

Social Network Effects on Performance and Layoffs:

Evidence from the Adoption of a Social Networking Tool

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ABSTRACT

By studying the changes in employees' networks and performance before and after the introduction of a social networking tool, I find that a structurally diverse network (low in cohesion and rich in structural holes) has a positive effect on work performance. The size of the effect is smaller than traditional estimates, suggesting that omitted individual characteristics may bias the estimated network effect. I consider two intermediate mechanisms by which a structurally diverse network is theorized to improve work performance: information diversity (instrumental) and friendship (expressive). I quantify their effects on two types of work outcomes: billable revenue and layoffs. Analysis shows that the information diversity derived from a structurally diverse network is more correlated with generating billable revenue than is friendship. However, the opposite is true for layoffs. Friendship in a diverse network of colleagues is more correlated with reduced layoff risks than is information diversity. Field interviews suggest that friends can serve as advocates in critical situations, ensuring that favorable information is distributed to decision makers. This, in turn, suggests that having a structurally diverse network can drive both work performance and job security, but that there is a tradeoff between either mobilizing friendship or gathering diverse information. Furthermore, it is important to examine the mechanisms by which friendship reduces the risks of being laid off. If friendship promotes team effectiveness, delegating decisions rights to managers is optimal. However, if managers choose to optimize their own power at the expense of the firm, the positive impact of friendships on layoffs is evidence that delegating layoff decisions to managers can incur important costs.

Keywords: Social Network, Productivity, Layoffs, Information Diversity, and Friendship

INTRODUCTION

Social network theory predicts a structurally diverse network that is low in cohesion and spans structural holes to be associated with higher work performance. By linking unconnected groups, the brokers, who bridge these holes, are endowed with early exposure to novel information and can act as hubs to facilitate information flow between otherwise disconnected groups. Studies have shown that people whose networks are rich in structural holes have a competitive advantage over their peers. They tend to receive superior performance ratings and higher compensation, and to be promoted faster (Burt 1992; Podolny and Baron 1997; Burt 2005; Cross and Cummings 2004; Lin 2002). For example, bankers with structurally diverse networks are more likely to be recognized as top performers (Burt 2000). Similarly, employees in research and development positions maintaining diverse contacts outside of the team are more productive than their peers (Reagans and Zuckerman 2001).

While previous research has provided important theoretical insights (e.g., Burt 1992; Coleman 1988), the question of how social network positions drive productivity gains remains open. Past research often treated network structure as a proxy for the distribution of information (Burt 2008). However, information content was rarely directly observed. This is problematic because information benefits are theorized to be the primary reason why a structurally diverse network endows individuals with work advantage. Without examining the information content transmitted inside the network, it is difficult to verify if these positions actually generate information benefits that ultimately affect performance. Burt has theorized that three forms of information benefits—access, timing and referrals—ultimately drive superior work performance (Burt 1992: 13-15). If so, it is important to quantify different types of information benefits and their relation to work outcomes.

I examine whether structurally diverse networks can generate information benefits by focusing on how information diversity and friendship—two information benefits that emerge from structurally diverse networks—can lead to superior work performance. I define information diversity as the heterogeneity of the information content in individuals' electronic communications. As a measure, it combines access to

and timing of information,¹ the first two types of information benefits in Burt's framework. Earlier access to a variety of information sources allows an individual to gather more, and more diverse, information. I also create a friendship index that measures the frequency of socializing or informal activities in a person's electronic communications. Because socializing can help generate friendships and friends are more likely to serve as advocates, the friendship index can be seen as a proxy for the referral process, Burt's third type of information benefit.

I attempt to bridge the literature on network structures with the literature on tie content by examining the expressive and instrumental elements in a structurally diverse network. I find such a network can generate both instrumental and expressive types of information benefits, with information diversity being the instrumental element and friendship being the expressive one. This finding runs contrary to the belief that due to their contrasting natures, there is a tradeoff between having either expressive or instrumental networks (Bale and Slater 1955: 290-92; Etzioni 1965: 696-97; Slater 1965). While it is possible to have both kinds of benefits in a structurally diverse network, there is a tradeoff between the two that re-emerges in the relative returns on the investment from either forming friendships or gathering diverse information. The decision to mobilize friendship or information diversity may depend on the work outcome one hopes to achieve.

To better understand the tradeoff, I examine the impact of information diversity and friendship on two types of performance measures—billable revenue and layoffs—for a group of technology consultants at a large information technology firm. I choose billable revenue as an objective measure of a worker's productivity, because it is one of the most important performance metrics for evaluating employees in the consulting industry. Because accessing diverse information is critical for solving difficult problems, information diversity derived from a structurally diverse network is more likely to be beneficial in generating billable revenue. I also explore the effect of information diversity and friendship on layoffs, a

¹ Although this approach does not capture all communications by a person, email and instant messaging represent a significant proportion of the overall communication. Furthermore, calendar events also capture some of the face-to-face meetings in addition to phone conferences. This approach can significantly mitigate lack of direct measures of verbal and face-to-face communication.

negative and traumatic experience for most workers, and one which can negatively affect the remaining employees through network destruction, especially when friends are laid off (Krackhardt and Porter 1985; Shah 2000).

It is possible that the mechanism for generating billable revenue may fundamentally differ from that for determining the risk of layoff. Often, firms delegate layoff decisions to managers. A manager's favorable opinion is likely to protect a person from being laid off. Effective promotion from referrals gets the actor's name mentioned at the right place and the right time, maximizing the job retention rate. I find that information diversity derived from a structurally diverse network is more associated with improving billable revenue than is friendship, but that friendship derived from a structurally diverse network is more positively correlated with job retention than is information diversity. To exemplify their possible tradeoff, I show whether information diversity and friends are substitutes in generating billable revenue and avoiding layoffs.

To lend a causal interpretation to the analysis, I take advantage of a variation generated by a technology that can change the network positions of its users over time. This technology is an expertise discovery tool that allows users to search for experts by keywords. Our survey results show that people use the search tool when they cannot locate anyone with the right expertise in their immediate network neighborhood. Contacting these experts gives the user an opportunity to strategically reach out to different groups of people within an organization, and thereby induces a change in the user's network position. By examining the network change and the changes in information diversity and the friendship index before and after the adoption, it is possible to determine if a structurally diverse network can generate information benefits. Similarly, by examining the change in work outcomes before and after the adoption, it is possible to determine if this technologically induced network change can actually alter billable revenue and layoff risks. If an improvement is detected, it is reasonable to infer a causal relationship, in which occupying a desirable network position actually causes an improvement in work outcomes beyond what one's inherent abilities, popularity, past performance history or other factors would otherwise allow.

My results show that using the expertise search tool can alter employees' network positions in a significant way, even after controlling for possible self-selection biases. Overall, users' network positions become more structurally diverse after adopting the expertise search tool, suggesting that the adoption can serve as an instrument for network diversity. I find that having a structurally diverse network can generate more billable revenue and increase job retention. While this conforms to earlier studies, the effect from having a structurally diverse network is much smaller than traditional ordinary least square (OLS) estimates that do not address the reverse causality issue. This shows that unobserved individual heterogeneity could lead to overestimating the effect of network positions on performance.

Using technology adoption as an instrument, I find structurally diverse networks can generate both information diversity and friendship. Comparing the two types of information benefits, I find that information diversity is more positively correlated with improving billable revenue than is friendship while friendship is positively correlated with job retention than is information diversity. Lastly, I provide evidence of a substitutive relationship between information diversity and friendship. I find that a structurally diverse network can generate both instrumental and expressive types of information benefits, as measured by information diversity and friendship indices, respectively. However, there is a trade-off between the two in their relative returns from investing in either friendship or information diversity. Whether information diversity or friendship is mobilized depends on the goal one wants to achieve.

THEORY

Network Positions and Performance

The structural perspective of network studies (Coleman 1988; Burt 1992) often focuses on the configuration of ties as opposed to the content of ties in the ego-network. One of the most prominent features of social network structure that has received an enormous amount of theoretical and empirical attention is brokerage or network diversity (e.g., Burt 1992; Granovetter 1973), characterized by a network that is low in cohesion and structural equivalence and rich in structural holes. Such networks are often positively correlated to various measurements of work performance. For example, Burt (1992, 2000,

2004) shows that structural holes can create a competitive advantage for individuals in dimensions such as wages and promotion. He attributes the normalized performance differences to actors' ability to access and gather information from non-redundant social groups (Burt 1992; Ancona and Caldwell 1992; Sparrowe et al. 2001; Reagans and Zuckerman 2001; Cummings and Cross 2003; Zaheer and Bell 2005). This information advantage is particularly important in knowledge-intensive industries where the success of a project relies on identifying and assimilating existing information in order to create new knowledge and innovation (Burt 1992).

Thus, a structurally diverse network is assumed to confer information benefits by providing the access to novel information from loosely connected network neighborhoods (Burt 1992). The economic value of information stems from the fact that information is distributed unevenly in a network and thus, tapping into various information sources that are distributed throughout the network is important for solving difficult problems and finding new opportunities. Structurally diverse networks can provide actors with the capability to reach out to distant information sources. A redundant network, on the other hand, tends to provide repeat information. In such a network, no one can monopolize information long enough to derive rents because the dense network of strong ties can quickly disseminate any information throughout the network.

In addition to information diversity, brokers are also theorized to control the flow of information and reap rents from brokering between two disconnected parties (Burt 2004, Obstfeld 2005). In Burt's theory of control (Burt 1992), relationships are understood primarily as conduits of information and resources exchanged by actors in pursuit of instrumental objectives. Endowed with preferential access to information, brokers are in a unique position to identify arbitrage opportunities and reap benefits through strategically linking disconnected actors. However, as Reagans and Zuckerman (2008) commented, there is a fundamental tradeoff in the social-structural foundations of power and knowledge. The same mechanism that endows brokers with power as the providers of information also reduces their power as acquirers of information because network contacts in a non-redundant network are also monopolist themselves when the broker tries to acquire information from them (Reagans and Zuckerman 2008).

However, regardless of the control benefits, information benefits derived from a structurally diverse network are still greater than what is provided in a redundant network. In this paper, I focus on the information benefits and examine how they affect performance independent of whether individuals control the information flow to their advantage. Thus, I hypothesize that a structurally diverse network can affect work outcomes as measured by individual billable revenue as well as the risk of being laid off

Hypothesis 1a: Structurally diverse networks cause increase in billable revenue

Hypothesis 1b: Having a structurally diverse network reduces layoff risks.

