Network-biased Technical Change: Evidence from Enterprise Social Media Adoption

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Lynn Wu, The Wharton School, University of Pennsylvania

Abstract

We examine the performance impact from the adoption of an enterprise social media tool at a large consulting organization. While the average return to using social media is positive, some individuals are experiencing a disproportionately higher return than the rest. The phenomenon is similar to skill-biased technical change (SBTC) in which information technology complements skilled or more educated workers, enabling them to earn a higher wage premium. However, in contrast to information technology, social media are shown to complement social capital as opposed to human capital. Specifically, we find that the return to using social media is greater for individuals with high network diversity because they are better at persuading an expert to share information. Coupled with social media’s ability to efficiently locate the source of expertise, individuals with high network diversity can thus experience a greater return to using social media. At the same time, senior ranked employees benefit less from social media than their junior peers because the technology can replace their deep organizational knowledge and eliminate their opportunity to arbitrage information. This more nuanced network-biased technical change (NBTC) has important implications for firms as enterprise social media are becoming rapidly adopted.
Introduction

Social media adoption in recent years has revolutionized how people form and maintain relationships. Through social networking tools, people can more easily make new connections and share information. With the rising popularity of Facebook and Twitter, the adoption of consumer facing social media has grown exponentially in the past ten years. Recently, organizations are also becoming interested in using social media to improve information access and worker productivity (Wu 2013). McKinsey Global Survey reported in 2013 that more than 53% of surveyed firm has adopted some type of social networking tool, compared to only 28% in 2009 (McKinsey 2013). As enterprise social media have become more ubiquitous, understanding their effects in the workplace has also become more important.

Because a social networking tool has the ability to easily locate others, it could potentially benefit peripheral or more constrained members of the organization. Due to their inferior geographical, organizational, and network positions at work, constrained members have limited means to find new connections and resources they need at work. With the help of social media, they can more easily find information and expertise that are essential for improving work productivity. However, technology adoptions often have unintended consequences (Barley 1986). Instead of leveling the playing field and empowering constrained and disadvantaged members of the organization as intended, social media could actually entrench the existing hierarchical and social order and accrue most of the benefits to people who are already endowed with plenty of work advantage. At the same time, those who desperately need additional resources are further marginalized. Thus, before implementing a social networking platform at a large scale, it is important for firms to understand the impact of social media at workplace. Not only is it important to understand the average performance effect from social media adoption, it is also important to understand its distribution as well.
To understand the implication of social media at work, we draw from the skill-biased technological change (SBTC) literature. SBTC shows that information technology (IT) complements high-skilled labor, enabling more educated workers to earn a wage premium over their low-skilled counterparts (Card and DiNardo 2002). As firms increasingly adopt IT and disproportionately hire high-skilled workers who can work with the technology, the wage gap between skilled and unskilled workers also grows larger. Consequently, technology is often placed at the center of the income distribution debate. While the increase in IT investment and the associated organizational change have dominated the IT productivity debate in the last 30 years (e.g., Brynjolfsson and Hitt 2000), the rapid growth in the use of social media, especially at the enterprises, has moved the debate to a new frontier. As social media start to transform how individuals and organizations are connected, it is critical to explore whether social media would engender similar biases as the SBTC did in the workplace.

In this paper, we theorize on the organization and network conditions that support the use of enterprise social media. We argue that similar to SBTC, social media are far from being factor-neutral. In contrast to general information technology that complements skilled workers, social media are a specific type of technology that complements social capital. Consequently, individuals who are already endowed with plenty of network advantages could benefit more from using social media. Magnifying their ability to make new connections, individuals with a network advantage can leverage social media to accrue even more work benefits and reap greater rewards. As the result, social media may inadvertently worsen the disparity at the workplace. However, social media would not necessarily reinforce all existing advantages. Just like information technology can replace routine labor and thus render certain types of work obsolete, social media could also replace certain skills. For example, people who are adept at knowing where to locate the source of information could lose their competitive advantage since people can simply use social media to find experts as opposed to going through a middleman.
To explore these propositions, we captured employees’ work performance before and after the adoption of an enterprise social networking tool inside a large consulting organization. We also captured network characteristics, ranks and demographics to explore whether they affect the return to using enterprise social media. To lend a causal interpretation to our analysis, we utilize a marketing campaign, initiated at the company’s headquarter, that promotes the use an in-house social media tool. Examining the performance change, and focusing on only the individuals who adopted social media during the campaign, we find the distribution of the work benefits from using social media is far from being uniform. While the average work performance, measured in billable revenue, has improved, the performance gain is disproportionately accrued to employees who are already endowed with high network diversity. This suggests that social media can actually reinforce the existing social order, allowing people with superior network capital to reap even greater benefits from using social media.

Interestingly, in contrast to SBTC, social media can also have a leveling effect, specifically on seniority and the formal hierarchy of the firm. We find that junior consultants can also disproportionately benefit from using social media, erasing some of the earlier benefits enjoyed by the senior consultants. Due to their positions and ranks, senior consultants tend to have a rich repository of organizational knowledge and thus they can find information sources without resorting to technologies. However, junior consultants may lack this type of knowledge and a social networking tool can be very helpful for them to find new information sources. Instead of paying rents to a middleman, junior consultants can now use social media to find experts for free and thus catch up to their senior peers. Similarly, the advantage of senior consultants could further erode with social media, because they also lose their ability to arbitrage information on where to find experts. Overall, these findings indicate the start of a pervasive but nuanced network-biased technical change within enterprises. Individuals rich in network diversity are becoming even better off with social media while people who have a more constrained network are further
marginalized. At the same time, social media also empower junior consultants, allowing them to find information sources more easily and thus catch up to their senior colleagues. This type of network-biased technical change is starting to have a profound impact on employees and organizations.

**Theory**

Expeditious access to information and expertise is key to productivity. Especially in information-intensive industries such as consulting, a significant amount of time is spent on assembling, analyzing, and assessing information gathered from various sources. These information-processing activities are essential for understanding clients’ problems and producing workable solutions. A large body of literature has documented that having an information advantage at work can help a person achieve superior work outcomes such as information worker productivity, compensation, careers and job security, and job search (e.g., Aral and Alstyne 2011, Burt 1992, Wu 2013).

Thus, having a social networking tool that can reduce the search costs of finding the sources of information should in theory help people obtaining the information and expertise they need. Because anyone can use the tool to find experts regardless of any social and geographical constraints, the tool should particularly benefit constrained members of the organization who have limited means to access experts. Thus, social media could help leveling the playing field of finding information, empowering disadvantaged members to catch up to their peers. However, many technological innovations often have unintended consequences (Acemoglu 1998, Barley 1986, Card and DiNardo 2002, Machin and Van Reenen 1998). A recent example is the skill-biased technical change (SBTC) that documents the unintended, but growing wage premium between skilled and unskilled workers as the result of the IT investments.
**Skilled-biased Technical Change**

The rapid adoption of information technology over the 1990's has lead to a pervasive skill-biased technical change (Acemoglu 1998, Machin and Van Reenen 1998). While information technology has been shown to improve the overall productivity (Basu and Fernald 2002, Bresnahan et al. 2002) the distribution for the productivity improvement has not been uniform. As IT investment grows over time, there has been a similar uptick in the wage premium for skilled workers. Evidence suggests that the premium is generated because information technology can complement human capital. As firms invest in information technology, the demand for skilled workers who can effectively use computers has also increased, shifting the wage premium toward these workers. This phenomenon has become known as skill-biased technical change (SBTC).

