EMAIL AND OUTPUT: COMMUNICATION EFFECTS ON PRODUCTIVITY

by

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A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
(Information)
in the University of Michigan
2006

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Acknowledgements

My dissertation would not have been possible without the contributions and support of many others. My advisor, Marshall Van Alstyne, and Jun Zhang, a fellow doctoral student, played key roles as research team members. Marshall had the vision to initiate the study that led to my dissertation. His encouragement and ideas helped shape the entire process. Jun wrote the email capture software and made many helpful suggestions along the way.

All of my committee members made important contributions. Co-chair Michael Cohen provided early encouragement and detailed feedback that helped clarify interpretations of results. Jerry Davis's enthusiasm shaped the methodological emphasis of my dissertation. Jeff MacKie Mason contributed specific expertise in econometric modeling and asked good challenging questions. Tom Finholt helped me see big picture implications and make connections with the work of others.

Outside my committee, multiple conversations with Wayne Baker, Ed Rothman and Peter Gloor led to many useful ideas. The Visible Path Award provided an important source of external validation.

Others provided personal support. Friendships with Doug Van Houweling, who introduced me to the School of Information and Maurita Holland, my advisor in the Master's program, helped me through the doctoral program. Pat Pasick played an invaluable coaching role. My parents provided encouragement and a willingness to listen throughout the whole process. Many others not specifically mentioned, including classmates at the School of Information and other friends, played important roles.

Finally, my wife Candace deserves special mention for successfully balancing the roles of friend and task master. In many ways she had the most difficult role waiting for my dissertation to be done. I am deeply grateful for her support through the entire process.

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Abstract

My dissertation is an econometric case study of relationships between email patterns and individual performance that develops techniques aimed at improving the measurement of white-collar productivity. While interpersonal communication patterns are likely to influence individual and organizational performance, researchers have had difficulty measuring these effects in white collar settings. I address the problem of measurement by using email as proxy for more general communication patterns, within a setting, executive recruiting, in which I was able to obtain individual measures of output.

My work contributes to existing knowledge in two main areas. First, I develop methodology for using email data as an alternative to social network surveys. This includes developing email measures and assessing their validity and reliability. Second, I use email measures to operationalize novel tests of classic theories that may explain variation in individual performance within organization settings.

Multiple theoretical perspectives, including sociology, economics, coordination theory and organizational learning, motivate hypothesis testing. Findings are consistent with existing research that relates social network centrality to performance. In addition, an individual's benefit from intra-organizational networking appears to evolve over the course of a career from an emphasis on accumulating to exercising social capital. Non-topological measures related to performance include message sizes, response times and proportional measures of information flow. They suggest that aspects of how people communicate also predict performance. Perceptual data, gathered in an online survey and interviews, provide context for interpreting results.

Chapter 1

Introduction

Over the past decade, the U.S. economy has experienced above average rates of productivity growth (Jorgenson, Ho et al. 2006). Scholars and pundits commonly attribute this growth to globalization and advances in information and communication technologies. Abundant anecdotal information suggests strategies individuals, teams and organizations pursue in navigating this increasingly interconnected world influence their economic and social effectiveness (e.g. Saxenian 1994; Castells 2000; Friedman 2005).

Interpersonal communication patterns are likely to influence individual and organizational performance. However, researchers have found these effects difficult to measure in white collar settings. Good measures of independent variables associated with communication patterns and dependent variables associated with individual output are often hard to find. I address the problem of measurement by developing strategies that use email as proxy for more general communication patterns within a setting, executive recruiting, in which I was able to obtain revenue-based measures of performance at the individual level.

My work contributes to existing knowledge in two main areas. First, I develop methodology for using email data as an alternative to social network surveys. This includes developing email-based measures of communication and assessing their validity and reliability. Second, I use email measures to operationalize novel tests of classic theories that may explain variation in individual performance within organization settings.

My research design is an econometric case study. I use a combination of email and survey measures to help define the nature of relationships in the workplace. I use hypothesis tests to evaluate whether these relational measures explain a statistically significant portion of variation in individual performance. My goal is to use a single setting case study to develop a transferable methodology for assessing relationships between communication patterns and performance.