Network Diversity, Information Diversity and Friendship

While the information benefit derived from a structurally diverse network has received much scholarly attention, few have actually measured it; the vast majority of empirical work on network and information is content-agnostic (Hansen 1999). As Burt explained, network structure is often used as a proxy for information flow because structures can be measured more easily than the actual content of what is transmitted in the network (Burt 2008). He calls for the next phase of network research to investigate how individuals gather information from their network positions. While some research, especially in the connectionist perspective, has also stressed the importance of measuring the content of the network, they often characterize the network as channels, pipes or conduits, and the content as attributes of the nodes (Podolny 2001; Rodan and Galunic 2007). Under this assumption, information flow is implicitly assumed to be proportional to the distribution of links among nodes of the network (Granovetter 1978; Schelling 1978). However, information exchange may occur strategically; individuals do not always share all available information (Reagans and McEvily 2003; Aral and Van Alstyne 2007). Hence, it is critical to open the black box of networks to investigate information that is being transferred between individuals inside a network. Instead of using characteristics of nodes as a proxy for information content and structural topology as a proxy for information flow, the next phase of research should examine if and how network positions generate information benefits and whether these information benefits ultimately induce superior work performance (Burt 2008; Aral and Van Alstyne 2007).

One notable exception in advancing the information content analysis of networks is the recent work by Aral and Van Alstyne (2007). Using encoded email content, the authors analyzed the email traffic at an executive recruiter firm and showed that brokers are more likely to have more heterogeneous information, which is also associated with higher work performance (Aral and Van Alstyne 2007). While calculating information heterogeneity is a notable breakthrough, it is also important to measure other aspects of information benefits, especially comparing them in the same setting to show how their capabilities differ in influencing work outcomes. As Burt (1992) theorized, there are three forms of information benefits: access, timing, and referrals. Access refers to receiving a valuable piece of information, while timing refers to the ability to receive a key piece of information faster than others. Referrals are a process in which personal contacts promote the actor to others. As Burt explained, “they are motors expanding the third category of people in your network, the players you don’t know who are aware of you.... [They] are strong personal advocates in decision-making process...to ensure both favorable information and response to any negative information get distributed during decisions” (Burt, 1992: 14-15).

However, measuring access, timing and referrals is extremely difficult, because it is hard to directly observe the information content in people’s interactions. I address this issue by quantifying two types of information benefits: information diversity and friendship, through encoded electronic communication such as email, text messages, and calendar events. Information diversity can be viewed as a combination of information access and timing. Specifically, I compute the diversity of information content by counting the number of distinct topics in an actor's electronic communications. Obtaining information from diverse sources is the key to making better decisions, solving difficult problems, and generating innovative solutions. Thus, I hypothesize information diversity to be the primary mechanism for a structurally diverse network to generate rents and competitive advantage.

Hypothesis 2a: Structurally diverse networks can generate information diversity.

Friendship contributes to the referral process. It measures how much of an actor's communications is related to socializing and informal social activities. Through these activities, network contacts get to know an individual better and are more likely to serve as strong personal advocates, particularly in situations of crisis and uncertainty (Ibarra 1995). Having a diverse circle of friends is more likely to help the actor, trumpeting his accomplishments and advertising his work to a diverse group of people, including decision makers.

Hypothesis 2b: Structurally diverse networks can generate diverse friendships.

Content of Ties: Expressive and Instrumental Network Relationships

Information diversity and friendship can also be viewed in the framework of expressive and instrumental network relationships where information diversity is a proxy for instrumental relationships and friendship is a proxy for expressive relationships. Research on expressive and instrumental networks often focuses on the content of relationships (Borgatti and Foster 2003), as opposed to the structural properties. It argues that topological studies of networks often neglect the resources flowing between ties and focus exclusively on the structural perspectives (Lin 2001; Snijder 1999). This is problematic because actors are only successful when they can mobilize resources from their network contacts (Podolny and Baron 2001). One way to classify these resources is through their instrumental or expressive nature. Instrumental ties are often used to exchange work-related resources, and they typically involve actions that seek information, expertise, and professional advice (Ibarra 1993; Fombrun 1982; Lincoln and Miller 1979; Podolny and Baron 1997). Expressive ties, on the other hand, are often affective and friendship-based and involve the exchange of alliance, trust, and social support (Krackhardt 1995).

Although instrumental ties and expressive ties are theorized to be distinct, they can also overlap in a dyadic relationship. Often expressive ties have instrumental values and some instrumental ties are also affective; thus the line separating the two often blurs (Scott 1996). Some have suggested that the two types of networks may interact positively: workers with overlapping instrumental and expressive ties are more effective (Ibarra 1992). On the other hand, expressive and instrumental activities often conflict

because it is difficult to fill both roles at the same time (Bales and Slater 1955; Etzioni 1965; Slater 1965). For example, having friendship or expressive ties can make it difficult for a manager to enforce rules and sanctions to subordinates. Thus, expressive ties dampen the effect of instrumental actions or vice versa, leading to a tradeoff in having either one or the other (Fernandez 1991). Similarly, because people tend to distinguish between the two roles, expressive and instrumental networks can have a substitutive relationship (Homan 1974; Fernandez 1991).

Drawing upon the literature on expressive and instrumental networks, I show that information benefits derived from a structurally diverse network can have both instrumental and expressive properties. Specifically, information diversity is coupled with instrumental actions, much as friendship is to expressive actions. Instrumental actions, which generate task-related information and advice, increase the information diversity crucial to higher work performance. Expressive actions generate friendship, and friends are more likely to advocate and promote an individual, helping the person avoid crises and find new opportunities. However, the literature on instrumental and expressive networks focuses more on tie contents rather than on the network's structure, while the structural perspective often disregards instrumental and expressive elements in the network due to the difficulty of directly observing the information flow. I bridge the gap between the structure- and tie content-centric views by showing that structurally diverse networks can generate both instrumental and expressive properties. This is contrary to the notion that it is difficult to build both expressive and instrumental networks because they are often at odds (Bales and Slater 1955: 290-92; Etzioni 1965: 696-97; Slater 1965).

However, unifying friendship and information diversity in a network comes with its own costs and tradeoffs. Because an actor's time and energy are necessarily limited, gathering information must in effect be traded off against forming friendship. Although gathering information and socializing may overlap, friendship and information diversity are still distinct. For instance, to increase information diversity, actors can form ties with individuals whom they do not like or normally interact with for the sole purpose of gathering information. However, one can spend the same time and energy socializing, making friends and thus facilitating the referral process, even if this effort does not necessarily increase

information diversity.

Hypothesis 3: There is a tradeoff in mobilizing both information diversity and friendship.

Network Effect on Billable Revenue and Layoffs

The tradeoff between information diversity and friendship lies in the ability to take advantage of the two different types of social capital to achieve desired outcomes. To understand how information diversity and friendship are used to achieve different goals, I examine their effects on two types of outcome: billable revenue and layoffs. Billable revenue is an objective measure of work performance and is one of the most salient metrics for evaluating consultants. Information workers, such as consultants, are especially valued for their ability to access valuable information, which can have two effects in enhancing work performance. First, accessing information related to the task at hand directly improves the quality of work. Second, accessing diverse information also exposes actors to new opportunities and valuable resources (Burt 1992, 2004). Consequently, these actors would be the first to learn a new opportunity, placing them at the front of the queue to strategically seize the opportunity. In the IT consulting business, accessing information expediently is the key to performance. Since consultants' performance is largely measured by billable revenue, it is crucial to do well in the current project as well as spending time to look for future opportunities. Knowing where to obtain expertise through networks helps an individual solve difficult problems and produce high quality work, enhancing his reputation and his future prospect for finding opportunities. All else equal, a manager would prefer reputable consultants to handle important projects, because they are more likely to satisfy customers and generate repeat business. Thus, if a structurally diverse network is to produce informational benefits, it should have a strong effect on information workers in knowledge-intensive settings.

Friendship may also help improve billable revenue. By socializing informally with a diverse group of people, consultants are more likely to encounter opportunities serendipitously. Friends can also provide important information that eventually results in billable revenue. The operative factor in these situations, however, is information diversity resulting from information generated by a structurally

diverse network, including work-related interactions with friends. Friendship, on the other hand, is distinct from informational diversity in that it captures the referral process. Through informal interactions, an actor's network contacts are more likely to know his expertise and can serve as his advocates to others. Although having someone to advocate for an actor is helpful, it rarely generates billable revenue directly, because having access to useful information, opinions, and perspectives is ultimately responsible for solving difficult cases and generating profits. Hence, I hypothesize that a performance improvement arises from a structurally diverse network primarily by means of information diversity but not necessarily by friendship.

Hypothesis 4a: Structurally diverse networks induce higher billable revenue primarily through information diversity, not through friendship.

While structurally diverse networks are shown to provide information diversity that directly improves work performance, they can also produce friendships that function as referrals to enhance a person's prestige and reputation. Functioning as means to trumpet one's accomplishments and promote one's work, referrals ensure the actor is protected in crisis situations, such as layoffs. Thus, the same channel through which actors derive diverse information also provides them with a diverse network of potential referrals. Through informal activities to generate affective relationships, individuals can mobilize their network contacts to serve as their referrals.

Thus, friendships in an employee's structurally diverse network can reduce the risk of layoff and increase job retention. An employee is much less likely to be laid off if a wider range of people, including managers, has a favorable opinion of the person. Referrals can greatly facilitate this process by functioning as means to broadcast one's achievements to others. The advantages of the referral process also flow from the theory of recognition heuristics (Goldstein and Gigerenzer 1999, 2002); according to this theory, people place higher values on objects they recognize than on objects they don't, regardless of their actual values. Thus, when key decision-makers have heard of a person, that recognition value alone may keep the person from being laid off. In contrast, people with comparable, or even superior work evaluations, may face higher risks of layoff if they lacked a diverse group of referrals because decision-

makers are less likely to know their contributions to the organization. From qualitative interviews of managers who participated in layoff decisions, many of them expressed the importance of reputation and general awareness of a person's work through the referral process.

When we sit down at a meeting to make layoff decisions, we discuss people's work and what we think of their work, not just billable hours. Usually, when more than one person in the meeting is aware of the person or speaks on his behalf, this person is much less likely to be laid off than someone nobody has heard of.

This confirms that actors with friendships in a structurally diverse network are able to effectively advertise their work and promote themselves through referrals. Consequently, their visibility is increased, and they are less likely to be laid off.

