approval network density is perhaps the most interesting among those that did not support our hypotheses, and it is worth further discussion to try to account for this finding. Mizruchi and Stearns (2001) found that sparse alter network density in the bankers' approval networks was associated with high performance, in terms of the successful closure of deals. In this study we presented competing hypotheses for the effect of network density, arguing that there were reasons to believe that either high or low-density approval networks would be associated with high bonuses—the performance benefits of ties to a broad range of superiors in the former case and the positive subjective evaluation associated with the support of a normatively-cohesive group of superiors in the latter case. The effect of approval network density was slightly positive, but did not approach statistical significance in any of our models. One possible reason for this null finding is that the factors that led to negative and positive effects of density on bonuses were both operative. In other words, it is possible that low-density approval networks contributed to strong performance, which contributed to high bonuses, as we suggested in Hypothesis 5a, while at the same time high-density approval networks contributed to a normative consensus of positive evaluations, as we suggested in Hypothesis 5b. The outcome of these two competing forces might have led to a null effect of density on bonuses.

There is an alternative possibility, however: perhaps the association between approval network density and bonuses is curvilinear. That is, perhaps both low and high-density networks are associated with high bonuses. If this were the case, we would expect to observe a U-shaped curve, in which bankers with either low or high approval network density would receive high bonuses while those with intermediate densities would receive low bonuses. An alternative is that an intermediate level of density is optimal, since such networks contain elements of both low and high density. If this were the case, we would expect an inverted U-shaped relation between density and bonuses. To examine these conjectures, we recomputed the basic model (from Equation 1 of Table 3) but inserted a quadratic term for approval network density. Because we predicted either a U-shaped or inverted U-shaped relation, we used a two-tailed test to evaluate the coefficients. The result indicated a U-shaped pattern. The coefficient for density was -572.92 (T = -1.91, p = .061) while that for density squared was 471.57 (T = 2.14, p = .037). The sizes and probability levels of all other variables in the model were substantively equivalent to those in the original equation. Although the first-order term had a probability level above .05 (although below .10), the quadratic term was significant at a .05 level. This finding suggests that bankers benefited from either a low-density approval network or a high-density one, and that they fared least well when their approval networks were of medium density. To the extent that Hypotheses 5a and 5b both implied the value of either low or high density to the exclusion of the other, this finding is consistent with both hypotheses.[18]

CONCLUSION

[18] The fact that we found a positive interaction effect between approval network density and tie strength raises the question of whether the U-shaped effect that we found for approval network density might vary at different levels of tie strength. To examine this, we created an interaction term between approval network tie strength and the quadratic term for density. We then examined the first-order interaction between density and tie strength and the interaction between density^2 and tie strength. The two coefficients were negative (-1954.03, T = -1.41, two-tailed p = .165) and positive (19.46, T = 1.81, two-tailed p = .076) respectively. Although these coefficients only approach statistical significance, the trend is consistent with a further U-shaped relation. This indicates that the interaction effect between density and tie strength itself

That social networks, and their associated resources, now known as social capital, provide benefits to organizational actors is no longer news. The question is what kinds of networks provide what kinds of benefits. Various network ties and structures have been shown to affect job performance as well as compensation, but researchers have tended to conflate these two outcomes, without considering the relation between them. We have argued that although performance and reward may be linked, they are two distinct variables, and that the relation between them deserves investigation in its own right. Examining the determinants of year-end bonuses among relationship managers at a large commercial bank, we addressed this issue in three ways. First, we showed that while performance is positively associated with reward, the two performance measures that we examined accounted for only a minority of the variation in compensation. In managerial positions there is often a gap between the formal and informal evaluation of performance, and this means that discretion may play a significant role in determining one's reward. Our finding on the performance-bonus relation is consistent with this notion. Second, we showed that the factors that lead to improved performance may differ from those that lead to increased rewards. Whereas earlier research with the data used in this study suggested that sparse networks among one's superiors lead to improved performance (Mizruchi and Stearns, 2001), these same sparse networks do not appear to lead to increased rewards. Instead, a combination of dense networks and strong ties among superiors are associated with higher bonuses. Third, we suggested, nevertheless, that network ties may increase one's reward precisely because they lead to improved performance. Our finding on the benefits of sparse information networks and strong information network ties—a combination that provides a broad range of information from trusted alters—is consistent with this point.