While information technology has driven many changes in organizational practices since the 1990’s, the recent rapid adoption of social networking technologies in the last 10 years has revolutionized how individuals connect and share information. Not only have social media become the top activity on the web and mobile devices, they have also transformed how consumers, employees and organizations relate to each other and to the marketplace (IDC 2012, Qualman 2012). While information technology is shown to be factor-biased for skilled labor under SBTC, it is unclear if social media could also create unintended biases. It is possible that social media is factor neutral, allowing everyone to benefit equally from using it. However, social media could have the opposite effect, allow certain type of individuals to disproportionately benefit from social media. As organizations are increasingly interested in adopting enterprise social media tools, it is important to understand how they interact with various types of human and social capital to affect information worker productivity.

**Social Media and Network-biased Technical Change**
Whether social media is factor-biased is closely related to how they interact with the existing social and human capital. One particular social capital that has received an enormous amount of theoretical and empirical attention is network diversity, or brokerage (e.g., Burt 1992, Granovetter 1973), characterized by an information-rich network that is low in cohesion and structural equivalence and rich in structural holes. This type of networks is often positively correlated to various types of performance outcomes. For example, Burt (1992, 2000, 2004) show 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 diverse sets of information from non-redundant social groups (Aral et al. 2012, Burt 1992). This information advantage is particularly important in knowledge-intensive industries where identifying and assimilating various information sources is the key to innovation and productivity.

Specifically, network diversity has been theorized to confer three forms of information benefits: access, timing, and referrals (Burt 1992). 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, the third advantage of having a structurally diverse network (Burt 1992), are a process in which personal contacts promote the actor to others. They are critical for information acquisition, because referrals can help persuading an expert to respond even if the expert does not personally know the information seeker. While structural diverse networks can provides three types of information benefits, social media could also provide some benefits in finding information. Because anyone can use the technology to find experts, social media could in theory ease the burden of information access, especially for those who lack the necessary social capital such as having high network diversity. However, social media cannot replace network diversity as they could only provide a subset of information benefits that network diversity could. While social media allow anyone to easily search for any expert regardless of social, geographical and organizational barriers, they do not confer referral benefits. Without having referrals to motivate an expert to
share information, information seekers would still fail to acquire the information they need even after social media have successfully located the right expert.

On the other hand, people with high network diversity would continue to have a work advantage. With social media, they can simply use technology as opposed to spending their social capital to find the source of expertise. However, having a structurally diverse network is still invaluable for finding referrals who can make the necessary introduction to the expert and get a response to the request. Without referral benefits, constrained members of the organization are still disadvantaged because they could still fail to acquire information from experts even after they are able to find the them through social media. In fact, having referrals could become even more important with social media, as the technology eliminates the need to know who the experts are, shifting the bottleneck in information acquisition to finding referrals. Consequently, the disparities between those with referrals and those without would worsen with social media. Prior to having the technology at work, experts may receive just a few requests for information and thus have enough bandwidth to answer them even when they are from strangers. However, as their expertise becomes more visible through social media, experts would also receive more requests than before. As their bandwidth has become more constrained, experts would have to prioritize these requests in answering those that have referrals. A stranger’s request for information would be far less likely to be answered after social media become available. As the results, individuals with high network diversity would disproportionately benefit from social media, accruing even more information advantage at work. Their ability persuade an expert to share information through referrals would become an even more important asset, enabling them to further outstrip their peers who do not have the network advantage in finding referrals.

For the same reason, people with more constrained networks could become further disadvantaged. Even when their search costs are significantly reduced through social media, constrained members still face significant hurdle in persuading an expert to respond to their
request. Without referrals, constrained members cannot easily convince an expert to share information. They may contact the expert directly, but the expert is unlikely to respond especially if the request is sensitive or requires substantial time and energy to respond. As experts’ resources become more precious due to their increased visibility, we expect that constrained members would continue facing significant obstacles in information acquisition even after a social networking tool reduces the search costs of finding experts. As the result, they may benefit less from social media relatively to their peers who have more diverse networks.

**Hypothesis 1:** After a social networking tool is introduced, individuals with high network diversity will become more productive than individuals with low network diversity.

While individuals with high network diversity can benefit disproportionately from using social media, people who are information-rich but not necessarily network-rich may not. Although social media can provide valuable information on where to locate the source of expertise, they are not necessarily useful to an information-rich individual who already possesses such information. At the same time, information-rich individuals do not always have a structurally diverse network that can provide referral benefits. Without having referrals to persuade an expert to share information, people who are information-rich but not network-rich would face similar obstacles in obtaining information as people with constrained networks.

Senior ranked employees tend to be rich in information but not necessarily rich in network diversity. Due to their position at the firm, senior consultants are more likely to have a better overview of the various projects at the firms and are thus more likely to know who has what expertise. However, if they do not have high network diversity, senior ranked employees would still lack the ability of finding a referral to the expert. Thus, a social media tool would be of limited use to senior ranked employees. On the other hand, employees in junior ranks could significantly benefit from using the tool. Perhaps due to their shorter tenure and limited scope on the various projects at the firm, junior employees lack extensive knowledge about where expertise lies. With a
social networking tool that can reduce the search cost to finding the right experts, junior ranked employees can now catch up to their senior peers, narrowing the performance gap between ranks.

Furthermore, because social media can effectively locate the source of expertise, senior employees could also lose the ability to control and trade information on where to find experts. Essentially, social media would replace their deep organizational knowledge about where expertise is located and thus erase their advantage in arbitraging such information. Consequently, after social media is widely used, their advantage within the organization would be further reduced as social media eliminate their intermediary function between the information seeker and the source of expertise. As the result, the work performance of senior ranked employees would also suffer compared to their junior peers. By contrast, social media would not displace the intermediary role for individuals with high network diversity. Although with social media, a person would no longer need assistance in locating the source or expertise from individuals with high network diversity, they are still useful for finding referrals. Having a referral to help persuading an expert to share information would substantially ease the burden of obtaining the information. Consequently, we expect senior ranked employees to benefit less from social media.

**Hypothesis 2:** After the social media adoption, senior ranked employees benefit less than their junior peers.

In summary, the inherent nature of social media can generate a substantial variation in the return to using social media. Just like information technology complements skilled labor, social media can also complement certain types of capital such as having high network diversity. As social media use is becoming prevalent, a pervasive network-biased technical change (NBTC) is also emerging. Because a social networking tool can facilitate the search process of locating relevant experts, but not necessarily the referral process of persuading an expert to share information, social media can create greater advantages for people with referral benefits. Thus, people with high network diversity would become better off after social media are used. At the same time, individuals whose primary work advantage was possessing information about where to locate
expertise could lose their work advantage with social media. Senior employees who have a better overview of various projects at work may lose their work advantage of finding experts after social media are widely used. By contrast, junior ranked employees now possess a tool to help them locate experts, allowing them catch up to their senior peers.