Information diversity can also reduce the risks of layoff through generating more billable revenue, because firms are less likely to lay off their star performers who disproportionately contribute to generating profits for the firm. However, friendships play a more important role in reducing the risk of layoff than does information diversity, possibly because layoffs do not only affect the person who got laid off; it can affect the team and other colleagues who are connected to the person. Once the person leaves the organization, he is permanently removed from the social network of his contacts and network destruction from layoffs can have a drastic effect on the remaining employees (Krackhardt and Porter 1985). Qualitative interviews show that when a key person is removed from the organizational network, it can drastically affect other team members (Shah 2000). One person during the interview lamented:

We were just in the process of forming a project that involves the collaboration of several groups when layoff happened. When Bob got laid off, the project also fell apart, because Bob was the key person connecting all of us together. Once he was gone, we were not able to mobilize everyone to continue the effort.

Billable revenue, on the other hand, tends to affect the person himself rather than the group, because generating more billable revenue has less effect on other group members than layoffs. Accordingly, the mechanism for reducing the layoff risk is different from the one that generates billable revenue. When network contacts are friends with a person, they are likely to protect the person from

layoffs, because not only would they lose a potentially important information source, they may also experience the negative consequences of losing a friend (Shah 2000). Informal activities and socializing with a diverse group of people can promote friendships that, in turns, shield an actor from layoffs. Thus, friendship can protect a person from being laid off more than information diversity, even after controlling for billable revenue.

Hypothesis 4b: Friendship is more correlated with protecting an actor from layoffs than is information diversity.

Tradeoff between information diversity and friendship

One can also view the tradeoff between information diversity and friendship in a multi-task framework. Information diversity primarily drives billable revenue, which is a measurable and contractible performance metric. On the other hand, friendship is intangible and un-contractible and can affect the welfare of others. For example, those with more affective relationships could be great team players, facilitating collaborations and distributing their resources to other team members when needed. Because their services are instrumental to the success of the team, they are less likely to be laid off despite having lower objective performance evaluations. However, friendship can also be viewed negatively. For example, if multiple factions and cliques have formed as the result of politics, members of the same faction are more likely to protect their own members even if their objective performance evaluations are inferior. However, regardless of why friendship matters to layoffs, there is a tradeoff between forming friendships and gathering information, because there is only limited time and energy available to a person for either activity. The proportion of time invested into each activity depends on the goal one is trying to achieve. If the reward structure is more aligned with generating more billable revenue, employees would spend more time and energy gathering diverse information to generate profits for the firm. However, when the culture of the firm is more group-focused or when the work outcome of individuals, such as layoffs, may also depend on the team, employees are more likely to spend time socializing, forming

friendships, and lobbying supporters. In the case of layoffs where the decision is not purely based on observable performance metrics such as billable revenue, having supporters to advocate on one's behalf can significantly reduce the layoff risk. From the firm's perspective, delegating the layoff decisions to managers would be optimal if friendship can improve effectiveness of collaborations among team members and contribute to the profitability of the firm, because managers have private information about the employees, including friendships, that the firm cannot observe. But, it is also possible for the managers to have a different objective function from that of the firm; and managers would choose to lay off a person to maximize his own power inside the organization, even at the expense of the firm. Thus, delegating the layoff decisions to managers can potentially incur a huge cost to the firm, and the firm should re-consider the decision right allocation to avoid the cost.

Thus, if one focuses on only a single performance metric, such as billable revenue, information diversity may appear to be the sole driver for improving work performance. By incorporating into the analysis information diversity and friendship, which are rarely directly observed or quantified, I can observe if friendship has important impacts on layoffs, especially when the firm delegates the layoff decision to managers. Furthermore, the impacts could be much more pronounced than that of information diversity in preventing a person from getting laid off regardless if friendship promotes the profitability of the firm or if it maximizes the power of the managers, though the latter would not necessarily be optimal for the firm.

Similarly, without examining both information diversity and friendship in the context of having a structurally diverse network, we miss how these two properties of information benefits can have different impacts on performance. By viewing information diversity as instrumental and friendship as expressive, I theorize that it is possible to have both expressive and instrumental elements in a structurally diverse network. However, there is a tradeoff in a person's ability to leverage them in achieving desired outcomes. Generating more billable revenue requires the actor to mobilize the information diversity generated from a structurally diverse network. On the other hand, if the goal is to prevent layoffs, developing friendships and lobbying for support from a diverse group of contacts are more useful. Figure

1 below captures the theory development and hypothesis testing.

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DATA AND SETTING

Setting

To test these hypotheses, I have collected data at a large information technology firm. High-tech firms have been a fertile ground for researchers to understand how network characteristics play important roles in information-intensive work settings such as the search and transfer problems across organizational units (Hansen 1999), research and development productivity (Reagans and Zuckerman 2001), and mobility in the workplace (Podolny and Baron 1997). If information benefits derived from network positions matter for performance, they should matter especially in a knowledge-intensive setting, such as in the high-tech sector.

To characterize the social network in the firm, I captured the internal electronic communication exchanges. Previous work has validated the benefits of using electronic communication data to understand intra-organizational networks within a firm or an institution (Wu et al. 2004; Kossinets and Watts 2006, 2009). While using digital traces left by users can construct a more accurate portrait of a network, more importantly it allows for the direct observation of the information transmitted inside the network. Examining the variation of the information content across individuals can definitely confirm whether the information-based assumptions about the network are valid (Burt 2008). As explained by Aral and Van Alstyne (2007), analyzing the content of communications as well as the topological structures of networks can open new avenues for answering questions at the heart of the sociology of information. Thus, by examining the content, I can compute the total number of distinct topics in each person's electronic communications to capture the information heterogeneity across individuals. Furthermore, I extend the content analysis by constructing a friendship index that quantifies informal and socializing activities in individuals' communication.

Without recording of the content of people's communication transmitted inside an electronic communication network, it would be difficult to measure and classify different types of information benefits. Traditionally, content analysis is often done through detailed ethnography studies. While these studies are useful, they are also limiting because it is difficult to capture the communication content for a large group of people using ethnography. Similarly, traditional social network data is generated using self-reports such as surveys and questionnaires that require the subjects to recall their network connections. While respondents are generally good at remembering recent and frequent interactions, they are poor at recalling weak and distant ties (Marsden 1990; Krackhardt and Kilduff 1999). The recall bias as well as the general inaccuracy in memory can be problematic for constructing network relations that are socially distant, resulting in errors in measuring many network parameters (Marsden 2005; Kumbasar, Romney and Batchelder 1994). Using the archive of electronic communications directly can greatly alleviate this type of bias, because electronic records can precisely capture when and what exact information content is exchanged between actors.

In particular, I focus on employees in the consulting division of this firm whose primary function is to solve problems for clients and generate profits from billable revenue. Typically, consultants are involved in four broad categories of projects: IT consulting, business processes, application supports, and outsourcing services. Consulting projects are in general information-intensive and require solving difficult problems for the client. According to qualitative interviews, consultants often spend a large amount of time assembling, analyzing, and assessing information gathered from various sources to fully understand clients' problems and make decisions and recommendations based on the information. To access diverse information that is critical for decision-making, consultants often need to reach out to experts in the organization. Having connections to the experts either directly or through colleagues is crucial for the consultants to gather and integrate information into viable solutions. Satisfying clients is extremely important because generating repeat business is the key for maintaining a continuing stream of revenue and avoiding bench time.

In addition to working on the current project, consultants also have to look for future projects.

Consulting work in this firm functions like an internal labor market. To avoid bench time, consultants constantly spend time searching for future opportunities. While an internal placement manager is assigned to each consultant, the manager has limited capacity to help individual consultants. Qualitative interviews indicate that a typical placement manager is responsible for 50-100 consultants at a time, and thus, relying on the placement manager alone is not enough to find suitable projects as needed. Accordingly, consultants need to be proactive to find opportunities, and social contacts can play an important role in this process. Having access to information about project opportunities from social contacts is useful, because hearing about an opportunity early gives a consultant a timing advantage in applying for the job. Obtaining more information about the project and the person leading the project also help the consultants to present their skills strategically to suite the needs of the project lead. Hence, they are more likely to be hired.

Data

To understand how social networks affect billable revenue and the risk of layoff, I analyze an electronic communication social network of 8037 employees over 2 years. The data contains email, calendars and instant messaging activities inside a global information technology firm. To the best of my knowledge, this is the largest social network ever tapped to study the impact of social networks on information worker productivity. The data is collected using a privacy-preserving social network analysis system (Lin et al. 2008) that deploys social sensors to gather, crawl, and mine various types of data sources, including the hierarchical structure of the organization, and individual role assignments as well as the encoded content of email and instant messages and calendars of employees who volunteered their data for the study.

The system is deployed globally and has collected detailed electronic communication records of 8,037 volunteers. Although the volunteers only represent about 5% of the global population of the firm, it represents about 15% of employees in English-speaking regions and 23% of employees in the consulting services, which will be the primary focus in this study. To alleviate the potential problems arising from

the missing parts of the whole company's network, I only examine the local network structure of each volunteer, because the system captures all the direct communications that the volunteers are involved in, including communication to non-volunteers. Furthermore, because more than 50% of the direct contacts of these volunteers (1 degree away) are also volunteers themselves, I can also determine their dyadic relationships. For the case when the network contacts are not volunteers, it is possible to make some inference about their network connections by examining if they co-occur frequently in the same email, IM, or calendar event. When two people (B and C) are listed together as the correspondents of a third (A), they (B and C) are likely to be connected to each other as well. However, it is still possible to miss some connections among the non-volunteers, and the network structural parameters may be biased as a result. This is a common problem for network studies in the field that requires setting a boundary on the population studied. But the missing connections among non-volunteers would not bias the content analysis that calculates the parameters of information benefits using the electronic communication records of the volunteers, which is fully captured.

From these volunteers, it is also possible to derive a partial social network of everyone in the firm. However, I constrain the analysis to focus on the sub-network for the 8,037 volunteers whose complete electronic communication data is available. To eliminate any potential bias from the volunteered data, I compare the job roles, demographics, the types of business functions, and hierarchical ranks of the volunteers with the rest of the firm. I find minimal differences between the two populations. However, the volunteers in my sample are on average less likely to be laid off than others in the firm. Perhaps these volunteers are more likely to be high performers or they are more socially connected than the rest. After all, that they have donated their data for this research in exchange for accessing social networking tools signals that they are more interested in social networking than others. However, with a large sample, more than 8,000 people, there is sufficient variation to detect the local average effect from networks in this sub-population of more socially inclined people.

To construct a precise view of the network that reflects the real communication patterns among actors, I eliminate spam and mass email announcements. Since each electronic message includes a

timestamp, I can map a dynamic panel of social networks from January 2007 to January 2009. Each monthly network is built using a sliding window of 6 months with a 1-month step size and includes all electronic messages in the current month, plus three months prior and two months after the current month. This construction of network panels can more accurately reflect the network relationships than the network activities in only a single month. Using the communication data, I construct a network panel of 17 periods for 8,037 employees, which provides an opportunity of rare scale and scope to study how a person's social network evolves over time.