In Chapter 2, I use existing literature to motivate the use of email as a data source and develop the theoretical basis for my hypotheses. Chapter 3 covers methodology. After describing my data and research setting, I outline the analyses I use to define and evaluate the validity and reliability of email-based measures of communication. I use these measures within the context of regression models to test hypotheses relating email communication patterns to measures of individual performance. Since no known existing research has established relationships between email communication patterns and economic measures of individual performance, I test the null hypothesis of no relationship. In Chapter 4, I report the results of my hypothesis tests. In the final chapter, I interpret and discuss the implications of results, outline opportunities for future work, and summarize limitations and contributions.

By using email data as an alternative to network surveys, I avoid well documented problems with informant inaccuracy. In addition, I am also able to measure non-topological features of communication, such as information flows, response times and message size. Email data collection also reduces demands on respondent’s time.

The use of email as a substitute or complement to network surveys may be feasible in some settings, but not others, based on specific features of email communication in the workplace. In an ideal setting, “anytime, anywhere” use of electronic media would produce data that researchers could use as proxies for general communication patterns. In my methodology chapter, I outline the analyses I used to assess whether email could be used as a proxy for general communication patterns in this research. In my discussion, I consider ways this framework might be generalized. Step-by-step descriptions of analyses that supported my development and assessment of email measures can be found in Appendices A-D.

My work on email measures serves as a prelude to testing hypotheses relating email communication patterns to individual performance. I explore four sets of hypotheses. These involve multiple levels of analysis that emphasize different communication related features of relationships. Hypotheses relate to network position, differences in networking strategies across job levels, co-specialization and potential efficiencies in email behavior related to response times and message size.

My first group of hypotheses considers effects of network position. Exchange and resource dependency theories suggest individuals who occupy central positions in an organizational network are likely to be high performers because these positions offer greater access to and control over information. I find positive associations between more central positions in the firm email network and performance, a result that is consistent with the findings of many survey-based studies. I evaluate the effects of network position with respect to differences in networks, centrality measures and performance measures. These multiple measures increase the specificity with which I can interpret results.

My second group of hypotheses considers job level differences in networking strategies. I develop theoretical predictions from an intra-organizational network interpretation of the tradeoff between exploration and exploitation in organizational learning (March 1991). As people age, the investment time horizon shrinks. Applied to strategies for managing social and intellectual capital this observation leads to predictions of job level differences in networking strategies. Among junior recruiters, I predict investment strategies, such as relationship building and learning, will be associated with higher levels of performance. Among senior recruiters, I predict strategies that capitalize on previous investments, such as delegation, will be associated with higher levels of performance. In support of this hypothesis, I find job level differences in relationships between information flows and performance and between information behaviors and network topology.

My third group of hypotheses considers relationships between a recruiter's performance and the performance of colleagues. My co-specialization hypothesis suggests that individual performance in one dimension will be related to the performance of colleagues in the alternate dimension. I test this hypothesis using both email and contract data to weight the interactions between a recruiter and his or her colleagues. My co-specialization hypothesis is not supported by the data. However, I suggest an alternative explanation based on the higher value recruiters ascribe to performance in the dimension of landing as opposed to executing search contracts. This corresponds to an alternative way individuals may increase the dollar value of output in information work. Instead of increasing joint output through complementarities, they may use relationships to hand off essential, but lower valued work to others.

My final set of hypotheses considers potential efficiencies in email communication. I develop my theoretical prediction through an analogy with queuing theory models that suggest short jobs can be swapped in and attended to more quickly than long jobs of the same priority. Themes from contingency theory and media richness theory provide additional support. I predict that on average shorter, more frequent communication between team members will outperform longer, less frequent communication. Although the results are generally consistent with the hypothesis, I find it difficult to rule out potential alternative explanations.