Data and Setting

Our setting is a large information technology firm with a focus on their consulting division. The primary role of the consultants is to generate billable revenue for clients they have been assigned to. Typically, consultants are involved in four broad categories of projects: IT consulting, business processes, application supports, and outsourcing services. Consulting projects are often information-intensive and require solving difficult problems for the client in a timely fashion. Consultants typically spend a large amount of time assembling, analyzing, and assessing information to make business decisions. Because these information-processing activities are critical for decision-making and addressing clients’ problems, consultants often need to reach out to experts outside of their immediate groups. Locating the experts within the firm and persuading them to share information is crucial for the consultants to gather and integrate various information sources into viable solutions. Satisfying clients is extremely important because it can generate repeat business, which is the key to maintaining a continuous stream of revenue and avoiding bench time.

Having a social network that can facilitate the process of finding and integrating information would be extremely useful for a consultant. To characterize the social network at the firm, we use internal electronic communication messages of more than 8,000 employees for three years. The sample represents 25% of the employees in the consulting services division, which will be the primary focus of the study. The data contains email, calendars, and instant messages for employees’ internal communication at work. A privacy-preserving social sensor (Lin et al. 2008) is
used mine various types of data sources, including the hierarchical structure of the organization, individual role assignments, the types of client engagements, industries of the clients, and general demographics. Through the sensor and with user consent, we also encoded the content of email and instant messages and calendars of employees who volunteered their data for research. Based on the electronic communication data, we constructed a precise and dynamic picture of how people’s social networks evolve over time. To alleviate the potential problems arise from missing parts in the company’s entire communication network, we only measure the local properties of individuals’ social networks using only one-degree and two-degree connections. Local network properties are also less prone to errors in our setting because we captured all direct communications of the volunteers including ones with the non-volunteers who are not a part of the study. While we may not be able to precisely capture all second-degree connections, we are able to infer many links. For cases when one-degree contacts are not volunteers themselves, we can still deduce their local network structures by examining if they have co-occurred in the same communication instance. For example, if two people (B and C) are present in the same correspondence of a third person (A), they (B and C) are likely to be connected as well. We are mindful that there could still be missing connections and network parameters calculated even within just 2 degrees of separations could still be biased. This is a common problem for network studies in the field and requires setting a boundary on the population studied. Furthermore, we can never accurately capture people’s entire social networks unless we observe every action of the volunteers, which would be prohibitive.

Selection biases could also come from the employees who choose to participate in the study. Thus, we compared our sample with the rest of the firm. Overall, we did not discern any significant differences in demographics, job roles, business functions, and hierarchical ranks. We also compared the productivity differences between the two groups before the enterprise social media platform was introduced. Controlling for job roles and ranks, and other demographic information,
we find both groups had similar work performance as measured by billable revenue generated in a month.

We aim to construct a precise view of the network that reflects the real communication patterns at the firm. Thus, we eliminated spam and mass email announcements that involve more than 15 people\(^1\). Because each message has a timestamp, we are able to create a dynamic panel of social networks for each person in our sample from January 2007 to January 2010. Each month-level network is built using a sliding window of 6 months with a 1-month step size, and includes all the messages occurred in the current month, three months prior and two months after. The sliding window approach can more accurately reflect the network relationships than just the network activities occurred in a single month. Using the communication data, we are able to construct a network panel of 19 periods for 8,059 employees. This provides an opportunity of rare scale and scope to understand how social media adoption and social networks affect work performance.

To measure the productivity impact of social media, we obtain detailed financial performance records for the consultants at the firm. We focus on the 2,038 consultants in the sample who have also shared their electronic communication data. To protect the privacy of the research subjects, their identities are replaced with hash identifiers, and the content of their messages is also encoded. Furthermore, clients are also masked with hash identifiers. To ensure selection biases are not driving any spurious results, we only examine the employees who adopted the social networking tool during a marketing campaign that promote the use of the tool. Since the campaign comes from the CIO office at the headquarters, it is unlikely that the timing of the promotion would coincide with any unobserved factors that could simultaneously affect the number of adoptions. By examining the work performance change for those who adopted during the campaign, we can lend a causal interpretation on whether social media have an impact on work performance. Next, we examine how social capital and ranks could affect the return to using social

\(^1\) We have verified that using 15 people is a good measurement for detecting spams or mass email announcements.
media. Specifically, we examine individuals with high network diversity as well as senior ranked employees because they tend to have more work advantage than their peers. Table 1 and Table 2 present the summary statistics of the consultants, including their demographics, job roles and various local network characteristics.

<<Insert Table 1 and Table 2 about here>>

Social Media Adoption

The firm in our study developed an in-house social networking tool that we call Expertise-Find. It is primarily designed to help consultants locate sources of expertise inside the firm. The key feature of this tool is the search function that looks for experts based on keywords. In contrast to Internet search engines such as Google or Bing, the tool searches for people instead of URLs. For each search query, it returns a list of people whose expertise is relevant to the keywords in the query. For example, when searching for the phrase “Social Media Development,” the search tool would return a list of people ranked by how much their expertise is relevant to the phrase. As shown in Figure 1, the tool lists the name of the expert, a picture (if available in the public HR directory), the job role of the expert, and the division the expert belongs to. Clicking on the person would then direct the user to a more detailed webpage about the person including the contact information such as physical work location, an email address and a phone number, as well as information about the person’s current position, work group, co-workers and management chain. The page also links any blogs and wiki pages the person has contributed recently. This can help the searcher to verify if the expertise of the person is indeed relevant. Similar to search query indices, an expertise index is created for each person in the firm using various information sources within the firm’s Intranet including online profiles, resumes, online forums, wikis, and blogs. With user consent, electronic communication data are also used. While the tool indexes everyone’s expertise
at the firm, only those who signed up for the tool can use it. In return, users volunteer their electronic communication data to help improve search quality.

<<Insert Figure 1 about here>>

**Dependent Variables**

Our performance measure is the billable revenue generated by each consultant in each calendar month from January 2007 to January 2010. It is a clear and objective productivity measure that is widely used for evaluating performance of information workers such as consultants, lawyers, and accountants. Managers at the consulting organization indicate that billable revenue is a very important performance benchmark, particularly for gauging long-term performance. In the short term, inefficient consultants could potentially generate high billable revenue if they happen to be placed in a long-term project thus significantly reduce the probably of being benched. They could also generate high billable revenue because inefficient consultants could take longer to complete a task. However in the long run, it is very difficult to consistently land long-term projects or mask inefficiency. Because a typical project lasts only about 6 months on average, capturing the billable revenue of each person for multiple years should be sufficient to detect the true performance. In addition to working on the current project, consultants also need to line up future projects months ahead of time in order to maintain a healthy revenue stream. Having a strong reputation for being efficient and producing high quality work is critical for consultants to find future assignments. Inefficient consultants would have a hard time finding new projects and their billable revenue would suffer as the result. Furthermore, the project managers have the discretion to reduce the billable revenue if they believe the quality of the work does not represent the amount that is being billed. In this case, an inefficient consultant could be spending 10 hours on a project but only able to bill 5 hours.
Explanatory Variables