To explore how social networks are related to work performance, I obtain detailed financial performance records of more than 8,000 consultants. I focus on 2,038 consultants in this sample who have volunteered their electronic communication data and the 2,592 projects that these consultants participated in from January 2007 to January 2009. The sheer volume of the data allows a more precise estimate of how population-level topology in a network, information diversity, and friendship affect objective performance measures and layoff risks. To protect the privacy of the volunteers, their identities are replaced with hash identifiers, and the content of their messages is encoded. Tables 1 and 2 show the summary statistics of these consultants, including their demographics and job roles as well as network characteristics.

To study the network effect on the risk of being laid off, I use data during a round of layoffs in January 2009 when approximately 8% of the work force is eliminated. The firm's corporate policy allows for a two-month grace period during which the laid-off employees could retain their work privileges, including access to the corporate email system, intranet, and internal job postings. If they were able to find other positions within the firm during the grace period, they could be internally transferred and thus remain at the firm. However, due to the recession's severity, the firm simultaneously instituted a worldwide hiring freeze, making such internal transfers unlikely. Although I have no roster of exactly who got laid off, I can infer one by comparing the human resource (HR) directory shortly after the layoff announcement and right after the actual layoff event. From the difference between the two HR databases, I can derive who has left. It is possible that some employees may have left voluntarily, although unlikely

in light of the severe recession and the difficult labor market worldwide, especially in North America. Several regional offices were closed and everyone in them was laid off. I exclude them from the dataset.

Dependent Variables

The dependent variables are two types of work performance outcomes. First, I measure the objective work performance using the monthly billable revenue generated by each consultant in a two-year period from January 2007 to January 2009. Because billable revenue is the benchmark for gauging productivity in the consulting industry, it is a clear and objective performance measure widely adopted for evaluating the performance of information workers such as consultants, lawyers, and accountants. The second dependent variable is whether a consultant was laid off in January 2009. Measured using job retention, the variable is binary, equaling 0 if a person is laid off and 1 if a person is retained. I explore how network positions and the information benefits derived from these positions can increase the rate of job retention.

Explanatory Variables

I use Burt's measure of network constraint (Burt 1992) to measure network diversity, or brokerage positions.

$$Network_Diversity_i = 1 - C_i$$

$$C_i = \sum_j \left(p_{ij} + \sum_q p_{iq} p_{qj} \right)^2, \quad q \neq i, j.$$

Network constraint C_i measures the degree to which an individual's contacts are connected to each other as well as their connections to the individual. p_{ij} is the proportion of actor i 's network time and energy invested in communicating with actor j . Network constraint is a local property that measures the cohesiveness of a person's network (Burt 1992), and ***network diversity*** is the opposite of network constraint and is computed as $1-C$. Since relationships may erode over time, I use a 6-month sliding window of electronic communication to gauge the network relationships in the current month.

P_{ij} is calculated from the tie strength, which is measured using the frequency of one's electronic communications. Granovetter (1982) described four identifying properties for the strength of ties: time, emotional intensity, intimacy, and reciprocity. In practice, tie strength has been measured in many ways. Some use reciprocation to represent strong ties and a lack of reciprocation to represent weak ties (Friedkin 1980). Others have included the recency of contact or the frequency of interactions as a surrogate for tie strength (Granovetter 1973). To measure the tie strength in electronic communications, I primarily use the frequency, but with some modifications.

Because a single electronic message does not constitute an actual tie, especially when it is sent to a large number of people, counting any message exchange between actors as a dyadic tie would overestimate the number of ties and the overall tie strength. Thus, I eliminated all messages that have more than 15 recipients (Lin et al. 2008). In addition, to accurately reflect the tie strength between two actors, I normalized the measure to an interval between 0 and 1, with 0 indicating no tie between the two actors and 1 indicating the maximal tie strength (Lin et al. 2008). The detailed calculation is described below.

$$Tie_Strength_{ij} = \frac{\log(X'_{ij})}{\text{Max}_k \log(X'_{ik})}$$

$$X'_{i,j} = \begin{cases} 0 : \text{if } \{X_{i,j} \leq 3 + \log(X_{i,j})\} \\ X_{i,j} : \text{otherwise} \end{cases}$$

where X_{ij} is the total number of electronic messages between actors i and j . Basically, the formula indicates that a tie exists only when the number of electronic messages between two actors reaches a certain threshold. This threshold is personalized; for active users of electronic media, the threshold to register a tie is higher than for those who seldom use electronic media. This measure of tie strength has been extensively tested and shown to accurately reflect the tie strength between actors (Lin et al. 2008).

Content Analysis

To measure information diversity and friendship, I use the content of electronic communications, after ensuring privacy is preserved. Individuals are hashed with unique classifiers, so it is impossible to determine their identities. To preserve the privacy of each message, the original textual content is also not recorded. Instead, I create a set of tokenized one-gram and two-gram keywords after eliminating stop-words and stemming. Stop words are common words such as articles (“a,” “an,” “the”) and prepositions (e.g., “from,” “of,” “to”). Stemming involves stripping each word to its root. For example, the word “running” will be recorded as its root, “run.” With these precautions, it is virtually impossible to reconstruct the original message from these tokenized keywords, which are further anonymized with hash identifiers to preserve privacy.

I model the diversity for information content using Latent Dirichlet Allocation (LDA) to classify the content into distinct topics. LDA is an advanced statistical technique that is widely used in information retrieval and machine learning. It is a generative probabilistic model that extracts topics from a corpus of documents² (Wen and Lin 2010). Each topic is a vector of words that are statistically related to each other. For example, in Figure 4, LDA classifies the sample text into four specific topics. The topic “Children” has words including “women,” “child,” “care,” and “parents.” Similarly, the topic “Budget” includes words such as “tax,” “federal,” “state,” and “spending.”

LDA classifies topics in two specific steps. The first step is a discovery phase that searches the entire topic space using every document in a corpus. Once words are classified into topics, LDA finds the topic space in each individual document. A document, in this setting, is an aggregate of all the electronic messages in a person’s communication. I use LDA to classify 100 topics using the entire corpus of electronic communications of 8,037 volunteers from January 2007 to January 2009. Information diversity is then calculated for each person in every month as the total number of topics in the person’s electronic

² Given a document corpus, LDA models each document d as a finite mixture over an underlying set of topics, where each topic t is characterized as a distribution over words. A posterior Dirichlet parameter $g(d; t)$ can be associated with the document d and the topic t to indicate the strength of t in d . For details of the algorithm, please refer to D. Blei, A. Ng, and M. Jordan, Latent dirichlet allocation, *Journal of Machine Learning Research* 3:993-1022, 2003.

communications during that month.

To measure friendship, I obtain a dictionary of every word ever used in the corpus of electronic messages. Each word is ranked by its TF-IDF³ weight, which measures how important a word is to a document. I used this list to create a sub-list of words that are related to social communications and social activities with friends but also have relatively high TF-IDF values. For example, some examples of keywords are “lunch,” “coffee,” “football,” and “baseball.” Two firm employees also verified that the words on the list are often used for social and informal activities. An employee then calculated the frequency of this set of words in each person’s monthly communications. I created a friendship index to measure friendship as the ratio of words relating to social activities to the total number of words.

$$Friendship_Index = \frac{Words_related_to_social_activities}{Total_number_of_words}$$

Control Variables

I include controls for individuals’ demographics such as gender, managerial roles, and job ranks. A managerial role is a dummy variable indicating whether the person is a manager. Job ranks have an ordinal value ranging from 6 to 12 where level 6 is a junior consultant while level 12 is an executive vice president. A dummy variable is also created for each job rank but results do not fundamentally change between using a set of dummy variables and the ordinal job rank. To control for the differences across various divisions and geographical locations, I include dummies for the four business divisions as well as a dummy for each geographical location. To control for the current workload, I include the average monthly revenue billed in the past six months. Lastly, to control for individual preferences to use electronic media, I include a person’s total number of electronic messages (email, calendar, and instant messaging) in a month.

³ TF-IDF stands for “term frequency-inverse document frequency.” It is often used in information retrieval and text mining. The weight is a statistical measure used to evaluate how important a word is to a document. The importance increases if the word is rarely used. Frequently occurring words such as “have” will have relatively low TF-IDF weights, whereas a relatively exotic word such as “haematoma” has a high weight.

IDENTIFICATION

Use Technology Adoption as an Instrumental Variable for Network Positions

Despite the overwhelming evidence for strong correlations between network positions and work performance, the causal mechanism underlying the association is underexplored (Reagans and McEvily 2003). A plausible explanation is that people actively seek high performers for advice and collaboration opportunities, and hence high performers tend to display a structurally diverse network. Similarly, certain individual characteristics may manifest in their social networks. For example, a popular person tends to have a more diverse network, which may also enable the person to be an effective employee in an organization. In essence, individual traits are the missing variables that mediate both network positions and performance, so their observed relationship may be spurious. That there are positive correlations between certain individual characteristics and network positions suggests that individual heterogeneity may moderate the relationship between network positions and performance (Burt 2004, 2007; Hargadon and Sutton 1997). For example, Burt and Ronchi (2007) suggest that high-status individuals such as executives are more likely to occupy brokering positions in the firm because their roles as executives require them to reach out to a diverse range of people. Similarly, Burt (2007) suggests that inherent abilities, such as possessing performance-enhancing cognitive skills, are ultimately responsible for improving work performance. In short, in this view, network positions are a function of human capital.

To detect a causal relationship between network positions and performance, an exogenous source of variation is needed (Munshi 2003). I exploit the adoption of a social networking tool that can exogenously change a person's network position over time. The primary function of this technology (Expertise-Find) is to allow users to search for experts using keywords. Because people resort to technologies only when they cannot find relevant experts in their immediate network neighborhood (Borgatti and Cross 2003), the experts in a user's search are often outside of the person's existing social circle. If users decide to reach out to these experts, the network diversity of the users is likely to increase after using this tool. Accordingly, the adoption of Expertise-Find could exogenously change a person's network position. If observable improvements in work performance are detected after the technology

adoption, it is likely that the increase in network diversity induces the performance improvement, suggesting a causal relationship between network positions and performance.