We have found that there is a difference in the effect of networks based on collegial relations—from whom one seeks information—and networks based on relations of authority—from whom one seeks the support of superiors. In the former case, it is beneficial to have strong ties with a diverse set of alters. We argued that this provides actors with a broad range of information that, because it emanates from strong ties, is

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might follow a U-shaped function: if this were the case, then the positive density-tie strength interaction effect would be greatest at both low and high levels of tie strength.

likely to be trustworthy. This leads to increased rewards, we suggest, because it helps employees do a better job. In networks of superiors, on the other hand, it is valuable to have strong ties that are densely connected. Performance evaluation has a more subjective, discretionary side that may lead some actors to earn more favorable evaluations, and hence rewards above and beyond what their objective performance would otherwise indicate. This is more likely to occur, we argue, when an actor has close ties to superiors who are themselves close, and who thereby are able to achieve a normative consensus. This represents the non-universalistic side of networks.

Most of the traditional literature within the network approach, going back to Granovetter ([1974] 1995), has operated with either an implicit or explicit conception that the benefits of network ties are indicative of the force of particularistic, as opposed to universalistic, factors in individual attainment. Even in the more recent literature focusing on the benefits of networks for job performance (Mehra, Kilduff, and Brass, 2001; Seibert, Kraimer, and Liden, 2001; Sparrowe, Liden, and Kraimer, 2001; Ahuja, Galletta, and Carley, 2003), there is an implicit view that the opportunities to perform one's job may be unequally distributed based on network ties. In what way do our findings speak to this issue? Several of our results are fully consistent with the idea that individual success is a result of achievement. The positive effect of strong information network ties on bonuses, for example, is consistent with the idea that in situations requiring complex knowledge, actors who are able to rely on strong ties will experience improved performance as a result. Similarly, our finding on the benefits of a sparse information network when ties are strong is consistent with the idea that such networks allow actors to acquire superior information, which then allows them to experience performance benefits.

On the other hand, our story is not only one of achievement. Our findings suggest that those with strong ties to superiors who themselves are densely-connected experience greater rewards than do those who lack such ties. Although compensation is often determined by the performance evaluations of one's superiors, that performance itself can be open to interpretation. Situations in which a banker was strongly tied to superiors who themselves were strongly tied to one another created the conditions for a positive normative consensus, that may have led to favorable evaluations of performance. Those

without such networks might have received a less favorable evaluation for performance that was equal in objective terms. This positive interaction effect between strong tie and high density approval networks thus suggests that connections to an inner circle of prominent colleagues allow an actor to receive a disproportionately high reward. This finding is consistent with the idea that more than pure achievement is at work.

It is important to note, nevertheless, that a network story need not be either entirely particularistic or universalistic. As Merton suggested, in his discussion of the Matthew Effect (1968), differential access to resources resulting from particularism may actually contribute to superior achievement, and connections to knowledgeable and supportive colleagues within an organization may lead to superior performance as well. Moreover, there is a difference between outstanding performance and the appearance of outstanding performance.

All of this points to the importance not only of identifying the portion of an actor's performance that is accounted for by her network ties, but of decoupling, and studying the relation between, performance and reward. Clearly much more needs to be done to address these issues, and doing so will require data and analyses more refined than what we have presented here. We believe that we have shown the value of making the distinction between performance and reward manifest. Our task now is to bring further data to bear on this issue.

