Social Network Effects on Performance and Layoffs: Evidence From the Adoption of a Social Networking Tool

Lynn Wu

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Abstract

While a large body of literature has examined the correlations between certain network positions and performance, little research has shown a causal link between social networks and productivity. I address this issue by introducing a social networking tool that could alter a person’s social network inside a large information technology firm. By examining work performance before and after the adoption of the expertise search engine, I show evidence of a potential causal relationship between brokerage and performance. However, the size of the effect is much smaller than traditional OLS and fixed-effect estimates. Using both positive (billable revenue) and negative (layoffs) outcomes as performance measures, I show the primary mechanism driving work performance is the informational advantage derived from structurally diverse networks. However, to reduce the risks of layoffs, having a socially diverse network is at least as important as achieving superior work performance. Increasing visibilities to key decisions makers through a diverse network protect actors from layoffs despite having a lower objective performance.

Keywords: Social Network, Productivity, Layoff, Network Mechanisms
Introduction

A prediction of social network theory is that a network spanning structural holes is expected to be associated with higher work performance. By linking unconnected groups, the brokers, who bridge these holes, are endowed with early exposure to unique and novel information and can act as a hub 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 have superior performance ratings, are promoted faster and receive higher compensation (Burt, 1992; Poldony and Barron, 1997, Burt, 2005; Cross and Cummings, 2004; Lin, 2002). For example, bankers in socially diverse networks are more likely to be recognized as top performers (Burt, 2000). Similarly, research and development team members 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, the questions whether network positions really cause performance improvement and how social network positions are driving productivity remains open. A large body of literature on social networks and organizations describes the benefit of social networks on work performance in various settings. However, little research leverages the ample data that is created by people’s interactions, such as e-mail, call logs, text messaging, document repositories, and so on. This gap is problematic, because the current literature tends to be focused on small, static networks and as a result, these studies generally show a general correlation between performance and network positions but they cannot tease out the micro mechanisms of how network positions affect productivity. Without detailed, large-scale longitudinal data, it would be difficult to understand how and why certain network structure is beneficial for work performance.

To address these concerns, I first examine if there is a possible causal relationship between certain network position and work performance. Once a causal relationship is established, I focus on two specific mechanisms—information advantage and social affect—in understanding how certain network positions endow individuals with work advantage. To establish a possible causal relationship, I take
advantage of a technology adoption that has the potential to change the network positions of its users over time. This expertise discovery tool provides a keyword-based search function that finds people whose expertise matches the query. Users can then choose to make the contact. In general, our survey results show that people use the search tool when they cannot locate anyone with the right expertise in their immediate network neighborhood. Consequently, contacting experts from the search gives the user an opportunity to strategically reach out to different groups of people within an organization and accordingly, induce a change in the user’s network position. By examining the work performance before and after adopting the search tool, it is possible to determine if this technologically induced network change can actually alter work performance. If an improvement in performance is detected, it is reasonable to establish a causal relationship, in which occupying a desirable network position actually causes an improvement in worker productivity beyond what one’s inherent abilities, popularity, past performance history or other factors would otherwise have allowed.

Next, I explore two specific mechanisms—information advantage and social affect—in understanding how certain network positions endow individuals with work advantage. By examining two different types of work outcomes—billable revenue and layoffs, I study how technology consultants use their network to improve work performance and avoid layoffs, and whether they use different strategies to achieve these outcomes. First, I explore the network effect on billable revenue, which is an objective measure of a worker’s productivity and one of the most important performance metric for evaluating consultants. As accessing unique and diverse information is critical for solving difficult problem and instrumental for billing revenue, the information advantage derived from network positions, such as brokerage is more likely to have an impact on performance. Next, I explore if network position can also have an impact on layoff risks after controlling for objective performance. Although a low performance review is often an indication for increased layoff risks, it is not the sole predictor. Often, firms dedicate layoff decisions to managers who have the discretion to decide whom to let go. Thus, favorable opinions, especially from key decision makers, are likely to reduce a person’s layoff risks. In addition, I expect social networks to have a strong effect on layoffs. Unlike promotions and compensation, layoffs are a
traumatic experience for most people. If networks are to have effects on work outcomes, they should have a significant, if not more pronounced, impact on layoffs since the stakes for keeping a job, especially in difficult labor market, are much higher than promotions or better performance review. Furthermore, I hypothesize that the mechanism for driving productivity may be fundamentally different from the mechanism that shields a person from layoffs. Information advantage derived from a diverse network may be more salient for improving objective work performance. However, after controlling for objective work performance, social affect and effective self-promotion derived from diverse network may have an important impact on layoffs.

My results show that using the expertise search tool can alter employees’ network positions in a significant way, after controlling for possible self-selection biases. Overall, users’ network positions become more diverse after adopting the expertise search tool. Using the adoption of this search tool as an instrument for structural holes, I find that consultants who broker connections tend to generate more billable revenue than their peers. While this conforms to earlier studies on network brokerage and work performance, the effect of the network change is much smaller than traditional OLS estimates that do not address the reverse causality issue. This shows that unobserved individual heterogeneity and past history could lead to overestimating the effect of network positions on performance. Because people use this tool to primarily search for information, I attribute this performance gain to the information advantage derived from a diverse network. Ultimately, people use this tool to search for people who possess knowledge they need. Thus, any new connection made using this technology is likely in pursuit for information and any reward from this change in the network position can be attributed to timely acquisition of relevant information. Next, I explore the type of employees who would derive the most benefits from having a more diverse social network. Comparing junior and senior consultant, I find that marginal benefit from an increase in network diversity is higher for junior consultants than senior consultants. Junior consultants who may still be new to the organization generally have a less diverse social network inside the firm and therefore are less able to leverage their existing network ties to find relevant knowledge. Using this tool allows the junior consultants to quickly find relevant information and enhance their work performance.
Senior consultants may already have an established and diverse social network. Accordingly, they may have less need for an expertise search tool and the marginal benefit from an increase in network diversity is less useful when they already have a diverse network. Thus, from an organization design point, it may be strategic to help junior consultant to build a more diverse network, as their marginal benefit from network diversity is higher.