Expertise-Find

Expertise-Find is similar to popular search engines on the Web, such as Google, with the only difference being that instead of URLs, it returns a list of people whose expertise is relevant to the search query. This tool aggregates as much information as it can about the employees inside the firm using the intranet. For example, the tool can crawl and mine information about employees using their online profiles, resumes, online forums as well as communication data if they decide to volunteer their electronic communication data. These data from the intranet serve as the basis to infer individual expertise at the firm. For example, when searching for the phrase “Social Networks,” Expertise-Find would return a list of people ranked by whether their expertise is relevant social networks (Figure 2). Each search result lists the name of the expert, a picture (if available in the public HR directory), the job role, and the division the expert belongs to. If one clicks on the person, the system shows more details, such as the physical work location and contact information. In order to understand how employees use the search tool and how often they actually contact the experts from the search, I conducted an extensive survey about the general usage and search behaviors. The consistent pattern from the survey reveals that the vast majority of people use Expertise-Find when they have already exhausted their existing local networks, conforming to earlier studies (Borgatti and Cross 2003). By contacting experts suggested by the tool, users are more likely to find the information they need either directly, or through further recommendations from the expert. Evidence also suggests that the relationship formed between the expert and the searcher can become more permanent with repeated interactions. One person interviewed commented that she made a friend after contacting an expert through the tool. One of the experts who had helped her earlier was transferred to the same work location as she was, and she offered to help the expert through the transition and they became friends afterward. Some experts also mentioned that they received thank-you gifts from the searchers they helped, and this helped to enhance their relationship. The firm has a program that sponsors this type of

gifts so that individuals can use them to thank people in the organization who are helpful to their work.

Overall, by contacting people from the search result, users are more likely to reach out to a distant group of people, increasing their network diversity. Because I have the historical electronic communication data of the volunteers, it is possible to measure the network change for the same person before and after the adoption. If there is a change in the network position after the adoption, it is plausible to attribute the change to using the search tool. If we simultaneously observe a performance change, it is likely that the performance gain is due to the change in network positions. However, there may be self-selection factors that could induce both a network change and the adoption of the search tool, and it is important to address them.

Selection Effect

An important concern is that there is a selection bias in choosing when and why to sign up for Expertise-Find. The bias can simultaneously drive the adoption of the tool as well as any change in network positions. However, three factors help alleviate the bias. First, I examine the change in a person's network position before and after the adoption. If there are any unobserved individual characteristics, such as the propensity to use new technologies, that can drive both the adoption and the network change, I can eliminate this type of bias through a fixed-effect specification. Second, people adopted this tool at different times throughout the study, allowing me to control for any temporal shocks that can affect the adoption choice. For example, if people are more likely to sign up for the tool after their annual performance review in February, controlling for the February-effect can eliminate this bias. It is also plausible that people would choose to use Expertise-Find when they already have many consulting projects. Consequently, it may seem that a network change is affecting the change in billable revenue, but it is actually a reverse causality in which having a heavy workload induces people to use the technology and change their network positions as a result. In order to eliminate this bias, I use the average monthly billable revenue in the past 6 months to control for the existing workload. It is also possible that a person chooses to adopt the tool when a project requires different knowledge from what they had before. Hence,

the person uses the tool to access information. I argue that the adoption of Expertise-Find can be particularly helpful because it provides a means for the person to reach experts in distant pockets of the organization. Thus, the tool can reduce the search costs of finding information and help the person complete projects and satisfy clients.

One could also argue that it is not the network, but the ability to locate information quickly, that is ultimately responsible for inducing the performance change. Because Expertise-Find can effectively locate the source of information, it reduces the search cost of information that is ultimately affecting performance. However, as I argued earlier, a structurally diverse network is reason for reducing the search cost because such networks can generate information benefits that expose people to more information, and more unique information, than their peers. Hence, using Expertise-Find as an instrument for network diversity, I can directly observe if network diversity produces information benefits in the forms of information diversity and friendships.

After controlling for factors that may drive the adoption choice, it is plausible that the adoption is exogenous for changing the network position. Although I am aware that there could still be other unobserved heterogeneities that violate this assumption, interviews and surveys on user behaviors do not show any other consistent pattern that could drive both the technology adoption and the change in network positions.

EMPIRICAL METHODS

I estimate the relationship between network diversity and work outcomes using the adoption of Expertise-Find as an instrument for network diversity. To understand how a structurally diverse network induces superior work outcomes, I examine if network diversity actually generates information diversity and friendship, the two types of information benefits theorized to arise from a structurally diverse network. Using the adoption of Expertise-Find, I hope to find evidence of causal relationships between network diversity and information diversity, between network diversity and friendship, and between network diversity and work outcomes.

Furthermore, I am interested in how information benefits—information diversity and friendships—ultimately affect different types of work outcomes: billable revenue and layoffs. However, the instrumental variable approach is not sufficient to identify the relationship because I have two potentially endogenous variables but only one instrument. Hence, in order to control for the differences in individuals' characteristics, I incorporate attributes such as gender, demographics, and job roles that may affect both information benefits and work outcomes. If the unobserved heterogeneity in individuals' characteristics is correlated with the error terms in the model, estimates using pooled OLS will be biased. To address this issue, I examine the variation within and across individuals over time using both fixed and random effect models to control for the bias. However, this technique can only be applied when studying the impact of network positions on billable revenue, because I have a longitudinal panel of both. But layoffs are cross-sectional because being laid off is a one-time event. Thus, I can only control for observable individual characteristics, instead of exploiting the variation within individuals as I could with the analysis on billable revenue. To alleviate the endogeneity concern in analyzing layoffs, I employ the lagged measurements of network characteristics at time $t-1$ to predict layoffs at time t . Specifically, I use the electronic interactions six months prior to the layoff events to calculate network variables. If networks are to have an effect on layoffs, the network of communications prior to the layoff event should have an important impact. Furthermore, I also included individuals' objective performance, billable revenue, to predict layoffs, because employees with superior performance should have lower probability of being laid off. To mitigate the estimation problem arising from the endogenous relationship between network characteristics and billable revenue, I use the billable revenue generated 6 months prior (at time $t-2$) to when network characteristics are calculated (at time $t-1$).

RESULTS

Network Change from the Technology Adoption

First, I examine if the adoption of Expertise-Find can actually induce a change in network positions. It is possible that the adoption is not a random event. However, because I examine the network

change for the same person over time, fixed-effect models can eliminate many individual heterogeneities, such as human capital, that might bias the estimates. I also control for temporal shocks to mitigate some biases from time-varying characteristics. By including a dummy for each calendar month, I eliminate the seasonal effects that can drive the adoption choice. However, there might still be time- and individual-varying biases. For instance, it is possible that people are more likely to adopt this technology when facing high workloads. Thus, I use the average billable revenue in the past six months to control for the general workload at the time of the adoption.

To construct the technology adoption variable, I use a binary variable that equals 1 for every month after the person has adopted Expertise-Find and zero before the adoption has happened. Overall, there is a positive and significant correlation between the instrument and the endogenous variable in the first-stage regression. Using the fixed-effect model, I find that the correlation between network diversity and the adoption of Expertise-Find is .114 ($t = 17.86$) after controlling for seasonality and past performance. To estimate the validity of the instrument, I calculate the concentration parameter, which is 86.7, indicating that the adoption of Expertise-Find is not a weak instrument (Hansen, Hausman, and Newey 2004).⁴ Figure 2 shows the relationship between network diversity and the timing of the adoption in an event study. Each data point on the graph shows the coefficient estimates calculated from regressing the network diversity on each month before and after the adoption event in the 2-year period in my sample. After factoring out seasonality, individual fixed-effects, and past performance, the coefficient estimate for months after the adoption event ($X > 0$) is increasing over time, indicating that Expertise-Find can induce a change in network diversity (Figure 1).

The reduced-form regressions in Table 3 show that the adoption is positively associated with generating billable revenue as well as reducing the risk of layoff (or increasing job retention). After controlling for temporal shocks, individual fixed-effects, and a person's past performance, Model 1 of

⁴ The test for weak instrumental variable requires the concentration parameter to be greater than 10 (Hansen, Hausman, and Newey 2004). Any value less than 10 indicates the presence of a weak instrument.

Table 3 shows that the adoption of Expertise-Find is positively associated with generating more billable revenue. As with layoffs, the adoption is also positively correlated with job retention. However, because the layoff event has only one observation for each person, it is impossible to use the earlier instrumental variable approach that relies on the network change before and after the adoption. Instead, I use the number of months since a person has signed up for Expertise-Find to instrument for network diversity. As shown in Figure 3, network diversity gradually increases after a person has started to use the tool. Thus, other things being equal, early adopters should have more structurally diverse networks than late adopters. To test the validity of this instrument, I calculate the concentration parameter in the first-stage regression and the value is 11, slightly above the cut-off for the validity of the weak instrument test. The reduced-form regression (Model 2) shows that the number of months passed after the adoption is positively correlated with job retention.

Network Effect on Billable Revenue

Next, I show if a technology-induced change in network positions can induce a change in performance over time. Model 1 of Table 3 shows the OLS estimate on the correlation between network diversity and billable revenue, after controlling for demographics, the work division as well as the managerial and technical level for the person. This is what has been traditionally estimated in understanding the relationship between network diversity and performance in previous research. As shown in Model 1, coefficient estimate for network diversity is positive and the effect is relatively large. A 1% increase in network diversity is correlated with billing 886 US dollars in a month. However, when a fixed-effect specification is used (Model 2), the size of the coefficient is reduced by 17% ($\beta_{\text{network diversity}} = 733.0, p < .01$). This shows that unobserved time-invariant individual characteristics could drive changes in both network diversity as well as work performance. In Model 3, I estimated the effect of network diversity on billable revenue using the adoption of Expertise-Find as an instrumental variable (IV) for network diversity. The coefficient from this IV regression is reduced dramatically by 82% ($\beta_{\text{network diversity}} = 126.5, p < .1$), demonstrating time-varying individual heterogeneity can still bias the estimate upward.

However, network diversity in the IV regression continues to be positive and statistically significant, demonstrating that it can induce a positive change in performance.

<< Insert Table 3 about here >>

In Model 4, 5 in Table 3, I incorporated the total number of electronic messages exchanged over a month as a control for individual differences in online media use. It is possible that tech-savvy individuals are more likely to adopt a new technology and simultaneously be high performers. After controlling for usage of electronic media, the results largely mirror earlier results. The parameter estimate of network diversity in IV model is significantly less than the estimates in the fixed-effect model, but the coefficient is still positive and statistically significant. It is also possible that existing workload may drive the adoption of Expertise-Find as people seek to use this tool to help with their high workload. To address this potential bias, I controlled for the average monthly revenue in the past 6 months. As shown in Model 6 and 7, while past performance is strongly correlated with the current billable revenue, the IV estimate for network diversity continues to be positive and significant. However, the size of the effect estimated in the IV regression is much smaller than estimates using the fixed-effect model and the OLS model. Overall, these results largely support Hypothesis 1a.