Network Diversity

The degree of having a structurally diverse network, or network diversity, is calculated using Burt’s measure of network constraint (Burt 1992). It is a common metric for measuring brokerage. Network constraint, $C_i$, measures the degree to which an individual $i$’s contacts are connected to each other as well as their connections to the individual $i$. $P_{ij}$ is the proportion of actor $i$’s network time and energy invested in communicating with actor $j$. Network diversity is computed as $2 - C_i$. Since relationships may erode over time, we use a 6-month sliding window of electronic communication to gauge the network relationships in the current month. The measurement for network constraint is similar to clustering coefficient. To understand how network diversity could interact with social media adoption to affect work performance, we use the network diversity at the time before a person has adopted the social media tool.

\[
\text{Network Diversity} = 2 - C_i
\]

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

Compared to global metrics of centrality, such as betweenness centrality and closeness centrality, that require knowing the entire network paths, network constraint is a local property that measures the cohesiveness of a person’s network (Burt 1992). It uses only a person’s direct contacts (1 degree of separation) and contacts that are two steps away (2 degrees of separation) from the person. Because global properties are prone to change significantly from a few missing links in the network or other measurement errors, we use local properties of a person’s immediate network that are not subject to this type of bias. We also have the complete electronic communication record for each person in our sample, allowing us to accurately construct a person’s
local network. However, we do not have everyone’s communication data, and thus global networks measures that require knowing every single path are likely to be biased in our data.

$P_{ij}$ can be viewed as a function of tie strength from person $i$ to person $j$. It primarily uses the frequency of one’s electronic communications. Granovetter (1983) describes the strength of ties as a function of time, emotional intensity, intimacy, and reciprocity. In practice, it has been measured in various ways using reciprocation, recency, and the frequency of interactions (Granovetter 1973). We adopt the frequency approach to measure tie strength but with some modifications.

Using a single electronic message exchanged between two individuals as evidence of a social tie would be grossly inaccurate, especially if the message is sent to a large of number of people. Thus, we eliminated all messages that have more than 15 recipients because they are likely to be spams or mass announcement. To more precisely reflect the tie strength between two actors, we normalized the measure to be between 0 and 1, with 0 indicating no tie between the two actors and 1 indicating the maximal tie strength (Lin, Ehrlich, Griffiths-Fisher and Desforges 2008). The detailed calculation is described below.

\[
Tie_{-}\text{Strength}_{ij} = \frac{\log(X'_{ij})}{\max_k \log(X'_{ik})}
\]

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

where $X_{ij}$ is the total number of electronic messages exchanged between actors $i$ and $j$. According to the formula, a tie exists only when there is a sufficiently number of correspondences between two actors. In addition, this threshold to register a tie is also personalized; for active users of electronic communication, the threshold is higher than for those who seldom use electronic communication. Lin et al. (2008) has extensively tested this measure to accurately reflect the tie strength between actors in enterprise settings.
Adoption of the Social Media Tool

We have a detailed record of when each user started using Expertise-Find. Using the record, we created a binary adoption variable, which is zero before the user adopted and one after the adoption. We also only included individuals in our sample that adopted during a promotional campaign from the CIO's office. The goal of the campaign was to promote the use of Expertise-Find, especially in the consulting division. During the campaign, a large number of people adopted (Figure 2). The sheer number of new adopters during the promotion makes it unlikely that any unobserved factor could coincide with the campaign and simultaneously causes a sharp increase in the number of new users. Thus, by focusing exclusively on the users who adopted during this period, we can attribute any performance change to social media adoption.

Seniority

Each employee has a job rank, ranging from 6 to 12, where level 6 is the most junior consultant while level 12 is the highest level a consultant can achieve. The primary role of consultants is to generate billable revenue as opposed to generating sales leads. Pre-sales teams are usually responsible for getting new contracts from clients. In general, consultants at level 7 or below are considered junior while consultants at level 10 or above is considered to be relatively senior inside the firm. Each promotion to the next level can take multiple years. The promotion from level 9 to level 10 is especially difficult as it moves from mid level to the executive level and level 9 is often considered the ceiling level for many consultants. It can take more than 10 years to be promoted to Level 10 from Level 9 if it happens at all.

We can also measure seniority using tenure, calculated as the total number of months a person has been in the firm. More than 10% of the consultants in our sample have worked in the firm for less than a year. The average tenure at the firm is about 5 years in the sample. The turnover rate is quite high, especially for junior ranks, but it is typical for consulting organizations.
Control Variables

We use a host of control variables including individuals' demographics, gender, job role, work division, and the industries of their clients. Demographics are represented using 6 dummy variables for each major geographical region in the world: US, India, China, Latin America and Europe. Gender is a binary variable with 0 being a male and 1 being a female. Industry of the clients is classified under SIC code at 2½ level. We also control for the past workload, which is measured as the average monthly revenue during the past six months. To control for variation induced through specific time periods, we include a set of dummies indicating for each month of the year.

Identification

Adoption of social media tool

The timing of the adoption may bias any performance effect because unobservable factors that drive a person's decision to adopt could simultaneously affect future performance. We address this issue through the panel structure of our data as well as a natural experiment in our setting. Specifically, we focus only on the network change before and after the adoption of Expertise-Find for those who adopted during the advertising campaign initiated at the firm's headquarter. If there are any unobserved individual characteristics, such as a propensity to use new technologies, that can drive both the adoption decision and the subsequent performance change, a fixed-effect model can eliminate these time-invariant factors. Second, we also control for other confounding factors, such as temporal variations and past workloads. Using monthly dummy variables, we can eliminate variations from time trends. If people tend to try for new IT tools in February, we can control for the February effect. Similarly, exiting workloads could prompt users to adopt new technologies. Thus, instead of having technology affecting future work performance, the observed performance effect may simply be the consequences of having a high or low existing workload. In order to
eliminate this type of bias, we control for the workload during the past 6 months before a person adopted the technology.

While fixed-effect models eliminate time-invariant factors, it is still possible that unobserved time-varying factors could still bias our estimates. To address this issue, we capitalize on a policy change when the CIO office at the headquarters launched a campaign designed to motivate employees to use Expertise-Find. During the campaign, more than 2,400 employees have adopted the tool, of which, 558 are consultants. Figure 2 shows the number of new adopters in each month over a 24-month period. The biggest increase in new adopters occurred during the promotional campaign that started in April and ended in October 2008. The sharp increase in new adopters during the campaign is unlikely to coincide with any unobserved factors that happen to also affect adoption during this time. Thus, by focusing only on the individuals who signed up during the campaign, we can treat it as an exogenous source of variation for social media adoption. Examining the performance change for individuals who adopted the social networking tool during the campaign allows us to more conclusively determine the causal relationship between social media use and the work performance.