Executive recruiters, colloquially known as headhunters, were chosen as research subjects because their work practices and skill sets are similar to those found in other white-collar occupations and their output can be precisely measured.[1] I measure output in the form of revenues associated with search contracts. The firm apportions these revenues as shares based on the division of labor in landing (booking) and executing (billing) searches. Revenue generating members of such firms are organized in a career ladder in which senior partners land the majority of contracts, while junior consultants land some smaller contracts and support partners in executing contracts. Skills used in executive recruiting, such as interviewing, negotiating, research, project management and the care and feeding of client relationships, are common to other forms of white-collar work. Similar skill sets are important in private sector occupations such as law, consulting, and accounting, as well as public sector occupations such as political action groups and university development offices.

The combination of email data and individual level accounting data provides the opportunity to investigate relationships between communication patterns and output. Since the mid-1990s, studies of the "productivity paradox" have generally supported a

[1] Data gathering for my dissertation was lead by my advisor, Marshall Van Alstyne. This includes implementation of a research design that combines accounting, survey and email data. Data gathering was supported by NSF Career Award 9876233 and grants from Intel Corporation.

positive correlation between investments in information technology and productivity (Brynjolfsson and Yang 1996; Lehr and Lichtenberg 1999; Brynjolfsson and Hitt 2000; Oliner and Sichel 2000; Jorgenson 2001). Researchers have consistently found that is not so much the investment in technology *per se* that influences productivity, but how it is used. The use of executive recruiters as subjects extends earlier research on relationships between information technology and productivity to white-collar work, a setting in which productivity has been notoriously difficult to measure. The research design includes individual level measures of revenue for both the landing and execution of search contracts as well as "quality" controls for industry and the job level of candidates to address issues associated with the economic measurement of individual output.

The data offer limited opportunities to assess changes in output over time needed to identify productivity gains. In addition, my models do not permit causal inferences. This means my model results do not distinguish between situations in which email communication may enable higher levels of individual performance from those in which email activity serves as an indicator of performance. For example, causality could run in the latter direction if recruiters tend to send more email to higher performing colleagues.

However, my performance measures compare favorably with those found in existing social network studies. My regression models allow me to test hypotheses relating email communication patterns to individual performance. This creates the opportunity to explore the application of classic theories within a modern white-collar context that includes distributed work and computer mediated communication. In some cases, directional and temporal aspects of the measures also suggest interpretations of results that take into account the most likely direction of causality.

Chapter 2
Literature and Motivation

My interest in the question of how email patterns might be used to explain variation in individual performance evolved from two distinct literatures. Literature on information technology investments and organizational productivity suggests how information and communications technologies are used influences productivity. It provides quantitative support for organization level hypotheses, but has less to say about how individual practices involving information and communication technologies might influence performance. Literature on social network analysis and economic performance has a great deal to say about communication patterns at the individual level. It has accumulated less evidence involving economic measures of performance. Few researchers have sought to connect these literatures.[2] However, I believe that research spanning the gap between these literatures could significantly increase current understanding of relationships between communication patterns and individual performance within white-collar settings.

My use of email data as opposed to social network surveys represents a departure from traditional practice in social network research. My rationale comes from a desire to study subjects who were unlikely to spend the time to complete network surveys. In addition, network surveys are subject to well documented problems with informant inaccuracy. By developing methodology for using electronic archival data in social network research, I suggest a strategy for addressing a longstanding methodological problem in social network research.

[2] I am not aware of any existing research that relates social network measures based on electronic archival data to economic measures of individual performance.

My decision to use email data led to considerable work developing measures and assessing their validity and reliability. Opportunities and challenges associated with the use of email as a social network data source can be better understood through existing research on email adoption and use in organizations.

After surveying literature that speaks to the methodological underpinnings of my research, I explore theoretical relationships between communication patterns and individual performance. My approach emphasizes the application of classic theories that seek to explain how relationships with colleagues contribute to differences in individual performance. I focus my inquiry around four general sets of hypotheses drawn from literature in sociology, organizational theory, economics and coordination theory. My literature review concludes with descriptions of work that motivated each set of hypotheses.