Lastly, I explore if network positions have an effect on reducing the probability of experiencing negative work outcomes such as layoffs. I find that brokerage can significantly reduce the risk of layoffs even after controlling for individuals’ objective performance. This demonstrates that brokerage can provide two distinct advantages. First, brokerage endows workers with diverse knowledge. Second, the ability to access diverse groups of people enables brokers to effectively promote their work, making their contribution more visible throughout the organization. This, in turn, shields brokers from negative consequences such as layoffs. Effective promotion through social bonds has equal, if not more prominent, impact on layoffs than achieving superior work performance.

Theories and Literature

Network Position and Performance

Social network analysis allows for the development of abundant theories and empirical evidence that show a positive association between certain network characteristics and performance. Researchers have long studied whether network structures, such as structural holes, (e.g. Burt, 1992; Granovetter, 1973) is more beneficial with respect to various measurements of work performance. Burt (1992, 2004) show that structural holes can create a competitive advantage for individuals in dimensions such as wages and promotion. He attributes normalized performance differences to actors’ ability to access and gather unique information from non-redundant social groups (Burt, 1992; Ancona and Caldwell, 1992; Abuja, 2000; Sparrowe et al., 2001; Reagans and Zuckerman 2001; Cummings and Cross 2003; Zaheer and Bell, 2005). This information advantage from brokerage can be particularly salient 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. By analyzing email networks and message content, Aral and Van Alstyne (2009) demonstrate that networks with structural holes deliver diverse and novel information that explains a significant portion of the variance in productivity for executive recruiters – more so for instance than traditional human capital.

As a result, brokerage is theorized to play an instrumental role for accessing novel and unique 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 the ability to tap into unique information sources enables actors to solve difficult problems and find new opportunities. Structural diverse networks provide actors with the capability to tap into various pockets information sources within a network that are instrumental to productivity. A redundant network, on the other hand, tend to provide repeat information and its dense network of strong ties can quickly disseminate information and thus prevent anyone from taking advantage of it. Redundant networks also have high maintenance costs, since direct ties and dense networks of third-party ties require time and effort to maintain. Consequently, redundant networks are less likely to provide diverse information.

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 are in the pursuits of instrumental objectives. Being the only connection linking two actors, a broker stands in the middle of the information highway to control the flow of information. Endowed with preferential access to unique and novel 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 provider of information also reduces their power as the acquirer of information because alters in a non-redundant network are also monopolist themselves when the broker tries to acquire
information from them (Reagans and Zuckerman, 2008). However, because the amount of information obtained by a person in a structural diverse network is greater than in a redundant network, the effect from brokerage on productivity can be still positive regardless if the individual try to broker connections to his advantage.

**Self-Selection Process and Unobserved Individual Heterogeneity**

Despite overwhelming evidence showing a strong correlation between network position and work performance, the causal mechanism underlying the association is underexplored (Reagans and McEvily 2003). An equally likely explanation is that people actively seek high performers for advice and collaboration opportunities, and consequently high performers tend to display a diverse network as a result of their prior performance and work history. Similarly, certain individual characteristics may manifest in their social networks. For example, a popular actor tends to have a more diverse network, which may also enable a person to be an effective employee in an organization. In essence, individual traits are the missing variables that mediate both network positions and performance such that the correlation between brokerage and performance is spurious. The fact that there are positive correlations between certain individual characteristics and network positions suggest that individual heterogeneity may moderate the relationship between network position and performance (Burt 2004, 2007; Hargadon and Sutton, 1997). For example, Burt and Ronchi (2007) suggests that high status individuals such as executives are more likely to occupy brokering position in the firm because their roles as an executive requires them to reach out to a diverse group 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, network positions are a function of human capital.

It is also possible that network positions and performance form a virtuous cycle in which prior performance enhances network positions, which in turn, further improves work performance (Gould 2000). The superior work performance endows individuals with disproportionate opportunities to make brokering ties, which makes them even more productive. If this were the case, it would be particularly
hard for individuals, especially the junior members of the organization to acquire a brokering position,

*Teasing the Effect of Network Position on Work Performance Through a Technology Adoption.*

To detect a possible causal relationship between network position and performance, I use the adoption of a social networking and knowledge discovery tool\(^1\) that could exogenously changes a person’s network position. The primary function of this technology is allowing users to search for experts based on keywords, and providing contact information of these experts. A survey conducted on usage patterns shows that people resort to this technology when they cannot find the relevant experts in their immediate network neighborhood. Thus, the experts in the search result often reside outside of a person’s existing social circle. If the user decides to reach out to these experts, the network diversity of the user is likely to increase after using this tool. Accordingly, the adoption of the search tool could exogenously change a person’s network position.