However, selection effect remains an issue if there are systematic difference between adopters and non-adopters. For example, if adopters and non-adopters have different propensities to show up in the search result, it may affect an individual’s adoption decisions and the subsequent work performance. To explore this issue, we randomly selected 100 popular search phrases on Expertise-Find and compare the likelihood of showing up in the search result between adopters and non-adopters. Overall, we find that the two groups have similar propensity to show up on the first page of the search result, and are thus equally likely to be asked for advice. We also compared genders, demographics, past billable revenue, and client industries between the adopters and the non-adopters. There is no systematic difference between the two groups in these attributes. While it is still a choice to adopt the tool, there is no selection bias on the people displayed in the search
results because anyone can be displayed in the search result regardless of one’s adoption decision. The only criterion to be displayed in the search result is whether a person’s expertise is related to the query.

*Network Diversity*

Structural parameters such as network diversity could also be endogenous. Because unobserved factors could drive both network characteristics and work performance, it is important to find an exogenous source of variation in a person’s network position. To address this issue, we also leverage the promotional campaign designed to increase the use of social media technologies, albeit in a different way from how we identify social media adoption. Specifically, when a friend (one degree of separation from the focal person) adopts Expertise-Find, it could introduce a change in a person’s own network diversity because it is a function of a person’s connections two degrees away. Thus, a friend’s adoption event can be served as a source of exogenous variation in a person’s own network diversity. A social media search tool can be quite especially effective for increasing the network diversity for its adopters (Wu 2013). By contacting experts suggested by the tool, users are more likely to reach out to a distant group of people beyond their immediate social network. Being exposed to different types of people at the firm and having the opportunity to connect with them, users’ network position have become more structurally diverse (Wu 2013). Similarly, after a friend adopts the tool and experiences a change in network diversity, the person’s own network diversity could change as well. Because network diversity is a structural parameter about a person’s ego network within two degrees of separation, a change in a friend’s connections can change the person’s own network diversity without any action from the focal person himself.

To illustrate this concept, we show four actors who are maximally connected with each other, and each actor has a network diversity of 1.07 (Figure 3). After Actor 3 adopts social media and found a new connection, Actor 5, whose network is much more diverse than the other connections
of Actor 3 (Actor 1, 2, and 4). Even though Actor 2, being a friend with Actor 3, did not change any of its prior connections (connected to only Node 1, Node 3, and Node 4 before and after)\(^2\), Actor 2’s network diversity has changed (ND = 1.14). Because Actor 3’s adoption should not directly affect Actor 2’s work performance directly, we can use Actor 3’s adoption event as an instrumental variable for Actor 2’s network diversity. We construct friends’ adoption event both as a binary variable (1 if any friends adopted and 0 otherwise) and as a percentage of friends who have adopted. The results from the two constructions are largely similar, so we report the binary construction in our analysis. The concentration parameter for the first stage regression is 100.6, indicating we do not have a weak instrument (Hansen et al. 2006)\(^3\).

In Figure 4, we show an event study showing how a person’s network diversity changes when a friend adopts social media. To disentangle any effect that arise from a person’s own adoption event, we examine only network positions of a person before he adopted himself but after at least one of his friends has adopted. Each data point on the graph shows the coefficient estimates calculated from regressing network diversity on all the months before and after the earliest adoption event amongst the person’s immediate network connections (1-degree apart). After factoring out seasonality, individual fixed-effects, and past performance, the coefficient estimates for the months after the adoption event (X>0) are increasing over time, indicating that a friend’s adoption is in fact inducing a change in a person’s own network position.

**Seniority**

The relationship between seniority and performance is also subject to reverse causality. For example, high-ability individuals tend to be better performers and are thus more likely to be

\(^2\) Network diversity would still increase if we do not allow actor 3 to increase its network size (number of one-degree connections). In this case if Actor 3 forges a connection with actor 2 and replaces it with Actor 5, network diversity would be 1.49.

\(^3\) 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.
promoted to senior ranks. To address this issue, we rely on the fact that ranks, like most organizational practices, are quasi-fixed (Applegate et al. 1988, Bresnahan, Brynjolfsson and Hitt 2002, Brynjolfsson and Hitt 1996, Milgrom and Roberts 1990, Murnane et al. 1999). Unlike adopting a social search tool, which can happen instantaneously, a promotion, especially from junior levels to senior levels often takes many years, if it happens at all. Given the span in our sample is 3 years, it is unlikely that ranks will change significantly during this time, especially going from junior to senior levels. Thus, it is safe to assume that ranks are quasi-fixed in our setting. To indicate seniority in ranks, we created a variable describing whether a consultant is in junior, midlevel or senior ranks. For robustness checks, we eliminated border ranks from the data and the results did not qualitatively change. A few individuals were promoted during the study. Eliminating them from our sample did not change our result. In addition to rank, we also use tenure to measure seniority. Although senior ranked employees tend to have a longer tenure than junior consultants, they are only weakly correlated. Thus, we include both ranks and tenure to measure seniority in the model.

**Empirical Methods**

To examine the performance effect of using enterprise social media, we first use an OLS model with fixed-effects at the individual level after controlling for seasonality, past workloads and various demographics.

\[
\text{revenue}_{it} = \alpha + \beta_1 \text{adoption}_{it} + \beta_2 \text{nd}_{it} + \beta_3 \text{rank}_{it} + \beta_4 \text{tenure}_{it} + \beta_5 \text{gender}_{it} + \beta_6 \text{US}_{it} \\
+ \beta_7 \text{past revenue}_{it} \sum_d \beta_d \text{divisions}_{it} + \sum_f \beta_f \text{region}_{it} + \sum_t \beta_t \text{month}_{it} + \epsilon_{it}
\]

We then explore how certain individual characteristics—prior network positions and seniority—can provide additional benefits from using social media. Specifically, we explore the interaction effect between adoption and prior network diversity and between adoption and ranks.
\[\text{revenue}_{i,t} = \alpha + \beta_1\text{adoption}_{i,t} + \beta_2\text{nd}_{i} + \beta_3\text{rank}_{i} + \beta_4\text{tenure}_{i} + \beta_5\text{gender}_{i} + \beta_6\text{US}_{i} + \beta_7\text{adoptionXnd}_{i,t} + \beta_8\text{adoptionXrank}_{i,t} + \beta_9\text{adoptionXtenure}_{i,t} + \beta_{10}\text{adoptionXgender}_{i,t} + \beta_{11}\text{adoptionXUS}_{i,t} + \sum_d \beta_d\text{divisions}_d + \sum_j \beta_j\text{region}_j + \sum_t \beta_t\text{month}_t + \epsilon_{i,t}\]

We also include an interaction effects with adoption including tenure, another measure for seniority. To ensure that the interaction effects are not due to other observable characteristics, we created interaction variables with gender and geographical locations as well.

\[\text{revenue}_{i,t} = \alpha + \beta_1\text{adoption}_{i,t} + \beta_2\text{nd}_{i} + \beta_3\text{rank}_{i} + \beta_4\text{tenure}_{i} + \beta_5\text{gender}_{i} + \beta_6\text{US}_{i} + \beta_7\text{adoptionXnd}_{i,t} + \beta_8\text{adoptionXrank}_{i,t} + \beta_9\text{adoptionXtenure}_{i,t} + \beta_{10}\text{adoptionXgender}_{i,t} + \beta_{11}\text{adoptionXUS}_{i,t} + \sum_d \beta_d\text{divisions}_d + \sum_j \beta_j\text{region}_j + \sum_t \beta_t\text{month}_t + \epsilon_{i,t}\]

Lastly, we use instrumental variable approach to estimate these models again. Specifically, we use a friend’s adoption event to instrument a person’s prior network diversity before the person’ own adoption event.