<u>Information technology investments and organizational productivity</u>

Since the mid-1990s, studies of the "productivity paradox" have generally supported a positive correlation between investments in information technology and productivity (Brynjolfsson and Hitt 1996; 2000; Lehr and Lichtenberg 1999; Oliner and Sichel 2000; Jorgenson 2001). Researchers examining this question at the organizational and industry sector level have consistently found that is not so much the investment in technology *per se* that influences productivity, but how it is used. Studies have found firm level productivity gains due to investments in information technology (Brynjolfsson and Hitt 1996), human resource practices (Ichniowski, Shaw et al. 1997) and complementary business practices (Brynjolfsson and Hitt 2000).

However, there is very little data that relates the use of technology at the desktop level to performance. Most gains related to information technology use appear to have occurred in the manufacturing sector (Jorgenson 2001), where it is exceedingly difficult to separate the effects of information flows in worker communication from use of technology for process and quality control. In addition, many apparent gains in organizational productivity have been found to be gains in the output of the information technology and semiconductor industries (Jorgenson 2001). Taking these away, the measured economic influence of information technology at the organizational level appears smaller.

A common theme emerges from organizational level productivity research and historical case studies of information technology use in organizations. Over time, the value derived from computing technology has shifted from applications that emphasize raw computational power to those that emphasize communication (Brynjolfsson and Hitt 1998; Brynjolfsson and Hitt 2000a; Brynjolfsson and Hitt 2000b; Bresnahan, Brynjolfsson et al. 2002). The prediction that the most significant source of productivity gains from the application of information technology in the workplace would involve reorganization of work processes over a period of decades is consistent with themes articulated in literatures on general purpose technologies and the lag hypothesis (David 1990; Bresnahan and Trajtenberg 1995).

Studies of workplace communication

This suggests studies of workplace communication could be a promising place to look for evidence of business value associated with advances in information technology. Ironically, some of the most relevant empirical work may have been conducted before computers became common in white collar settings. Trends in scholarly research may be a contributing factor. These include a shifts away from both detailed studies of workplace communication and the use of individual performance as dependent variables (Meyer 1994; Barley and Kunda 2001).

An exemplar of work from the previous generation can be found in Allen’s (1977) detailed studies of relationships between communication patterns in R&D settings and performance. Allen’s work provided the basis for considerable innovation in the arrangement of physical space in the workplace. Organizational literature in the 1990s emphasized how much relationships among white collar workers could change through advances in technology that reduce the influence of physical distance (e.g. Pickering and King 1995). Yet it is not safe to assume that these technologies have necessarily led to sweeping changes in social norms and workplace conventions. Themes surfaced in detailed ethnographic accounts of managerial work from a prior generation may still be relevant today (e.g. Mintzberg 1973; Kanter 1977). How these potentially countervailing forces have played out remains unclear. Reasoning by analogy with the influence of Allen's work, contemporary research could potentially motivate significant innovation in the arrangement of virtual space.

Social networks and performance

Since these ethnographic classics were written, significant methodological innovations have occurred in social network research. Social network analysis has been used to offer empirical support for the economic importance of relationships in a diverse array of contexts including job search (Granovetter 1973; Lin, Ensel et al. 1981), commodities trading (Baker 1984), contracting in the garment industry (Uzzi 1997), and the financing of small business loans (Uzzi 1999). In addition, a number of studies have linked intra-organizational networks to performance: Cummings (2004) related social networks to work group rankings by senior executives in the context of knowledge sharing among structurally diverse work groups; Burt (2004) related structural holes to supervisor ratings of proposed organizational improvements; Sparrowe et. al (2001) found supervisor ratings from surveys were positively related to centrality in the advice network and negatively related to centrality in the hindrance network; Baldwin, Bedwell and Johnson (1997) found a positive relationship between centrality of MBA team members and grades; Rice (1994) used email data to relate the performance of interns in an R&D lab to the performance of permanent employees with whom they communicated at the beginning of their internships; and Podolney and Baron (1997) linked the structure and content of individual's networks to intraorganizational mobility in a large high tech firm.

Despite these examples, studies that relate social networks in organizations to performance are rare. All of these prior studies use performance metrics based on the perceptions of superiors as opposed to revenue based measures of output. However, Podolney and Baron (1997) is notable for its large sample size and use of promotions as a metric that represents commitment in the form of actual transfer of resources.