If there are also improvements in work performance after the technology adoption, it is likely that this change in performance is induced from an increase in network diversity, lending evidence of a possible causal relationship between network diversity and work performance. Because people use this tool to actively search for information, any connection made using this search tool is likely to pursue information. Since the search tool can increase a person’s network diversity by linking the person to different pockets of the organization network, any performance gain is likely to come from the information advantage derived from a diverse network.

The ability to access unique and valuable information is particularly important in a knowledge-intensive industry such as consulting. It can enhance the work performance in two ways. First, accessing information related to the current projects can directly improve the quality of work. Second, accessing diverse information exposes the broker to new opportunities and valuable resources (Burt 1992). Being the first to learn about a new opportunity places a person at the front of the queue and prompts her to strategically seize the opportunity. In the IT consulting business, accessing information expediently is the

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\(^1\) Detailed description of the experiment is in the next section.
key to productivity. Since consultants’ performance is largely determined by billable revenue, it is critical for them to do well in the current project as well as looking for future opportunities. Knowing where to obtain expertise through networks helps an individual solve difficult problem and produce high quality work. This can accordingly enhance the person’s reputation and the probability to participate in high-value projects. All else equal, a manager would prefer reputable consultants to handle important projects, as they are more likely to satisfy customers and generate repeat business. Accessing unique and valuable information not only helps consultants to solve difficult problems, it can also expose them to new opportunities before others. Thus, I hypothesize that network diversity induced from adopting the search tool causes performance improvement.

*Hypothesis 1: Structural holes causes higher work performance through timely access to diverse and novel information.*

While hypothesis 1 tests the average effect of structural diversity on performance, it is also important to explore the benefit of structural diversity for different types of individuals. The virtuous cycle hypothesis argues that a good performer is more likely to have a diverse network, which can further improve work productivity. Thus, it may be easier for a good performer or a person who is already a broker to attain an even better network position. However, if using an expertise search tool can lower the cost of becoming more structural diverse, a junior consultant who does not have a diverse network would potentially reap greater benefits than a senior consultant who may already have a diverse network. Senior consultants may not necessarily find the search engine useful since they are already capable in finding the relevant expert from their already expansive social contacts. On the other hand, junior consultants who are not endowed with an established network could reap greater benefits from using the search engine to discover experts in remote corners of the organization. However, while junior consultants may find the tool helpful for discovering resources, senior consultants are in a better position to use these resources. Because of their status and tenure at the firm, senior consultants command a higher probability of receiving a reply from experts who are also more likely to devote more time and energy answering
questions from senior consultants.

Thus, what type of employees would reap greater reward from technology-induced change in network diversity is an empirical question. I hypothesize firm culture and environment play a large role in determining who would benefit the most. In a collaborative environment, junior consultant would reap greater reward from an increase in network diversity if the response rate to a junior consultant were not disproportionately lower than a senior consultant. Detailed interviews with 15 people show that employees in this firm are highly receptive to respond queries from another employee. Thus, I hypothesize that at least in this setting, the marginal benefit of acquiring a structural diverse network is higher for junior consultants.

Hypothesis 2: Compared to senior consultants, junior consultants reap greater benefits from a marginal increase from network diversity.

Network Effects on Layoff (need to motivate more on different types of work outcomes)

While brokerage is shown to provide information advantage that directly improves individuals’ work performance and contributes to the profitability of the firm, brokerage can also enhance a person’s prestige and reputation that can help her avoid negative work outcome such as layoff. The same channel from which brokers derive diverse and novel information from their superior network positions also provides them a unique opportunity to effectively promote themselves to a broad audience, especially the decision makers, in the organization. When brokers choose to broadcast their success and accomplishments, they have the capability to spread the news faster and to a wider audience than her peers. At the same time, because the brokers control the information flow, they can also control the flow of information that may be damaging to their reputation.

This type of self-promotion can be important to protect a person against layoffs. If a wider range of people, including managers, knows about the person or formed a favorable view of his work, he is much less likely to be laid off as compared to his peers. In contrast, people lacking brokerage opportunities may face higher risks of layoff even if they have similar or even superior work evaluation
than the broker. Because without the diverse network to broadcast and market their success, their contribution would be less known throughout the organization and they are thus less likely to be protected from layoffs. Based on qualitative interviews with managers who participated in layoff decisions, many of them expressed the importance of reputation and general awareness of a person’s work.

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

Brokers who are able to access various groups can effectively advertise their work and promote themselves. Consequently, they increase their visibility and the general awareness of their work, and are thus more likely to be protected from layoffs.

*Hypothesis 3: Brokers are less likely to be laid off after controlling for their objective performance.*

**Data, Setting and Identification Strategy**

To understand the micro mechanism of how social networks affect objective work performance and layoff risks, I analyze an electronic communication social network of 8037 employees over 2 years. The data contains email, calendar and instant messaging activities inside a global information technology firm. To the best of my knowledge, this is the largest social network ever constructed 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 uses social sensors to gather, crawl and mine various types of data sources, including the hierarchical structure of the organization, individual role assignments as well as the content of individual email and instant message communications and calendars. The system is deployed globally and has collected detailed electronic communication records of 8037 volunteers. In exchange for their data, volunteers are given access to an expertise search engine. From these volunteers, it is possible derive a social network of more than 300,000 employees. In this study, I
constrain the analysis to focus on the sub-network for the 8037 volunteers whose complete electronic communication data is available. To eliminate any potential self-selection bias from using volunteer data, I compare the network characteristics and job roles of the volunteers with the rest of the firm. I find minimal differences between the two populations. However, my sample of volunteers is on average less likely to be laid off than others in the firm. This bias may come from the fact that these volunteers are in general more interested in social networking, since they have decided donate their data for this research in exchange for accessing social networking tools. However, with a sufficient large sample, there is enough variation to detect any network effect in this sub-population of more socially inclined group.