**Result**

Social media can facilitate the search process of finding experts. By simply typing a few keywords, users can find anyone at the firm whose specialties are closely related to the keywords. Often, these experts are located in different parts of the organization, and thus it is difficult to know who they are and their specific expertise. Consultants, often on the road or at the client sites, have even fewer opportunities to connect with other colleagues, especially in different areas of practice or geographical locations. Consequently, they cannot easily find experts even when they work in the same organization. Having a social media tool that can search for experts can help consultants finding the source of expertise and obtain the information they need. Overtime, their work productivity would also improve. To explore the performance impact from social media adoption, we first examine the average effect on billable revenue after using social media. Then, we explore the type of individual who could disproportionately benefit or hurt from using the technology.
In Column 1 of Table 3, we show the change in billable revenue for the entire sample of adopters once they started using social media. Using a fixed-effect specification at the individual level and controlling for past workloads, seasonality, work roles and demographics, we find that adopting social media is correlated with generating $481.52 in additional revenue per month. Reaching out to experts in different pockets of the organizational network, adopters are more likely to be exposed to a wider range of people, information, and expertise. These are critical resources for solving difficult problems (Aral, Brynjolfsson and Van Alstyne 2012, Wu 2013). However, the fixed-effect model is still subject to selection biases, despite having eliminated unobserved time-invariant variables. There could be other unobservables that simultaneously affect individuals’ decisions to adopt social media and their work performance. To address this issue, we leverage a firm-wide campaign designed to promote the use of Expertise-Find. During the campaign, we observe a sharp increase in the number of new adopters (Figure 2). Presumably, those adopted during this time is because of the campaign as opposed to other unobservable characteristics or events. In total, close to half of the users in the sample adopted during the campaign. Examining the performance change for these users who adopted during the campaign could give us a more causal estimate. Overall, we find the social media adoption generates $919.99 in additional monthly revenue (Column 2, Table 3). While it is a larger than the full-sample estimate, it is less subject to selection biases. For example, the full sample estimate could be smaller if low performers choose to adopt before the campaign because they seek additional help at work. Thus, in our subsequent analysis, we only analyze users who adopted during the campaign.

Next, we explore if prior network positions before adopting social media can affect the productivity return. Prior literature has shown that network diversity can provide information benefits that are critical to productivity, creativity, and job security (Aral and Alstyne 2011, Burt 1992, Wu 2013). If having a social networking tool could erase some of the information advantage enjoyed by individuals with high network diversity, we may expect social media to have a leveling
effect. However, if using social media alone is insufficient to obtain information, we may not necessarily observe a leveling playing field. In fact, if social media enhance the existing information advantage, we may observe the opposite that the performance disparity between those with network advantage and those without could become even bigger with social media. To explore this proposition, we examine if social media shrink or amplify the existing advantage of having high network diversity. In Column 3 of Table 3, we find people with high network diversity are able to generate even more billable revenue after adopting social media than people with a more constrained network. Note, network diversity is dropped out of the fixed-effect model because we use the prior network diversity right before a person adopted the tool. On average, a one-standard-deviation increase in the network diversity is correlated with generating $641.64 in additional revenue post adoption (Column 3). This shows that instead of leveling the playing field, social media can actually enhance the existing network advantage, allowing those with high network diversity to benefit even more after the technology adoption. While social media can facilitate the search process of finding experts, they do not facilitate the referral process of persuading the experts to share information. Without referrals, individuals with more constrained networks could still fail to obtain information from the experts even after finding them on social media. In contrast, people with high network diversity can have referral benefits and as the result, their work performance improved more from using social media than individuals with more constrained networks.

However, network positions are likely to be endogenous. While having high network diversity could positively affect work performance, it is also possible that high performers attract desirable social connections and are thus more likely to have high network diversity. While fixed-effect specifications with various controls can help addressing some of the biases, unobserved time-varying factors remain an issue. Thus, we leverage an instrumental variable approach by using a friend’s adoption event to instrument for a person’s own network diversity. Because network
diversity is a function of contacts within two degrees from the focal person, a person’s own network
diversity could inadvertently change when the immediate network contacts make new connections
through social media. Since a friend’s (1-degree away) adoption during the promotional campaign
is likely to be exogenous, any network change as the result of a friend’s adoption is likely to be
exogenous as well. Using this instrument, we estimate the return to adopting social media for
people with high network diversity. In Column 4 of Table 3, we find that having a structurally
diverse network gives an additional boost to a person’s performance after social media adoption.
Interestingly, the magnitude for the performance improvement is larger than OLS. Perhaps due to
measurement errors, the OLS estimates is downward biased and the IV approach corrected the
bias. It is also possible that a selection bias lowered the OLS estimates. Perhaps, the additional
increase in network diversity from a friend’s new social connections can provide more per-unit
benefits than what a person’s existing social network can. In turn, their work performance
improved from the newly gained network diversity.

<< insert Table 3 about here >>

We then explore if seniority has an effect on the performance return to using enterprise
social media by including a rank variable and its interaction with social media adoption. Ranks
could be also endogenous, presumably because those who had superior work performance tend to
be in higher ranks. To address this issue, we leverage the fact that ranks, like many organizational
characteristics, are quasi-fixed, because it takes many years to be promoted if at all. Given our study
horizon is 3 years, it is unlikely ranks would significantly change during this time. Our data only
have a few instances of promotions from junior to senior ranks. When we eliminate them from our
data, our main results do not change. As a robustness check, we eliminate border ranks between
junior and senior levels and they do not affect our results. Column 5 of Table 3 shows the
performance effect of ranks from social media adoption. Because ranks are stable during our study
period, they are dropped out of our fixed-effect analysis. Interestingly, we find lower ranking
consultants tend to benefit more from using social media than their senior colleagues. On average, junior consultants are generating $1609.66 in additional revenue a month after adopting social media. To ensure that the result is not due to other interaction effects, we also include the interaction between social media adoption and network diversity in the model. As shown in Column 6 of Table 3, the interaction between adoption and rank continues to be negative ($\beta=-2056.98$, $p<0.01$) even after controlling for the interaction between adoption and network diversity. Compared to junior consultants, senior consultants have an advantage in locating expertise due to their more senior job roles that allow them to be exposed to many different projects. Having a social media tool that can search for experts would essentially erase the advantage they have over their junior peers. Junior consultants who often face high search costs of finding experts can thus catch up to senior consultants. Holding network diversity constant, senior consultants do not necessarily have an advantage in finding referrals, the third information benefit that network diversity can provide. Without referrals, senior consultants also face similar obstacles of persuading an expert to share information. Thus, they would lose their competitive advantage over their junior colleagues and as the result we observe junior consultants to gain more benefit from using social media.