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Table 1

OLS Models of the Effects of Performance on Bonuses

Independent Variables	(1)	(2)	(3)
Constant	130.51**	-235.29**	-137.76*
	(5.30)	(-4.83)	(-2.35)
Performance Evaluation	65.90**	57.39**	56.89**
	(2.54)	(3.08)	(3.19)
Closure Rate	-214.99	-115.18	-116.79
	(-3.34)	(-2.07)	(-2.19)
Log Deal Size	-1.653	-6.254	-5.887
	(-0.17)	(-0.89)	(-0.87)
Closure Rate*Log Deal Size	43.14**	31.85*	28.54*
	(2.59)	(2.38)	(2.22)
Salary		2.671**	1.356*
		(7.97)	(2.35)
Rank			37.99**
			(2.74)
R^2	.154	.545	.588

*p < .05; **p < .01; probabilities are one-tailed, except that for the constant; significance tests for main effects are omitted for variables that include interaction effects; unstandardized coefficients are presented, with T-statistics in parentheses; the dependent variable is the 1998 bonus; N=80 in all models.

Table 2

Means, Standard Deviations, and
Correlations Among Variables

	Mean	SD	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1. Bonus	130.83	101.5	73	73	15	-03	12	10	15	30	28	13	18	-05	07	-07	15	02	08	-27
2. Salary	134.34	24.9		83	04	-14	-01	-06	17	37	30	14	18	09	06	-13	27	09	-03	-30
3. Rank	2.28	1.01			01	-02	08	07	09	20	27	17	22	07	12	-21	27	09	05	-33
4. Performance Evaluation	.247	.434				04	-00	-04	-19	-14	-05	07	06	-00	20	05	-06	-11	05	13
5. Closure Rate	.519	.370					71	90	03	-27	-10	00	-13	-26	20	-09	-33	-38	34	02
6. Log Deal Size	3.35	2.26						84	14	-03	02	-00	-06	-14	27	-08	-10	-09	41	-20
7. Close Rate*Log Deal Size	2.37	1.93							12	-13	-06	02	-10	-21	22	-07	-22	-26	39	-14
8. Race (1=white)	.793	.408								22	-02	02	-15	-25	18	17	03	-08	16	-14
9. Gender (1=male)	.671	.473									38	26	-04	01	-27	08	-01	08	-07	03
10. Marital Status (1=married)	.659	.477										12	07	-01	-31	01	04	02	-10	11
11. Elite Education (1=yes)	.212	.412											-06	10	-27	09	04	03	03	18
12. Information Tie Strength	.664	.144												64	04	-21	64	50	-09	-19
13. Information Density	.571	.185													-27	-27	49	55	-15	-21
14. Information Network Size	4.38	1.76														05	-03	-21	55	-22
15. Information Hierarchy	3.58	1.95															-14	-16	11	25
16. Approval Tie Strength	.690	.161																79	-24	-33
17. Approval Density	.650	.177																	-43	-27
18. Approval Network Size	3.64	1.67																		-20
19. Approval Hierarchy	.384	.278																		

Decimal points are omitted from the correlation coefficients to conserve space. Correlations are computed with listwise deletion; N=70 for all correlations. Summary statistics are computed from all cases; N=82 for most variables, and 74 or 75 for those involving the approval networks.