To construct a precise view of the network that reflects the real communication between actors, I eliminated spam and mass email announcements. Since each electronic communication exchange is recorded with timestamp, I mapped 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 that include all electronic communication incidents that occurred during the current month, three months prior and 2 months after. Including email communication before and after the current month can more accurately reflect the network activities instead of using the network activity in a current month alone (citation). This results a network panel of 17 periods for 8037 employees which a rare opportunity to study how a person’s social network evolves over time.

Exploring how a social network is related to work performance, I obtained detailed financial performance records of more than 10,000 consultants. I focus on 2038 consultants in this sample who have volunteered their electronic communication data, and collected detailed records of 2,592 projects these consultants participated in from January 2007 to January 2009. The sheer volume of the data allowed us to more precisely estimate how population level topology in a network contributed to information worker productivity, after controlling for human capital, work characteristics and demographics. To protect the privacy of the participants, their identities are replaced with hash identifiers. Table 1 and 2 show the summary statistics of these consultants including their demographics, job roles as well as network characteristics.
To study the network effect on layoff risks, I collected information about the laid off employees during a round of layoff in January 2009. About 8% of the work force received notification that their positions were eliminated. The corporate policy of the firm was to grant a grace period of 2 months during which affected employees retained the privilege of a full-time employee, e.g. access to all corporate email, intranet, and internal job posting. During this time, they could be internally transferred if they were able to find other positions within the firm. However, due to the severity of the recession, the firm simultaneously placed a hiring freeze worldwide, such that internal transfers were unlikely. Although I do not have the precise roster of people who received the layoff notice, I was able to derive who got laid off by downloading the human resource directory shortly after the layoff announcement and shortly after the actual layoff event. From the difference in the two snapshots of the HR database, I was able to derive who left the firm during the layoff. I consider the vast majority of those who left were the result of the layoff. However, it is possible that some employees may have voluntarily left the firm, although I expect the number of such cases to be minimal in light of the severe recession and the difficult labor markets worldwide, especially in North America. Several regional offices were eliminated entirely. In such case, everyone in the group is laid off and I exclude them from the dataset.

**Use Technology Adoption as an Instrumental Variable for Network Positions**

To provide incentives for users to donate their electronic data, we offer a keyword-based search tool to find experts. This search engine (Expert-Find) is similar to popular search engines on the Web, such as Google, with the only difference being it returns a list of people whose expertise is relevant to the search query instead of returning URL links. For example, when searching for the phrase “Social Networks”, Expert-Find would return a list of people, ranked by their expertise relevance (Figure 1). Each search result list the name of the expert, a picture (if available in the public HR directory), his or her job role, as well as the division the expert belongs to.
In order to understand how employees use the search tool and how often they actually contact any experts from the search result, I conducted an extensive user survey about general usage and search patterns. The vast majority of people use Expert-Find when they have already exhausted their existing social networks. This is consistent with an earlier finding that shows people resort to technology only after they cannot find relevant information from their colleagues (Borgatti and Cross, 2003). Because people tend to use this tool after an unsuccessful local search, they are less likely to know anyone in the search result. After all, if they are in the user’s network vicinity, the user may have contacted them prior to the search. Thus, by contacting people from the search, users are more likely to reach out to a distant group of people, and thus increase their structural diversity. Because I also have the historical electronic communication data from the volunteers, it is possible to measure the network change of the same person before and after the adoption. If there is a change in networks position after the adoption, it is plausible to attribute this change to using the search tool. If we simultaneously observe a performance change, it is plausible to attribute the performance gain to the change in network positions. However, there may be self-selection issues that could induce both network change and adoption of the search tool, and it is important to address them.

**Figure 1: Result from Searching for “Social Networks” using Expert-Find**
Selection Effect

An important concern is that there may be a selection effect in choosing when and why to sign up for Expert-Find. This selection effect may simultaneously drive the adoption as well as the network change. However, three factors help alleviate this bias. First, I examine the change in network position of the same person before and after the adoption of Expert-Find. If there are any unobserved individual characteristics, such as the propensity to use new technologies, that drive both the adoption and the network change, this type of bias can be eliminated through a fixed-effect specification. Second, people adopted this tool at different times throughout the study. This allows me to control for any temporal shocks that may induce a person to adopt the tool. For example, if people are more likely to adopt 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 Expert-Find when they already have many consulting projects. Consequently, it may seem that a network change is driving more billable revenue, but it is actually a reverse causality in which having a heavy workload induces people to use the technology and change network positions. In order to eliminate this bias, I control for the average number of billable revenue in the past 6 months to control for existing workload. Lastly, my sample is not a random sample of workers in the firm, so I can only estimate the local average effect for this group. But with more than 8000 volunteers, there should be enough variation to detect the network effect on performance in this subsample of individuals. After controlling for these factors that may drive the adoption of Expert-Find, it is plausible to assume the adoption is exogenous for driving a network change. Although I am aware that there could still be other unobserved heterogeneity that might violate this assumption, interviews and surveys on user behaviors do not show any other consistent pattern that may drive both adoption and network change.