Network Effect on Layoffs

While I show evidence of a causal relationship between network diversity and billable revenue, I also examine if network positions can affect a person's risk of being laid off. If network positions are to have an impact on work outcomes, it should have an even more pronounced impact on layoffs, because unlike promotions and performance evaluations, layoffs are a more traumatic experience for most people and network contacts should play an important role in keeping a person from being laid off. To understand how networks affect the risk of layoffs, I compare information diversity and friendships to determine which can have more impact on reducing the risk of layoffs. Table 7 shows the cross-sectional analysis of the network effect on layoffs using the network characteristics calculated from six months of electronic communications prior to the layoff event.

The first model of Table 5 shows the effect of network diversity on job retention (1-layoffs). Gender and job roles do not show any statistically significant effect on job retention, but geographical locations appear to have an effect. Compared to the European Union, workers in the US are more likely to be laid off. This difference is probably due to stronger labor laws in Europe, which make it harder for the firm to downsize. I also control for the usage of digital media and show that network diversity is positively correlated with job retention, but it is just short of being statistically significant (Model 1).

In Model 2, I examine if there is a causal relationship between network diversity and layoffs using instrumental variables. I use the number of months that have passed since a person has adopted Expertise-Find as an instrument for network diversity. However, the instrument can be problematic because there might be individual characteristics that drive both the network change and the likelihood to adopt early. This is more problematic in a cross-sectional analysis, because it is impossible to exploit the fixed-effect model to eliminate any time-invariant individual characteristics, such as the propensity to be early or late adopters. To address this issue, I control for demographics, gender, job role, and rank and other observable individual traits. However, I am aware that there might still be unobserved variables that may drive both changes in network positions and the risk of layoffs.

The instrumental variable approach shows that the coefficient on network diversity is positive. Specifically, a one-percentage increase in network diversity is correlated with an increase of 15.7 percentages in job retention, providing evidence that peripheral actors are more likely to be laid off than those who occupy more central positions in the network. However, it is possible that those with a structurally diverse network may just perform better and for that reason are less likely to be laid off. To address this issue, I control for the objective work performance using billable revenue. However, billable revenue is an endogenous variable because network positions can simultaneously affect billable revenue and the risk of being laid off. Hence, including billable revenue as an independent variable is problematic (Angrist and Pischke 2009). To address this problem, I use the lagged billable revenue 6 months before measuring the network characteristics. The timing difference implies that the billable revenue is predetermined before network positions are calculated. Thus, they are less likely to be the outcomes in the

causal nexus (Angrist and Pischke 2009). Using billable revenue from an earlier period is also beneficial because it controls for possibilities that people who are finishing their current projects may also face increased risk of layoff when they do not have any future projects lined up. As expected, the objective performance, measured by billable revenue, is a strong predictor for job retention (or reduced risk of layoff). Similarly, network diversity continues to be positively correlated with job retention (Model 3, Table 5). If the main advantage to having a structurally diverse network is the access to relevant information and expertise, the billable revenue generated should capture the performance impact from network diversity. But Model 3 shows that a structurally diverse network provides additional shields against layoff, even after controlling for the objective performance, and interestingly, the effect from network diversity is actually greater than that from billable revenue ($\beta_{\text{billable revenue}} = .090$, $\beta_{\text{network diversity}} = .150$). The F-test shows the significance of the test is at $p < .001$ level, demonstrating that in addition to information diversity, a structurally diverse network can protect a worker from being laid off, beyond generating more billable revenue for the person.

A possible explanation for why network diversity can reduce the risk of layoff even after controlling for billable revenue is that actors with a structurally diverse network can be instrumental for helping others to generate revenue for the firm. By providing key information and expertise to their network contacts, the actors can indirectly contribute to the profitability of the firm and, accordingly, they are less likely to be laid off. If this is the case, we would expect that the billable revenue generated from network contacts can reduce a person's risk of being laid off. However, the average billable revenue generated from a person's network contacts (1 degree away), is not statistically significantly correlated with retention (Model 4). This result provides some evidence that helping friends does not reduce a person's risk of being laid off.

Lastly, I examine if the results are causal using the number of months that have passed since a person has adopted Expertise-Find as an instrument for network diversity. Model 4 shows that a 1% increase in network diversity is associated with an increase of 11.8 percentages in job retention, demonstrating that network diversity has a significant impact on layoffs. However, the sizes of the effects

from network diversity and billable revenue are comparable. Interestingly, the billable revenue of network contacts increases the risk of layoffs. This is possibly because when others perform well, it actually decreases the relative performance of the person and thus increases the risk of layoff for the person. Taking these results together, a structurally diverse network can positively associated with job retention, supporting hypothesis 1b. To understand exactly how a structurally diverse network can increase the rate of retention as well as generating more billable revenue, I examine the effect of information benefits derived from a structurally diverse network. In particular, I focus on information diversity and friendship or referrals and their impacts on work outcomes.

Information Diversity and Friendship as a Function of Network Diversity

I explore if a structurally diverse network, as measured by network diversity, actually generates information benefits, specifically in the forms of information diversity and friendship. Information diversity is calculated as the number of topics in a person's electronic communications. Friendship is calculated using a friendship index that measures the frequency of words in the messages that are related to informal activities. Social activities and friendship are proxies for the referral process, because friends are more likely to advocate for the person, trumpeting his or her accomplishments at key junctions such as during layoffs.

Table 4 shows the relationship between information diversity and network diversity, and between the friendship index and network diversity. I find strong evidence that network diversity generates information diversity. Using a fixed-effect model, a one-standard-deviation increase in network diversity is associated with finding an additional 1.5 topics in one's electronic communication (Model 1). The effect continues to be positive ($\beta_{\text{network diversity}} = 6.11, p < .05$) when an instrumental variable is used for network diversity. This is also similar to findings in Aral and Van Alstyne (2007), which also finds a structurally diverse network to be positively correlated with accessing diverse information. Next, I examine if a structurally diverse network can also facilitate the referral process as measured by the friendship index. As with information diversity, the fixed-effect model shows that a one-standard-

deviation increase of network diversity is correlated with gaining .01 points in the friendship index, which is about a one percentage increase (Model 3). Network diversity continues to be positively associated with the friendship index ($\beta_{\text{network diversity}} = .216, p < .05$), using the adoption of Expertise-Find as an instrumental variable. Overall, the fixed-effect and the IV regressions show a causal relationship between network diversity and friendships. Having friends in a diverse network can facilitate the referral process where friends can serve as advocates for the person. These results support Hypotheses 2a and 2b.

In Table 7, I explore whether information diversity and friendships are complements or substitutes by examining their correlations. After controlling for temporal shocks, individual fixed effects, and past performance, the correlation between information diversity and friendship index is negative, suggesting a substitutive relationship between the two. Though they can overlap, gathering information and forming friendships are two distinct activities. Possibly because one has only limited time and energy for either pursuing information or friendships, the two activities seem to be substitutes, supporting Hypothesis 3. This substitutive relationship also demonstrates that a structurally diverse network can generate both expressive and instrumental elements, as shown by information diversity and friendship, respectively. However, there might be a tradeoff between the two in generating the desired work outcome, as I explore in the next section.

Information Diversity, Friendship and Their Relationships to Billable Revenue and Layoffs

To examine how a structurally diverse network improves work performance, I explore how information diversity and friendship or referrals differ in generating billable revenue and reducing the risk of being laid off. Table 8 shows the effect of these factors in generating billable revenue. Model 1 shows that, after controlling for the volume of communication, a one-standard-deviation increase in information diversity is correlated with generating an additional \$187.50 of billable revenue, while the friendship index is not statistically significantly correlated with billable revenue. When both information diversity and the friendship index are treated as independent variables in the same model (Model 3), I find that information diversity, but not the friendship index, is positively correlated with generating billable

revenue. In Models 4-6, I control for the past billable revenue, because it could be serially correlated with the current billable revenue. Results in these models largely mirror the earlier results in Models 1-3: only the coefficient on information diversity is statistically significantly correlated with billable revenue; the coefficient on the friendship index is not. Overall, these results support Hypothesis 4a. In Model 7, I explore whether information diversity and the friendship index serve as complements or substitutes. The negative interaction effect ($\beta_{\text{information diversity} \times \text{friendship index}} = -219.18, p < .05$) shows they are substitutes for generating billable revenue.

Next, in Table 9, I explore the effect of information diversity and the friendship index on job retention (reducing risk of layoff). The first model shows the correlation between information diversity and job retention after controlling for demographics, gender, job ranks, and dummies for regions and business divisions. Contrary to the result in the performance analysis, information diversity is not correlated with retention (Model 1). However, a one-standard-deviation increase in the friendship index is associated with an 11 percentages increase in job retention (Model 2). When both information diversity and the friendship index are jointly used in the model, the friendship index is still positively associated with retention but the coefficient on information diversity is not. The F-test shows that the effect of the friendship index is greater than that of information diversity at $p = .01$ level. This set of results suggests that friendship, which approximates the referral process, is more important for avoiding layoffs than is information diversity. This is the exact opposite from the performance analysis where information diversity is more correlated with generating billable revenue than is friendship.

Because work performance could also have a significant impact on layoffs, I control for the average billable revenue, using data 6 months prior to the layoff event (Models 4-6 of Table 9). All else being equal, high performers are more likely to be retained than low performers. It is also possible that a person contributes indirectly to firm profits by helping his colleagues. Thus, I control for the billable revenue of the network contacts in Models 4-6. As in Model 1-3, I find that compared to information diversity, friendship is more correlated with job retention (Model 4). The F-test shows that the coefficient of friendship is greater than that of information diversity in maximizing job retention ($p < .001$). Together

these results demonstrate that friendship, which approximates the referral process, is the primary channel through which a structurally diverse network drives job retention, lending support to Hypothesis 4b. From qualitative interviews, managers state that a person is less likely to be laid off when others have heard about his or her work either directly or indirectly. Because friends are more likely to advocate for friends, having a diverse group of friends is helpful in averting crises, such as layoffs.