Table 3- OLS Models of Determinants of Bonuses

Independent Variables	(1)	(2)	(3)	(4)
Constant	-118.78 (-1.25)	-94.37 (-0.56)	-99.33 (-1.10)	-114.81 (-0.74)
Salary	1.554** (2.40)	1.457* (2.38)	1.603** (2.82)	1.281* (2.35)
Rank	36.56** (2.42)	41.15** (2.93)	32.29* (2.32)	38.35** (2.94)
Performance Evaluation	47.87* (2.38)	42.01* (2.22)	47.44** (2.51)	44.61** (2.51)
Closure Rate	-132.99 (-2.06)	-127.66 (-2.11)	-132.18 (-2.28)	-109.94 (-2.01)
Log Deal Size	-.216 (-0.03)	-6.174 (-0.85	-.908 (-0.13)	-7.979 (-1.15)
Closure Rate*Log Deal Size	24.29* (1.80)	27.52* (2.20)	24.06* (1.88)	25.80* (2.16)
Race (1=white)	9.078 (0.43)	0.603 (0.03)		
Gender (1=male)	2.662 (0.11)	-6.126 (-0.28)		
Marital Status (1=married)	-4.542 (-0.23)	-18.94 (-0.96)		
Elite Education (1=yes)	-0.923 (-0.04)	-1.609 (-0.08)		
Information Tie Strength	245.12** (2.46)	851.92 (3.38)	257.10** (2.82)	849.19 (3.54)
Information Density	-208.46** (-2.60)	396.83 (1.57)	-225.08** (-3.06)	409.90 (1.69)
Info. Tie Strength*Density		-998.05** (-2.60)		-1004.2** (-2.73)
Information Size	-12.97 (-1.79)	-19.66** (-2.79)	-12.61* (-2.11)	-16.24** (-2.87)
Information Hierarchy	2.497 (0.05)	28.45 (0.63)	5.081 (0.11)	25.70 (0.59)
Approval Tie Strength	-111.56 (-1.11)	-564.54 (-3.08)	-100.02 (-1.09)	-507.93 (-3.08)
Approval Density	37.30 (0.39)	-481.53 (-2.30)	19.60 (0.22)	-452.68 (-2.37)
App. Tie Strength*Density		729.51** (2.82)		665.58** (2.84)
Approval Size	7.081 (0.93)	6.809 (0.96)	6.687 (0.95)	5.020 (0.76)
Approval Hierarchy	-21.49 (-0.57)	-65.94* (-1.78)	-34.63 (-1.03)	-80.23* (-2.38)
R^2	.701	.757	.689	.744

*p < .05; **p < .01; probabilities of performance and hypothesized variables are one-tailed; all others are two-tailed; significance tests for main effects are omitted for variables that include interaction effects; unstandardized coefficients are presented, with T-statistics in parentheses; N=70 in Eq 1&2, 71 in Eq 3&4.

Table 4- Determinants of Bonuses with Lagged Dependent Variable

Independent Variables	(1)	(2)
Constant	49.96 (0.61)	-3.110 (-0.02)
Salary	0.875+ (1.44)	0.691 (1.15)
Rank	-9.12 (-0.74)	0.839 (0.07)
Performance Evaluation	6.568 (0.44)	10.83 (0.75)
Closure Rate	-74.11 (-1.50)	-72.37 (-1.49)
Log Deal Size	2.243 (0.42)	-3.038 (-0.54)
Closure Rate*Log Deal Size	15.94+ (1.55)	19.37** (1.90)
Race (1=white)	-16.49 (-1.02)	-20.45 (-1.31)
Gender (1=male)	-25.42 (-1.44)	-32.22+ (-1.87)
Marital Status (1=married)	2.884 (0.18)	1.451 (0.09)
Elite Education (1=yes)	5.490 (0.34)	2.698 (0.17)
Information Tie Strength	144.57* (1.92)	610.85 (2.87)
Information Density	-157.48** (-2.43)	307.23 (1.46)
Info. Tie Strength*Density		-749.69* (-2.33)
Information Size	-7.366 (-1.29)	-10.40+ (-1.79)
Information Hierarchy	14.12 (0.42)	20.50 (0.62)
Approval Tie Strength	-142.13 (-1.90)	-405.41 (-2.38)
Approval Density	53.01 (0.73)	-224.72 (-1.19)
App. Tie Strength*Density		396.34# (1.65)
Approval Size	1.870 (0.33)	1.344 (0.24)
Approval Hierarchy	-18.44 (-0.68)	-38.83# (-1.41)
Bonus (t-1)	0.978** (6.26)	0.870** (5.43)
R^2	.868	.884

+p < .10; *p < .05; **p < .01; #p < .10 but p < .05 with robust standard error; N=63; see Table 3 for additional information

Table 5

Summary of Hypothesis Test Results for
Information and Approval Networks

Hypothesis/Predicted Direction	Support?
Information Networks	
Tie Strength/ +	yes
Density/ -	yes
Tie Strength*Density/ -	yes
Hierarchy/ -	no
Approval Networks	
Tie Strength/ -	no
Density/ + or -	no*
Tie Strength*Density/ +	yes
Hierarchy/ -	partial

*Support for this hypothesis was found in a subsequent analysis; see the Discussion section.