One may also argue that it is not the network, but the ability to locate information quickly that is ultimately responsible for driving the performance change. Because Expert-Find can effectively locate the source of information, it can essentially reduce the search cost and the reduction in search cost is
ultimately responsible for any improved performance. However, I argue that a diverse network is the mechanism enabling a person to reduce the search cost for information. Having access to a more diverse group of people through the use of Expertise-Find exposes people to more information and more unique information faster than before. Accordingly, diverse networks are ultimately responsible for faster information access and better work performance.

Variables

**Dependent Variables.**

The dependent variables are two types of work performance outcome. First, I measure the objective work performance by collecting the monthly billable revenue for each consultant over a two-year period from January 2007 to January 2009. Because billable revenue is the corner stone for measuring productivity for the consulting industry, it is a clear and objective performance outcome that is widely adopted for information workers such as consultants, lawyers and accountants. Thus, studying the network effect on billable revenue is salient for understanding the effect of network positions on performance. The second measure of performance is whether a consultant was laid off in January 2009 when about 8% of the workforce was eliminated due to the recession from housing bubbles. Layoff outcome is calculated as a binary variable that equals to 1 when a person is laid off and 0 otherwise. I explore how network positions can reduce the probability of getting laid off.

**Explanatory Variables**

To measure brokering positions, I calculate network diversity, adopted from Burt’s measure of network constraint (Burt, 1992).

\[ C_i = \sum_{j} \left( p_{ij} + \sum_{q \neq i, j} p_{ij} p_{qj} \right)^2 \]

**Network constraint** \( C_i \) measures the degree to which an individual’s contacts are connected to

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2 To really measure more and more unique information, one would need to do content analysis, examining the diversity of information in each person. This is for future work which I hope to present in December, 2010.
each other. $P_{ij}$ is the proportion of $i$’s network time and energy invested in communicating with $j$. Network constraint can be used as proxy for measuring network cohesion (Burt 1992), and network diversity, as proxy for structural holes or brokerage, is simply computed as $1-C$. Since relationship may erode over time, I use a 6-month sliding window of electronic communication networks with a step size of 1 month, over a two-year period, from January 2007 to January 2009.

$P_{ij}$ is calculated from tie strength, which is measured using the frequency of one’s electronic communication with others. Granovetter (1982) described four identifying properties for the strength of ties as 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 as evidence of weak ties (Friedkin, 1980). Others have included the recency of contact (Lin et al., 1978) or the frequency of interactions as a surrogate for tie strength (Granovetter, 1973). For measuring tie strength in electronic communication, I primarily use the frequency but with some modifications.

Because a single electronic communication exchange may not constitute an actual tie, especially when an email is sent to a large group of people, counting any electronic exchange as a tie would overestimate the number of ties and the overall tie strength. Thus, I eliminated all electronic exchange when the number of recipients is above 15 people. In addition, to accurately reflect the tie strength between two actors, I normalized the value to be between 0 and 1, with 0 indicating that there is no tie between $i$ and $j$ while 1 indicating maximal possible tie strength (Lin et al., 2008). The detailed calculation is described below.

$$strength_{i,j} = \frac{\log(X_{ij}^*)}{\max_j \log(X_{j,*}^*)}$$

$$X_{i,j}^* = \begin{cases} 0 : if \{X_{i,j} \leq 3 + \log(X_{i,j})\} \\ X_{i,j} : otherwise \end{cases}$$

where $X_{ij}$ is the total electronic exchanges between actor $i$ and $j$. Basically, the above formulation indicates that a tie exists only when the number of electronic communication exchanges reach a certain
threshold. This threshold is different for everyone because it is normalized based on each person’s own communication pattern. For active users of electronic media, the threshold to register a tie is higher than people do use electronic media often. This measure of tie strength has been extensively tested and is shown to accurately reflect the strength of tie between actors (Lin et al., 2008).

**Control Variables**

For all models, I include controls for individuals’ demographic information such as gender, managerial roles, and job ranks. Managerial role is a dummy variable indicating whether the person holds a managerial position or not. Job ranks has a ordinal value ranging from 6 -12 where level 6 is a junior consultant while level 12 is at the level or executive vice president. A dummy variable is also created for each job rank but results are not fundamentally different from using the ordinal job rank. To control for heterogeneity across different divisions and geographical locations, I include dummies for the 4 business divisions as well as a dummy for each geographical location. To control for current workload, I included the average monthly revenue from the last 6 months. Lastly, to control for individual preference for using electronic media, I included the number of all electronic exchange for a person (Email, Calendar and Instant Messaging) in a month.

**Empirical Methods**

I employ a fixed-effect model with instrumental variable to examine the effect of network positions on billable revenue. The dependent variable is the billable revenue in US dollars that a consultant $i$ has generated in month $t$. The independent variables are network characteristics of actor $i$, and the control variables include individual characteristics such as job rank, gender, job roles, regional characteristics and 24 month-dummies.

$$Revenue_{it} = \alpha + \beta_1 \text{network\_diversity}_{it} + \sum \text{personal\_characteristics}_{it} + \sum \text{job\_characteristics}_{it} + \sum \text{regional\_characteristics}_{it} + \sum \text{months}_{it} + \varepsilon$$

I expect the coefficient of network diversity to be positive as predicted in the theory. In order to
address possible endogeneity problems, I use the adoption of Expertise-Find as an instrumental variable for network diversity. After controlling for possible confounding factors, such as past performance and timing effect, the decision to use Expert-Find is unlikely to directly affect work performance.