The gap between social network literature and literature on information technology and productivity has parallels with other holes in the business literature. For example, operations management and human resource management literatures have been historically distinct (Boudreau, Hopp et al. 2003). This academic divide exists despite clear understanding in industry that human factors influence operations and understanding of operations can be used to identify leverage points for human factors. Such gaps may help explain why academic literature has not made as much progress as it might in understanding factors that influence white-collar productivity.

In a review of the social network literature, Rangan (2000) speculates that social networks have the greatest economic importance in contexts involving search and deliberation. This suggests executive recruiting would be an excellent setting for a study relating social networks to economic measures of output.

The problem of informant inaccuracy in social network surveys

While social network researchers typically collect data through network surveys, informant inaccuracy is a common and well documented problem. Informant inaccuracy issues were first highlighted in a series of seven experiments comparing respondent descriptions of communication with direct observation across a variety of media including teletype, ham radio and email (Bernard, Killworth et al. 1984). The BKS studies found that on average about half of what informants reported was probably inaccurate in some way. Techniques such as informant record keeping, slightly unobtrusive observation and telling people that they were expected to get more accurate in repeated experiments did not significantly improve the accuracy of reporting communications. The researchers were not able to relate individual differences in accuracy to characteristics of people or groups, such as age, sex, time in group, centrality, etc. nor did they see ways in which statistical techniques for washing the data could solve the problem. The BKS studies came to the pessimistic conclusion that "what people say about their communication bears no useful resemblance to their behavior." Other researchers have re-analyzed the BKS data and found that the more reliable informants gave reports that were highly associated with each other (Romney and Weller 1984). However, no subsequent research has seriously challenged the need to address problems surrounding the accuracy of network surveys.

Since the BKS experiments, research on informant inaccuracy has shifted from the gap between recall and observation to understanding how the two measures are related (Marsden 1990). A number of insights can be drawn from cognitive psychology research on recall biases. For example, memory decays over time, recall is biased towards routine structures, subjects have a tendency to recall events in the past as more recent than they actually are (ie. telescoping) and framing effects can lead to situations in which minute changes in survey wording significantly alter responses (Tversky and Kahneman 1981; Freeman, Romney et al. 1987; Anderson 1995). More recent studies have revealed variation in respondent tendencies to overestimate relationships with others (Feld and Carter 2002) as well as distortions on recognition based surveys related to respondent mood (Hlebec and Ferligoj 2001). For researchers using surveys to gather network data, implications for practice include: recognition methods yield substantially larger estimates of size than recall methods (Sudman 1985); reciprocated reports are substantially more likely to match observed interactions than are unreciprocated reports (Hammer 1985); and most network data appear to be of better quality for close and strong ties than for distant and weak ones (Marsden 1990).

The informant accuracy literature suggests that conclusions based on network survey data alone should often be viewed with a healthy degree of skepticism. While surveys are the most common method for gathering network data, this is not because they represent a gold standard. The informant inaccuracy literature identifies serious methodological problems. These can potentially be addressed through direct observation of communication using archival data sources such as email.

Email as an archival network data source

Ideally, email data would be used in combination with survey data. As Garton and Haythornthwaite et. al (1999) point out, when data are gathered electronically issues of accuracy are often replaced by issues of interpretation. For example, in this research, techniques used to preserve privacy make it extremely difficult, if not impossible, to distinguish between important and inconsequential messages. In network surveys, researchers can ask respondents to assess the importance or meaning of different communication patterns (e.g. differences between advice, trust and workflow networks) (Krackhardt and Hanson 1993). In the future, multi-method studies that combine surveys and electronic archival data are likely to emerge as a gold standard for social network research.

Despite these limitations, email may often provide the most practical way of obtaining accurate data on organizational communications patterns. Recent surveys suggest that email has become a nearly ubiquitous feature of modern office life. Ninety-eight percent of employed Americans are reported to have e-mail access at work, while the time business users devote to managing e-mail averages nearly an hour a day (Grey 2001; Fallows 2002).