Next, I explore whether information diversity and friendship are substitutes in preventing layoffs. Model 7 shows the interaction effect of information diversity and the friendship index to be negative and statistically significant, demonstrating that they *are* substitutes. I hypothesize that the negative interaction occurs because that one only has limited time and energy for either gathering diverse information or forming friendships. Spending more time on one would result in less time to spend on the other. Thus, I show that a structurally diverse network can have both instrumental and expressive elements, contrary to the notion that it is rare to have both because one may dampen the effect of the other. However, the tradeoff re-emerges in the ability of a person to mobilize *either* information diversity *or* friendship to achieve a desired work outcome. The substitutive relationship between the two shows the limitation in mobilizing them together. The return from investing in friendships will dampen the return to investment in information diversity. While access to diverse information is helpful for monthly billing revenue, it takes away time from forming friendships that are helpful for reducing the risk of layoffs.

DISCUSSION AND CONCLUSION

In this study, I examine the impact of social networks on billable revenue and layoffs. Using the adoption of a social networking tool that could change a person's network position over time, I show evidence of a causal relationship between network diversity and billable revenue and between network diversity and layoffs. However, the size of the effect is much smaller than the traditional OLS and fixed-effect estimates. Because this tool can improve a person's network position primarily through information-seeking activities, the improvement in work performance is likely to come from the information benefits derived from having a structurally diverse network. However, there are two different

types of information benefits—information diversity and referrals—and they could have different effects in generating billable revenue and avoiding layoffs. Using the adoption of Expertise-Find as an instrument for network diversity, I show that a structurally diverse network can generate both friendships and information diversity.

To examine how the effect of information diversity differs from the effect of referrals in generating superior work outcomes, I take advantage of information technology that captures the digital traces from people's daily communications. I use advanced machine-learning techniques to assess the content of people's electronic communications. To measure the diversity or the novelty of information content, I calculate the number of distinct topics in a person's communications. To measure referrals, I calculate a friendship index that captures the frequency of words in the electronic communications that are related to informal and social activities. Comparing the measurement of information diversity with the friendship index, I show that the former is positively correlated with generating billable revenue, whereas the latter is not. However, I find that in the case of layoffs, the friendship index is positively associated with retention, while information diversity is not. Interviews with managers who participated in the layoff decisions suggest that the referral is more important for job retention because layoffs can have a dramatic effect on one's colleagues. Thus, these colleagues are likely to serve as advocates in critical situations such as impending layoffs, promoting one's work and accomplishment to others. This can reduce the probability of being laid off.

Information benefits can also be classified as instrumental and expressive, with information diversity being the instrumental element and friendship being the expressive element. Contrary to the notion that it is difficult to have both in a network because instrumental ties may dampen the effect of expressive ties (Fernandez 1991), I show it is possible to have both in a structurally diverse network. However, information diversity and the friendship index are shown to be substitutes for generating billable revenue and avoiding layoffs, suggesting a tradeoff in the returns from investing in instrumental (information diversity) or expressive elements (friendships) in a structurally diverse network.

These results raise a question: what is the mechanism by which friendships reduce the risk of

being laid off? One hypothesis is that friendships directly enhance productivity, but there is no direct evidence of any such impact. My data analysis suggests that such friendships do not contribute to one's own billable hours or to the billable hours of one's contacts. An alternative hypothesis consistent with my data analysis is that managers' objectives may differ from those of owners. While the owner's objectives are (presumably) to maximize the overall profitability of the firm, managers may prioritize maximizing their own power within the firm. Managers may choose to retain people who are relatively poor contributors to firm productivity if those employees otherwise enhance the standing of managers within the firm. This suggests that the impact of friendship on layoffs is evidence that delegating layoff decisions to managers has important costs. Future work could attempt to examine more fully the costs and benefits of such delegation in order to improve our understanding of the optimal allocation of decision rights within firms.

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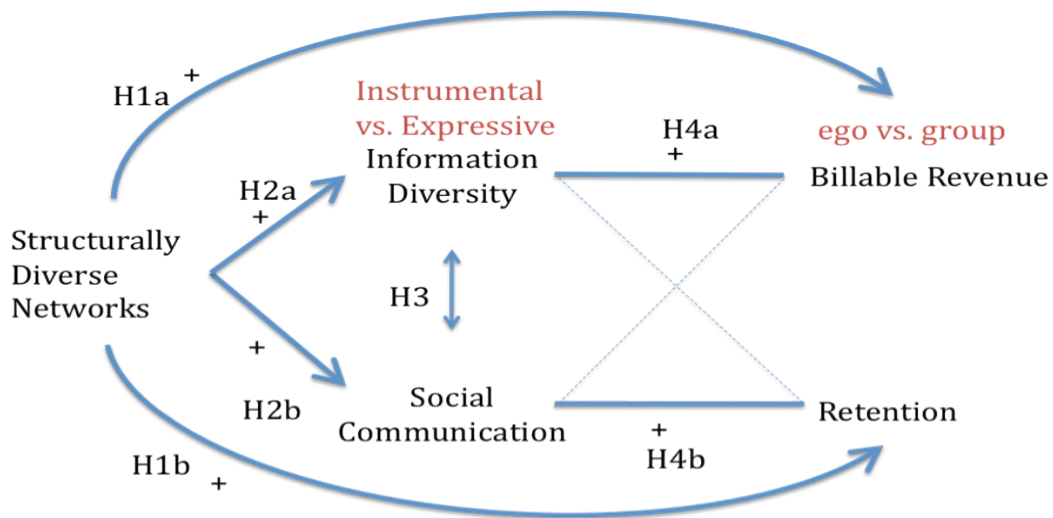


Figure 1: Hypothesis Testing.

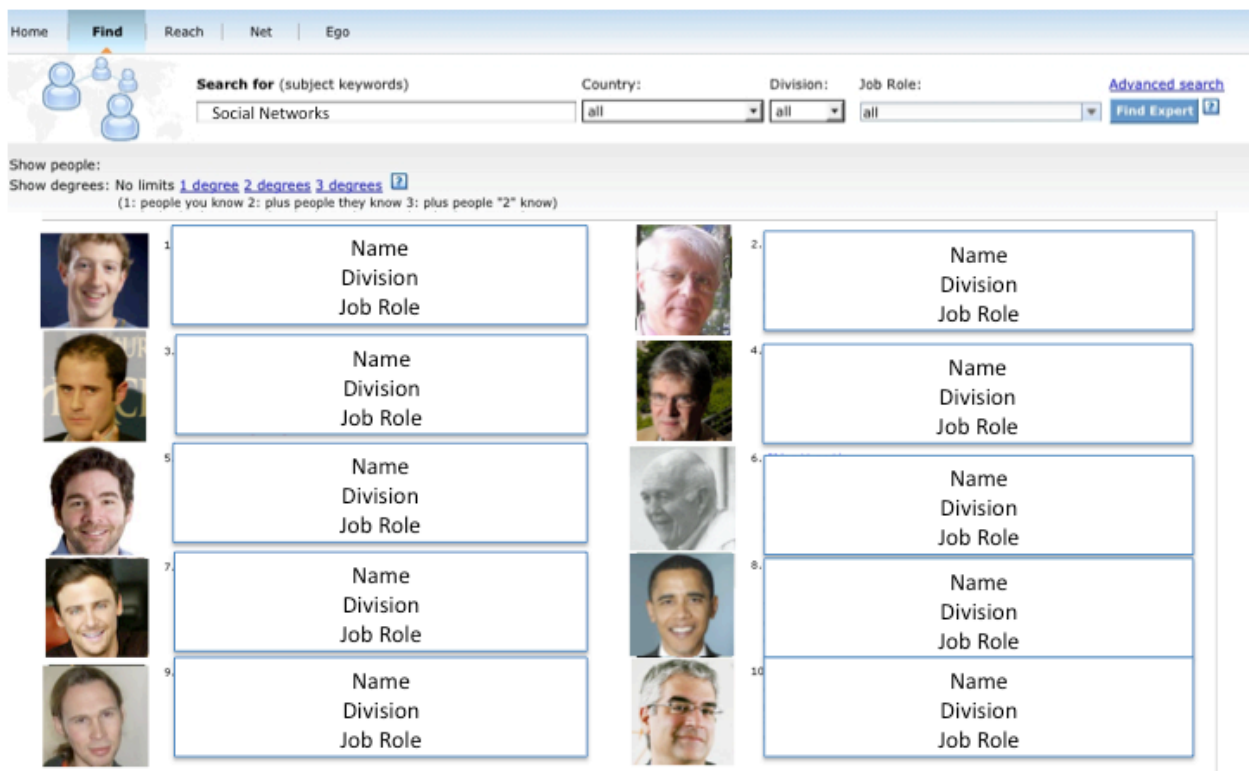


Figure 2: Snap shot of Expertise-Find. Result from Searching for “Social Networks” using Expertise-Find

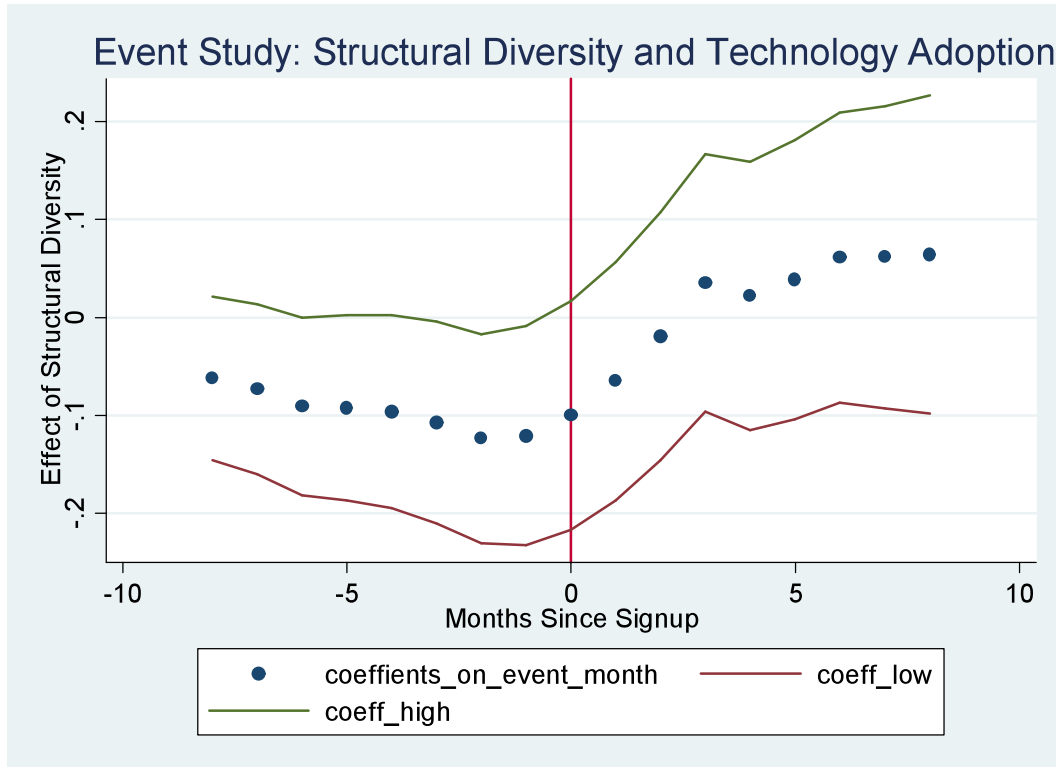


Figure 3: Event study for when people adopted Expertise-Find. Each point on the graph is the coefficient estimates calculated from regression network diversity on the month since adoption after controlling for calendar-month dummies, past billable revenue and individual fixed-effect. A value of zero on the X-axis indicates that Expertise-Find is just adopted. Negative values on the X-axis indicate the number of months before the adoption has occurred and the positive values indicate the number of months passed since the adoption. From this graph, it shows that the effect on structurally diversity gradually goes up since the adoption even at X=0.