Next, I use a Probit model to estimate the risk of layoff. The dependent variable is whether a person is laid off (it is equal to 1 when the person is laid off and 0 otherwise). The independent variables are network diversity and the objective performance of the consultant in the past year. I also control for demographics variables as well as the job roles and job ranks of the consultant.

\[
\text{Layoff} = \alpha + \beta_1 \text{Network Diversity}_i + \beta_2 \text{billable revenue}_i + \Sigma \text{personal characteristics}_i + \Sigma \text{job characteristics}_i + \Sigma \text{regional characteristics}_i + \epsilon
\]

**Results**

*Network change from technology adoption*

First, I examine if the adoption of Expert-Find can actually induce a change in network positions. It is possible that adopting Expert-Find is not a random event. However, because I am examining the network change for the same person over time, I can use fixed-effects to eliminate individual heterogeneity, such as human capital, that might bias the result. I also control for temporal shocks to mitigate some biases from time-varying characteristics. For example, people may be more likely to adopt the tool after receiving annual performance reviews. Similarly, people may be less likely to adopt the tool during December when most projects are winding down in preparation for Christmas Holidays. By including a dummy for each month, I can eliminate most of the seasonal effects on adoption. There might still be time and individual-varying biases. For instance, it is possible that people are more likely to adopt this technology during high workloads. Thus, I include the average monthly billable revenue in the past 6 months to control for the general workload at the time of the adoption.

To construct the technology adoption variable, I constructed a dummy that equals to 1 for every month after the person adopted the search engine and zero before the adoption. Overall, there is a positive and significant correlation in the first stage regression. Estimated using the fixed-effect model, the correlation between network diversity and the adoption of Expert-Find after controlling for seasonality
and past performance is .114 (t = 17.86). To estimate the validity of the instrument, I calculate the concentration parameter, which is 86.7, indicating the adoption of Expert-Find is not a weak instrument (Hansen Hausman and Newey 2004). Figure 1 shows the relationship between network diversity and the timing of adoption after factoring out seasonality, individual fixed-effects and past performance. Each data point on the graph shows the network diversity residual averaged over everybody who adopted Expert-Find at a given number of months since adopting the search engine. As shown in the Figure 1, network diversity starts to increase shortly after the adoption (X=0), indicating that Expert-Find can induce a change in network diversity.

![Network Diversity and Technology Adoption](image)

**Figure 2:** Relationship between average network diversity and the length of time since adopting Expert-Find. A value of zero on the X-axis indicates that Expert-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.

**Network change and performance change**

Next, I show if a technology-induced change in network positions can induce a change in performance over time. In Column 1 of Table 3, I show the OLS estimate for the performance regression estimating the correlation between network diversity on 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 previous research. As shown in Column 1, coefficient estimate for

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3 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.
network diversity is positive and the effect is relatively large. A 1% increase in network diversity is correlated with billing $886 monthly revenue. However, when a fixed-effect specification is used (Column 2), the size of the coefficient is reduced by 17% (b = 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 Column 3, I estimated the effect of network diversity on billable revenue using the adoption of Expert-Find as the instrumental variable (IV) for network diversity. The coefficient from this IV regression is reduced dramatically by 82% (b = 126.5 p < .1), demonstrating time-varying individual heterogeneity can still bias the estimate upward. However, the coefficient of network diversity continues to be positive and statistically significant, demonstrating that structural diversity could cause a positive change in performance. Because people use Expert-Find primarily to locate information from experts who are not in their immediate network neighborhood, any network change induced from using Expert-Find is most likely coming from timely access to unique and novel information that enables users to complete their work on time and generate billable revenue.

<< Insert Table 3 about here>>

In Column 4, 5 in Table 3, I incorporated the total number of electronic communication exchanges as an additional control for individual differences in online media use. It is possible that people who are tech-savvy are both more likely to adopt new technology and to 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 from the fixed-effect model, but the coefficient is still positive and statistically significant. It is also possible that existing workload drives the adoption of Expert-Find as people seek to use this tool to help with their high workload. To address this bias, I controlled for the average monthly revenue in the past 6 months. As shown in Column 6 and 7, past performance is strongly correlated with the current billable revenue and the IV estimate for network diversity continues to be positive and significant, though the size of the effect is much smaller than both
the Fixed-Effect model and the OLS model.

**Marginal Benefits of Network Diversity: Junior vs. Senior Consultants**

While Table 3 shows the average effect of brokerage, I explore the marginal benefit of network diversity for junior vs. senior consultants. Expert-Find could be more beneficial for senior consultants because people may be more likely to respond to senior consultants than junior consultants. On the other hand, junior consultants may find the additional network diversity to be more helpful since they lack having an expansive network. Accordingly, they may reap greater benefit from a change in network diversity. Thus, it is an empirical question as to who would reap the most benefit from a marginal increase in network diversity. Table 4 shows the effect of network diversity on performance for junior consultants (Column 1) and senior consultants (Column 2). While both senior and junior consultants derive benefits from having a socially diverse network, the size of the effect for junior consultant is much bigger than the senior consultant. The F-test for comparing the two coefficients is significant at the p= .001 level, demonstrating that junior consultants derive more marginal benefits from having a more structurally diverse network. Although senior consultants could perhaps command more attention from others and can thus create ties easily, junior consultants can reap greater benefit from a more diverse network after bridging ties are formed.