The length of tenure is another measure of seniority. Perhaps, rather than ranks, tenure is the reason behind why junior consultants would benefit more from social media adoption. Thus, we include tenure and its interaction with social media in the model. As shown in Column 7 of Table 3, the interaction between tenure and social media is not statistically different from zero, showing that tenure has relatively small effect on the return to using social media. While consultants who have been with the firm for a long time may know the history of the organization, they may not necessarily know who the current experts are. This may be in part due to the fast pace nature of consulting industry where the turnover rate is high and the information flow is dynamic. Thus, having a long tenure does not necessarily be beneficial. To rule out other potential confounding factors, we also include other interactions, between gender and social media and between
geographical locations and social media. Interestingly we observe that employees located in the US benefit more from using social media than those who outside of the US.

Next, we use instrumental variables and include all the interactions in model. As shown in Column 8 of Table 3, consultants with high network diversity continue to do better with social media than those with a more constrained network. Similar to earlier findings, junior consultants generate more billable revenue than their senior counterpart after adopting social media. As the search costs of finding experts are drastically reduced through using social media, junior consultants benefit while the earlier work advantage enjoyed by senior consultants is erased. In contrast to the OLS estimate, the IV model shows that tenure has a negative effect on the return to adopting social media. On average, each additional month on the job has a negative $34.40 return in adopting social media. This provides some evidence, albeit a small effect, that those with short tenure may benefit more from using social media as the technology eases the search costs of finding experts.

Collectively, these results show the emergence of a nuanced network-biased technical change within an organization. Individuals with high network diversity experience even more work benefit with social media because their ability to persuade expert to share information through referrals complement social media’s search function in finding experts. At the same time, social media can also flatten the organizational hierarchy, erasing some of the advantage that senior consultants previously enjoy. Because senior people tend to have deep organizational knowledge about where expertise lies but not necessarily the diverse ties needed to acquire information from the expert, their advantage is displaced after social media tool is used. On the other hand, junior consultants would benefit from the lower the search costs, allowing them to catch up to their senior peers.

What happens to senior people when junior people adopted
While we observe the performance effect for those who adopted social media, it is interesting to examine if there is any indirect productivity effect when a person's immediate network contacts adopt social media. If junior consultants predominately rely on others to find experts, a social media search tool can essentially eliminate this need. Senior people, being more knowledgeable about the organization and where the experts are, could lose their ability to trade information about experts after social media adoption. To explore this effect, we examine the performance change after at least one junior colleague adopted social media. First, we examine the performance effect before the person adopted the tool himself but after at least one friend did. As shown in Column 1 and Column 2 of Table 4, we observe that having more junior colleagues does not directly affect a person’s own billable revenue. However, it has a negative effect when the junior colleagues adopt the tool. On average, when a junior consultant adopts social media, a senior consultant generates $95.75 to $103.97 less in revenue. We also controlled for network diversity and its interaction with the number of junior colleagues who adopted in Model 2. In contrast to senior ranked consultants, individuals with high network diversity does not seem to suffer when their junior colleagues adopt social media. Social media did not displace the work advantage that people with structurally diverse network enjoy. While the technology provides an efficient way to find experts, people with high diversity continue to have referral benefits and thus more likely to actually obtain information from the expert. In Column 3, we also include the time periods after the person adopted social media himself and the results are similar to Column 1 and Column 2. In the next two columns, we also included individuals’ social media use and its interaction with network diversity, ranks, tenure, gender and geographical locations. In both OLS and IV models, we continue to find that senior consultants are worse off when their junior colleagues adopted social media while there is no effect for people with high network diversity. Similarly, the performance return to using social media is about the same as in Table 3. On average social media adoption can positively improve billable revenue. However, junior consultants tend to do better than senior consultants
after adoption while people with high network diversity perform better than people with a more constrained network.

<<insert Table 4 about here>>

**Conclusion**

Overall, our results show that enterprise social media can have a profound impact on work performance. Because the social media tool can reduce the search costs of finding experts, it essentially substitutes for some people's knowledge about where to find expertise in an organization. As search costs are drastically reduced for everyone, the ability to persuade an expert to share information becomes the new bottleneck in information acquisition. Thus, having resources that help persuading an expert to share information would ultimately benefits from social media. Because individuals with high network diversity can provide referral benefits that ease the process of acquiring information from experts, they benefit disproportionately from using social media than individuals with a more constrained network who cannot easily find referrals. As the result, social media can entrench the existing social hierarchy, enabling those who are rich in network connections to become even richer and derive even more work advantages. On the other hand, social media also provide some leveling effects in erasing some of the hierarchical benefits accrued to senior ranked employees. Because junior people can now use a search tool to find experts as opposed to relying on others, they become better off relatively to senior consultants who have less need to use a tool to find experts. At the same time, if junior consultants rely on their senior colleagues to find experts, they could derive additional benefit for not paying rent for the information. By simply using a social networking tool to find an expert, junior consultants can essentially bypass their senior peers. Consequently, senior consultants lose their power to arbitrage information and to derive rents from the arbitrage.
These set of results suggest that social media can both reinforce and disrupt the existing social and organizational structure. Because social media benefit people with superior network connections, people poor in network resources face an even greater challenge to improve their productivity. At the same times, social media can also be strategically used to help improving the work performance of new employees and junior ranked consultants, leveling some of the productivity differences induced by hierarchy. In turn, this could potentially help improve job satisfaction and reduce turnover rates, which is generally high for junior consultants.

Thus, we find the effect of social media on work productivity to be nuanced. Similar to how information technology generates a wage premium for skilled workers, a pervasive network-biased technical change (NBTC) is emerging from the widespread adoption of social media, enabling network-rich individuals to become even richer and have even more advantages at work. At the same time, NBTC also devalues the organizational knowledge accrued to senior ranked consultants and allow others to catch up to their senior peers. As firms decide to implement social platforms at work, it is important to not only understand their effect on the overall productivity but how it can change the existing social, organizational, and power structure.
Table 1: Summary Statistics for Person-Level Networks

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs.</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Direct Contacts</td>
<td>5,041</td>
<td>69.305</td>
<td>80.527</td>
<td>1</td>
<td>1213</td>
</tr>
<tr>
<td>Network Constraint</td>
<td>5,041</td>
<td>1.5899</td>
<td>0.297</td>
<td>0.875</td>
<td>1.980</td>
</tr>
<tr>
<td>Ties to Managers</td>
<td>5,041</td>
<td>1.401</td>
<td>2.164</td>
<td>0</td>
<td>18</td>
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<tr>
<td>Ties to Divisions</td>
<td>5,041</td>
<td>1.550</td>
<td>0.890</td>
<td>0</td>
<td>8</td>
</tr>
</tbody>
</table>

Table 2: Summary Statistics on Demographics and Job Roles

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs.</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender (0-male)</td>
<td>5,041</td>
<td>0.182</td>
<td>0.386</td>
<td>0</td>
<td>1</td>
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<tr>
<td>Job Rank</td>
<td>5,041</td>
<td>7.584</td>
<td>1.373</td>
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<td>12</td>
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<td>Managers</td>
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<td>0.118</td>
<td>0.323</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Tenure</td>
<td>5,041</td>
<td>54.556</td>
<td>25.913</td>
<td>1</td>
<td>96</td>
</tr>
</tbody>
</table>
### Table 3: Social media and evidence of network biased technical change