"Arts"	"Budgets"	"Education"
Opera	Million	School
Performing	Board	Education
Act	Grants	Monday
Lincoln Center	Support	Taught
New York Philharmonic	Research	Young
Leading	Services	
Music	Foundation	
Supporter	President	
	Announcing	
	Building	
	Fund	
	Receive	
	Annual	
	\$25,000	
	\$100,000	

The William Randolph Hearst **Foundation** will give **\$1.25 million** to **Lincoln** Center, Metropolitan **Opera** Co., **New York Philharmonic** and Juilliard **School**. "Our **board** felt that we had a **real** opportunity to make a **mark** on the future of the **performing** arts with these **grants** an **act** every **bit** as important as our traditional areas of **support** in health, medical **research**, **education** and the social **services**," Hearst **Foundation** **President** Randolph A. Hearst said **Monday** in **announcing** the **grants**. **Lincoln** Center's share will be **\$200,000** for its **new building**, which will **house** **young** artists and **provide new public facilities**. The Metropolitan **Opera** Co. and **New York Philharmonic** will **receive \$400,000** each. The Juilliard **School**, where **music** and the **performing** arts are **taught**, will get **\$250,000**. The Hearst **Foundation**, a **leading supporter** of the **Lincoln** Center Consolidated Corporate **Fund**, will make its usual **annual \$100,000** donation, too.

Figure 4: An Example of using LDA to Classify Text

Variable	Obs.	Mean	Std. Dev.	Min	Max
Direct Contacts	8071	106.15	116.584	1	1575
Network Constraint	8071	.531	.303	.052	1.735
Ties to managers	8071	17.518	18.349	0	256
Ties to divisions	8071	.642	1.096	0	11

Variable	Obs	Mean	Std. Dev.	Min	Max
layoff	8071	.054	.226	0	1
Gender (0-male)	8071	.184	.388	0	1
Job Rank	8071	7.768	1.508	1	12
Managers	8071	.161	.367	0	1

Model	(1)	(2)
Dep var:	Monthly Billable Revenue	Retention
Adoption	584.15** (282.30)	.028** (.123)
Individual Fixed Effect	Yes	No
Month Dummies	Yes	No
Control variables	Communication Volume Past Billable Revenue Work divisions, geographical locations	Communication Volume Past Billable Revenue Work divisions, geographical locations
#people	2,038	1,506
Average Month Billable Revenue	11,842	11,842
Observations	20,373	1,506
Clustered standard error, *** p<0.01, ** p<0.05, * p<0.1		

Table 4: Network Diversity and Performance							
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable	Monthly revenue	Monthly revenue	Monthly revenue	Monthly revenue	Monthly revenue	Monthly revenue	Monthly revenue
Model	OLS	FE	IV	FE	IV	FE	IV
Log Diversity: log(1-constraint)	886.4*** (18.20)	733.0*** (154.11)	126.5 (74.19)	843.6*** (160.55)	181.00*** (12.50)	882.4*** (160.28)	239.5** (117.90)
Volume of email/IM/calendar events				.290*** (.09)	-.320 (.290)	.253*** (.09)	-.463* (.27)
Average billable revenue in the past 6 months						.110*** (.01)	.121*** (.01)
Controls							
Gender (0-male)	-258.6 (388.9)	-- --	-- --	-- --	-- --	-- --	-- --
Manage (dummy)	-617.0 (692.8)	-- --	-- --	-- --	-- --	-- --	-- --
Job rank (6-12)	1,369*** (127.2)	-- --	-- --	-- --	-- --	-- --	-- --
Business Consultant Division (dummy)	7,367*** (874.1)	-- --	-- --	-- --	-- --	-- --	-- --
Technology Consultant Division (dummy)	2,363* (1,220)	-- --	-- --	-- --	-- --	-- --	-- --
Sales Division (dummy)	612.1 (1,160)	-- --	-- --	-- --	-- --	-- --	-- --
Headquarter (dummy)	161.8 (1,280)	-- --	-- --	-- --	-- --	-- --	-- --
Software Division (dummy)	4,348*** (1,088)	-- --	-- --	-- --	-- --	-- --	-- --
Observations	20,373	20,373	20,373	20,373	20,373	20,373	20,373
#employees	2,038	2,038	2,038	2,038	2,038	2,038	2,038
Controls: monthly dummy for each of the 24 months							

Table 5: Networks Diversity and Layoff/Retention					
Model	(1)	(2)	(3)	(4)	(5)
Dependent Variable	retention	retention	retention	retention	retention
Model	Probit	IV Probit	Probit	Probit	IV Probit
ln(network diversity): log(1- constraint)	.105 (.077)	.157*** (.019)	.150* (.085)	.105* (.062)	.118** (.060)
Log(Billable revenue)			.090** (.043)	.096** (.044)	.155*** (.042)
Log(Friends' Billable Revenue)				-.050 (.057)	-.197** (.093)
Controls					
Volume of email/IM/ calendar events	1.58e05 (1.48e05)	-7.72e-05*** (1.81e-05)	1.52e05 (1.62e05)	2.70e05 (1.94e05)	-8.89e-06 (3.03e-05)
Gender (0-male)	.089 (.125)	.112 (.0861)	.0480 (.135)	.064 (.136)	-.031 (.132)
Job Role (level 6-12)	.055 (.0360)	.163*** (.0467)	.0568 (.0412)	.056 (.0413)	.079 (.096)
Europe	.674*** (.157)	.102 (.240)	.646*** (.174)	.657*** (.175)	.406 (.293)
Asia	.510** (.225)	.249 (.193)	.478* (.248)	.474* (.250)	.358 (.254)
Australia	.423 (.259)	.0829 (.200)	.598* (.332)	.619* (.334)	.421 (.350)
US (dummy)	-.362** (.141)	-.194 (.134)	-.445*** (.157)	-.445*** (.158)	-.419*** (.160)
Technology Division (dummy)	.125 (.635)	.00747 (.384)	.773 (.744)	.716 (.764)	.663 (.666)
Business Division (dummy)	.133 (.575)	-.519 (.371)	.264 (.618)	.280 (.634)	.032 (.585)
Sales Division (dummy)	.353 (.705)	-.666 (.463)	.530 (.754)	.467 (.773)	.087 (.729)
Software Division (dummy)	.003 (.620)	-.546 (.383)	.0475 (.660)	-.0295 (.680)	-.314 (.612)
Headquarter (dummy)	.585 (.695)	.524 (.418)	.783 (.748)	.724 (.764)	.902 (.651)
Observations	1,927	1,927	1,927	1,927	1,927
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1					

Table 6: Relationships among Network Diversity, Information Diversity and Friendship				
Model	(1)	(2)	(3)	(4)
Dependent Variable	Information Diversity	Information Diversity (std)	Friendship Index	Friendship Index
Model	FE	IV	FE	IV
Network diversity (std)	1.466*** (.196)	6.105** (3.05)	.010*** (.003)	.216** (.105)
Controls				
Volume of email /IM/calendar events	.00207*** (.000267)	-.0111 (.00684)	7.39e-05*** (2.92e-06)	4.79e-05*** (1.37e-05)
Log(Billable revenue)	-8.41e-05*** (3.11e-05)	.000166 (.000169)	4.03e-08 (4.29e-07)	9.90e-07 (6.89e-07)
Observations	9,666	9,666	15,634	15,634
R-squared	.027		.064	
Number of people	1,912	1,912	1,912	1,912
Controls: monthly dummies for each of the 24 dummies and individual fixed effect				
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1				

Table 7: Correlations Between Information Diversity and Friendship	
	Information Diversity
Friendship Index	-.033*** (.0125)
Controls: monthly dummies for each of the 24 dummies, individual fixed effect, and past billable revenue	
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1	

Table 8: Network Position and Performance: Information Diversity and Friendship							
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable	Monthly revenue	Monthly revenue	Monthly revenue	Monthly revenue	Monthly revenue	Monthly revenue	Monthly revenue
Model	FE	FE	FE	FE	FE	FE	FE
Information Diversity (standardized)	187.5* (108.1)		192.4 (108.1)	244.6** (107.0)		249.5** (107.0)	239.9** (107.1)
Friendship Index (standardized)		5.695 (65.20)	147.3 (122.8)		42.76 (66.86)	178.3 (100.3)	-33.30 (163.48)
Information Diversity X Friendship Index							-219.18** (115.8)
Controls	volume of communication			volume of communication past billable revenue			
Observations	20,373	20,373	20,373	20,373	20,373	20,373	20,373
#employees	2,038	2,038	2,038	2,038	2,038	2,038	2,038
<i>Controls</i> : monthly dummy for each of the 24 months, individual-level fixed-effect							
Standard errors in parentheses *** p<0.01, ** p<0.05							

Table 9: Networks and Layoff Risks: Information Diversity vs. Friendship							
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable	retention	retention	retention	retention	retention	retention	retention
Model	Probit	Probit	Probit	Probit	Probit	Probit	Probit
Information Diversity (standardized)	.026 (.064)		.031 (.064)	.062 (.073)		.0683 (.074)	.0814 (.083)
Friendship Index (standardized)		.110* (.061)	.112* (.062)		.193** (.090)	.184** (.090)	.209** (.097)
Information Diversity X Friendship Index							-.264** (.139)
Log(Billable revenue)				.125*** (.047)	.116** (.048)	.120** (.048)	.123*** (.048)
Log(Friends' Billable Revenue)				-.020 (.066)	-.013 (.064)	-.027 (.067)	-.020 (.067)
Observations	1,927	1,927	1,927	1,927	1,927	1,927	1,927
<i>Controls</i> : Volume of email/IM/ calendar events, gender, job rank, regional dummies, business division dummies							
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1							