**Network effect on layoff**

While I show a possible causal relationship between network diversity and objective work performance, I examine if network positions can also influence negative work outcomes, such as layoffs. If network positions were to have an impact on work outcome, it should have an even more pronounced impact on layoffs, since unlike promotions and performance valuations, layoffs are a more traumatic experience for most people. More importantly, I compare the effect of network positions to the effect of objective performance on the risk of layoffs. While having superior performance should certainly reduce the layoff probability, having a structurally diverse network could provide additional protection on
layoffs. I address these issues in Table 5. Instead of using a panel set up as in the performance analysis, the analysis for layoffs can only use a cross-sectional network, because layoff in January 2009 is a one-time event and thus, there is only one layoff observation for each person. To calculate the network characteristics in a cross-section, I use all electronic communications in the 2 years prior to the layoff, from January 2007 to January 2009. The first four columns of Table 5 are Probit models, exploring the impact of network diversity on the probability of layoffs. The fifth column uses an instrumental variable for network diversity to estimate the potential causal relationship between network diversity and layoffs.

The first column of Table 5 shows the impact of network diversity after controlling demographics, job roles and other observable individual characteristics. Gender and job roles do not show any statistically significant effect on layoff probabilities, but geographical locations do. While workers in the European Union are less likely to be laid off, workers in the US are more likely to be laid off. This difference is probably due to stronger labor protection laws in Europe, which makes it harder for the firm to downsize. I also add control for media usage, which is calculated as the total volume of electronic communication, since it is possible that people who are heavy communicators in electronic media can also affect layoffs. After controlling for these characteristics, Column 1 of Table 5 shows that network diversity is negatively correlated with layoffs. A one-percentage increase in network diversity is correlated with a reduction of 24.5 percentages in layoff probability, 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 diverse network may just perform better and are therefore less likely to be laid off, since I show evidence that a diverse network could induce an improvement in productivity in the earlier section.

To address this, I controlled for the objective work performance using the billable revenue each consultant generated in from January 2007 to October 2008. I eliminated the billable revenue in the last two months because it is possible that people who face high layoff risks may also have reduced billable hours as they wind down their current projects. Therefore, I chose not to use the billable revenues generated immediately before the layoff event. As expected, the objective performance, measured by
billable revenue, is a strong predictor to reduce layoff risks (Column 2, Table 5). Interestingly, network diversity continues to have a strong negative correlation with layoff probability ($\beta_{\text{network diversity}} = .198$, $p = .01$). If the main advantage to having a structurally diverse network is access to relevant information and expertise, this should directly be correlated with billable revenue. However, Column 2 shows that network provides additional shields against layoff, even after controlling for billable revenues. Interestingly, the effect of network diversity on layoffs probability is comparable to, if not slightly bigger than the effect of objective performance on layoffs ($\beta_{\text{billable revenue}} = .168$, $\beta_{\text{network diversity}} = .198$). This demonstrates that in addition to information advantage that drives productivity, network diversity protects a worker from layoff beyond enabling a person to perform well at work.

An alternative hypothesis is that while brokers may not have billed as many hours, they may have been instrumental in providing critical information to their network contact and helping them to generate more billable revenue. Thus, brokers are less likely to be laid off as the result, because they produce values indirectly through helping their network contacts. If this were the case, we would expect billable revenue generated from network contacts to reduce a person’s risks of being laid off. I explore this hypothesis by incorporating the billable revenue averaged over everyone who is in a person’s direct contacts (1 degree away). Column 3 shows that while a person’s own billable revenue continues to be associated with reduced layoff probability, the average billable revenue from network friends is not statistically significantly correlated with layoff and the size of the effect is relatively small. This shows that while it is possible that brokerage may also benefit network friends, but helping network contacts is not the main driver to reduce the risk of layoff.

While the previous Probit regressions in Model 1-3 provide evidence of a correlative relationship between network diversity and layoff probability, I examine if it the relationship is causal using an instrumental variable approach. To establish a causal relationship between network diversity and layoffs, I use the technology adoption of Expert-Find as the instrumental variable. However, because the layoff is a one-time event and there is only one observation for each person, it is impossible to use the earlier IV setup that relies on the network change before and after a person adopts Expert-Find. Instead, I use the
number of months since a person signed up for the Expert-Find to instrument for network diversity. As shown in Figure 2, network diversity gradually increases after a person started to use the search tool. Thus, it is possible that a person’s network grows more diverse the longer she uses Expert-Find, and all else equal, her network is more diverse than someone who adopted the tool later. To test if using the number of months of usage is a valid instrument, I calculate the concentration parameter for the first stage regression and the value is 11, slightly above the cut-off for the weak instrument test, suggesting this is an adequate instrument for network diversity.

However, the decision to use Expert-Find may be an endogenous decision. Early adopters are more likely to display some characteristics that drive both adoption and network change. This is a more important concern in a cross-sectional layoff study than the panel performance study. In the performance regressions I exploit the individual-level fixed-effect to eliminate any time-invariant characteristics, such as early or late adopters, so I can examine the change within the same person. This is unfortunately, not possible in a cross-sectional data. To alleviate this bias, I controlled for demographics, gender, job role and ranks and other observable individual characteristics. However, I am aware that there might still be unobserved individual characteristics that may drive both networks and layoffs.