<table>
<thead>
<tr>
<th>Dependent var.</th>
<th>Billable Revenue</th>
<th>Billable Revenue</th>
<th>Billable Revenue</th>
<th>Billable Revenue</th>
<th>Billable Revenue</th>
<th>Billable Revenue</th>
<th>Billable Revenue</th>
<th>Billable Revenue</th>
</tr>
</thead>
<tbody>
<tr>
<td>Models</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
<td>(7)</td>
<td>(8)</td>
</tr>
<tr>
<td></td>
<td>OLS</td>
<td>OLS</td>
<td>OLS</td>
<td>IV</td>
<td>OLS</td>
<td>OLS</td>
<td>OLS</td>
<td>IV</td>
</tr>
<tr>
<td>Social Media</td>
<td>481.52***</td>
<td>919.99***</td>
<td>719.18***</td>
<td>454.27</td>
<td>2,885.52***</td>
<td>3,442.46***</td>
<td>2,792.68*</td>
<td>3,695.64***</td>
</tr>
<tr>
<td>Adoption</td>
<td>(92.353)</td>
<td>(104.266)</td>
<td>(138.711)</td>
<td>(510.705)</td>
<td>(660.264)</td>
<td>(568.143)</td>
<td>(1,459.570)</td>
<td>(978.637)</td>
</tr>
<tr>
<td>Adoption X Network Diversity</td>
<td>641.64***</td>
<td>2,599.87***</td>
<td>656.55***</td>
<td>678.31***</td>
<td>2,577.50***</td>
<td>(97.502)</td>
<td>(731.502)</td>
<td>(135.236)</td>
</tr>
<tr>
<td>Adoption X Rank</td>
<td>-1,609.66***</td>
<td>-2,056.98***</td>
<td>-1,998.91**</td>
<td>-1,037.52**</td>
<td>(444.709)</td>
<td>(439.970)</td>
<td>(588.387)</td>
<td>(438.694)</td>
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<tr>
<td>Adoption X Tenure</td>
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<td>-34.40***</td>
<td>(10.716)</td>
<td>(10.527)</td>
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<tr>
<td>Adoption X US</td>
<td>1,447.61**</td>
<td>1,154.44**</td>
<td>(552.664)</td>
<td>(490.477)</td>
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<tr>
<td>Adoption X Female</td>
<td>868.78**</td>
<td>-610.30</td>
<td>(355.835)</td>
<td>(469.895)</td>
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<tr>
<td>Individual fixed effect</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Month dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<td>Observations</td>
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<td>6,790</td>
<td>6,742</td>
<td>6,742</td>
<td>5,088</td>
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<td>Adj. R-squared</td>
<td>0.60</td>
<td>0.60</td>
<td>0.60</td>
<td>0.60</td>
<td>0.55</td>
<td>0.55</td>
<td>0.60</td>
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</tr>
</tbody>
</table>

Notes: Model 1 includes all adopters in the sample. Model 2-8 only include users who adopted during the firm-wide promotional campaign. Standard errors are reported in parenthesis. *, ** and *** denote statistical significance at the 10, 5 and 1% levels. Clustered standard errors are at the group division level. The fixed effects estimations drop the time invariant characteristics of a person – network diversity, senior, tenure, US, and gender.
Table 4: What happens when junior colleagues adopted social media

<table>
<thead>
<tr>
<th>Dependent var.</th>
<th>Billable Revenue</th>
<th>Billable Revenue</th>
<th>Billable Revenue</th>
<th>Billable Revenue</th>
<th>Billable Revenue</th>
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</thead>
<tbody>
<tr>
<td>Models</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
</tr>
<tr>
<td></td>
<td>OLS</td>
<td>OLS</td>
<td>OLS</td>
<td>OLS</td>
<td>IV</td>
</tr>
<tr>
<td>Junior Friends</td>
<td>134.39</td>
<td>100.19</td>
<td>107.07</td>
<td>87.75</td>
<td>115.81</td>
</tr>
<tr>
<td></td>
<td>(92.140)</td>
<td>(113.775)</td>
<td>(66.785)</td>
<td>(47.756)</td>
<td>(72.087)</td>
</tr>
<tr>
<td>Rank X #Junior Friends</td>
<td>-95.75**</td>
<td>-103.97**</td>
<td>-81.22***</td>
<td>-116.31***</td>
<td>-111.94***</td>
</tr>
<tr>
<td></td>
<td>(35.925)</td>
<td>(36.489)</td>
<td>(21.277)</td>
<td>(7.841)</td>
<td>(13.363)</td>
</tr>
<tr>
<td>Network Diversity X #Junior Friends</td>
<td>70.35*</td>
<td>10.44</td>
<td>44.48*</td>
<td>15.38</td>
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<tr>
<td></td>
<td>(32.151)</td>
<td>(28.538)</td>
<td>(19.784)</td>
<td>(22.867)</td>
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</tr>
<tr>
<td>Social Media Adoption</td>
<td>4,495.13**</td>
<td>3,888.88***</td>
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<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1,751.821)</td>
<td>(1,064.804)</td>
<td></td>
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<tr>
<td>Adoption</td>
<td>341.81</td>
<td>2,541.92**</td>
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<tr>
<td>Diversity</td>
<td>(199.209)</td>
<td>(1,030.380)</td>
<td></td>
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<tr>
<td>Adoption X Rank</td>
<td>-1,714.45**</td>
<td>-1,206.25**</td>
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<tr>
<td></td>
<td>(673.334)</td>
<td>(509.671)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adoption X Tenure</td>
<td>-32.40**</td>
<td>-34.52***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(13.669)</td>
<td>(10.256)</td>
<td></td>
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<tr>
<td>Adoption X Female</td>
<td>-889.97</td>
<td>-1,032.97**</td>
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<td></td>
<td>(690.916)</td>
<td>(501.101)</td>
<td></td>
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<tr>
<td>Adoption X US</td>
<td>464.64</td>
<td>-615.72</td>
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<td></td>
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<tr>
<td></td>
<td>(272.781)</td>
<td>(473.380)</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Individual fixed effect</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<tr>
<td>Month dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<td>Observations</td>
<td>5,770</td>
<td>5,729</td>
<td>6,390</td>
<td>6,742</td>
<td>5,088</td>
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<td>Adj. R-squared</td>
<td>0.55</td>
<td>0.55</td>
<td>0.55</td>
<td>0.55</td>
<td>0.54</td>
</tr>
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</table>

Controls: Region dummies, Business division dummies, Client industry dummies, Past workload

Standard errors are reported in parenthesis. *, ** and *** denote statistical significance at the 10, 5 and 1% levels. Clustered standard errors are at the division level. The fixed effects estimations drop the time invariant characteristics of a person – network diversity, rank, tenure, US, and female.
Figure 1: Snapshot of Expertise-Find. Search result from searching for the phrase “Social Networks.”

Figure 2: New adoptions in each month
Figure 3: Change in network diversity when friends adopt

ND (2) = 1.07

ND (2) = 1.14

Figure 4: Event study of network diversity as a function of friend's adoption.
References