Using the length of time since adoption as an instrument for network diversity, Column 4 shows that 1% increase in network diversity is associated with a decrease of 18.8 percentage in layoff risks, demonstrating that network diversity has a significant impact on layoffs. The Hausman test rejects that the coefficient from the OLS estimates is the same as the IV estimates at the p= 0.01 level, suggesting that OLS estimates bias the results upward. The size of the effect for network diversity and objective work performance are comparable. This shows that having a more diverse network has a similar impact on layoffs compared to achieving better billable revenue. Interestingly, average billable revenue of network friends increases the risks of layoffs. This could be because when network contacts perform well, it actually decreases the relative ranking of the person and thus increase the probability of layoffs.

Taking these results together, brokerage is associated with reducing layoff risk even after controlling for objective performance. If superior information is the primary channel from which brokers
can derive advantage, it should directly contribute to the objective performance. Thus, after controlling for work performance, brokerage should no longer have any impact on layoff risks. However, results in Table 5 collectively demonstrate that brokerage provides additional advantage to reduce layoff risks.

From qualitative interviews, I hypothesize that consultants with a diverse network can leverage their ability to reach out to a large and potentially important group of people in order to promote their work and make their contribution more visible in the organization. Effectively promoting themselves and advertising their work through their structurally diverse network, brokers are less likely to experience negative work outcomes such as layoffs. On the other hand, a consultant with similar work performance but without a diverse network could face higher layoff risks since they do not necessarily have an effective conduit to advertise and promote her work.

While I attribute social affect and effective self-promotion to be a mechanism reducing the layoff risks, it is still unclear what network mechanism is primarily driving performance and if it is different from the primary channel that reduces layoff risks. Since it is difficult to measure information diversity and self-promotion directly, it is hard to tease apart whether information advantage is the primary channel to improve work performance and if social affect and self-promotions are the dominant mechanism for reducing layoff risks. It is entirely possible that both self-promotion and information advantage drive productivity. While information advantage may help a consultant solve difficult problems, social affect could also help the consultant land high value projects and generate more billable revenue. However, this would actually underestimate the effect of social affect in avoiding layoffs when the model controls for objective performance. It is also possible that both mechanisms are driving objective performance and risk reduction for layoffs. In this case, the effect of social affect and self-promotion may be overestimated. However, based on interviews and user surveys, people actively search for information online primarily to solve difficult problems at work. If information has an advantage in improving work performance, it would primarily show up in the performance statistics. However, information diversity could help a consultant in finding the right contact to promote their work, but this effect is more likely to be picked up by the social affect and self-promotion mechanism.
One way to detect social affect and self-promotion is to examine network activities shortly before the layoff event. If network activities during months prior to layoff are positively correlated with layoff, it is plausible alleviating layoff risks comes primarily from self-promotion. To test this hypothesis, I plan to examine the network topology of the consultants three months prior to the layoff event. If self-promotion were the key mechanism for reducing layoff risks, I would expect increased communication activities and network activation for those who are facing layoffs. Initial results supports this claim, examining workers whose objective performance is at the bottom quartile compared to his peers, consultants with high network diversity is less likely to be laid off. Most importantly, I plan to use content analysis to precisely measure information diversity as well as social affect and self-promotion. Categorizing keywords in the electronic communication, I can estimate information diversity using natural language processing techniques, such as Latent Dirichlet allocation (LDA) that classify topic space within a large corpus of text. Similarly, I will also classify words that may indicate social affect and self-promotion, such as identifying leisurely and job-hunting activities. These measurements will allow me to precisely examine which mechanism is primarily driving productivity and which is driving layoffs.

Discussion and Conclusion

In this study, I examine the network effect on performance and layoffs. Using the adoption of a social network search technology that could change a person’s network position over time, I show evidence of a possible causal relationship between network diversity and performance. However, the size of the effect is much smaller than the traditional OLS and fixed-effect estimates. Because this technology can increase a person’s network position primarily through information seeking activities, the improvement in work performance is like to come from the information advantage derived from having a structural diverse network.

Next, I examine if brokerage provides any additional benefits to shield workers from negative

\[4\] I hope to present these results in December at Wise.
outcomes, such as layoffs. By gathering layoff statistics from a one-time layoff even in the midst of global recession in January 2009, I find that brokerage still has an impact on reducing layoff risks even after controlling for objective work performance. More importantly, comparing the effect of brokerage with the effect of objective work performance, I find that brokerage has a similar effect on reducing layoffs as compared to achieving superior work performance. This suggests that brokerage provides additional protection against negative outcomes, such as layoff. Through qualitative interviews, it is plausible that having a diverse network allows brokers to promote their work and market themselves to a diverse group of people, including key decision makers, making themselves to be more visible in the organization. This in turn reduces their chance of getting laid off.

Reference
Burt R., Ronchi, D. 2007 Teaching Executives to See Social Capital: Results from a Field Experiment, Social Science Research, 2007
### Table 1: Summary Statistics for Person-Level Networks

<table>
<thead>
<tr>
<th>Variable</th>
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<th>Std. Dev.</th>
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### Table 2: Summary Statistics on the Consultants

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### Table 3: Network Position and Performance

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<th>(4)</th>
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**Table 4: Network Diversity: Junior vs. Senior Consultant**

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<td>IV</td>
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<td>Log(Diversity: 1- constraint (normalized))</td>
<td>128.27* (70.9)</td>
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