In using email to identify relationships between communication patterns and performance, a central question is whether results should be interpreted as evidence regarding the effects of email as a mode of communication or the effects of general communication patterns for which email serves as an indicator. The answer hinges on how communication over email compares with communication in other media. This question prompted considerable interest among communications, human computer interaction and information technology researchers a decade ago. Unfortunately, since then the research stream has been largely dormant.

Email adoption and use in organizations

This literature on email adoption and use in organizations was defined largely by a debate between two sets of theories: media richness theory and social definition theory. Media richness theory adopts a rational choice perspective and suggests people choose communications media by matching media characteristics to aspects of the situation at hand (Daft and Lengel 1984; Daft and Weick 1984; Daft and Lengel 1986). Media richness theory predicts that richer media will be favored for tasks that involve the communication of more equivocal information. Face-to-face is considered the richest media because it is synchronous and provides a full range of cues. The most important thing to observe with respect to the classification of email within media richness theory is that development of the theory preceded widespread adoption of email. Text-based and asynchronous properties led some researchers to classify email as a lean medium. However, as researchers began to study how email was used within organizations, the proper classification of email within the media richness taxonomy became a matter of considerable debate.

Social definition theories, such as critical mass, provide an alternative explanation. They predict email use will be determined largely by institutional norms (Allen 1988; Markus 1990). Most subsequent studies support this interpretation. Applying critical mass theory to email use leads to predictions such as higher overall levels of email use in workgroups in which the leader is a proponent of email.

Three insights from the email usage and adoption literature helped me design my research. First, researchers offer evidence that email is frequently used as a complementary medium. Marcus (1994) uses the term "channel-switching" to characterize a common practice of selectively using email as part of a complex repertoire of media choice decisions within the context of extended discussions. In addition, she found managers often use email to provide background or context before face-to-face or telephone interactions and to gain temporary closure on tasks. Her work provides some of the best descriptive and analytical accounts of email use in white-collar settings.

Evidence that email is used as a complementary medium suggests that email patterns may track communications in other media fairly well. It suggests that if email is adopted universally within an organization, then the use of email to establish the presence or absence of relationships can probably be justified.

Second, empirical support for social definition theories suggests that "one-size fits all" theoretical predictions regarding the use of email in organizations are unlikely. In addition, different subgroups within an organization will not necessarily exhibit the same email patterns. Email patterns such as proportional flows, response times and message sizes may be more sensitive to site and individual specific differences in how email is used, so a decision to interpret them as proxies may require additional empirical support. These first two observations motivated my empirical investigation into email usage patterns aimed at assessing it viability as a general communication proxy in this setting (Appendix D).

Email and weak ties

The third insight is that email may play an important role in supporting weak tie networks based on communities of interest, particularly those that are geographically dispersed (Feldman 1986; Finholt and Sproull 1990). In analyzing email communication within a Fortune 500 office systems company, Feldman (1986) found messages that subjects believed they would not have sent without email were more likely to be between people who are spatially or organizationally distant. Pickering and King (1995) argue that inter-organizational computer mediated communication could catalyze a shift from hierarchical to market relations through its ability to support networking among geographically dispersed professionals. These observations and theoretical conjectures are relevant because they suggest email may be a particularly good way of obtaining information on weak tie networks.

The informant inaccuracy literature suggests respondents are likely to experience greater difficulty recalling weak ties as opposed to strong ones. If weak ties are related to individual performance in important ways as the literature suggests, this provides another point of support for email as a data source in social network research. An increase in the accuracy with which weak ties could be measured might make them more or less significant predictors of performance than they would be otherwise. If respondents neglect to report weak ties they accurately perceive as "unimportant", the significance of weak ties in survey research could be overstated. On the other hand, respondents may not be able to accurately predict the eventual significance of specific weak ties *a priori*.

If the prevalence of weak ties is a better predictor than their perceived "importance", more accurate reporting could show that the importance of weak ties is understated.

Collocation effects on email use

Literature on email adoption and use does not reveal a consensus around whether collocation leads to more or less email communication. Some studies have found a positive relationship, although the evidence is limited (Eveland and Bikson 1986). Collocation is associated with differences in face-to-face communication. For example, the Allen Curve reveals a distinct correlation between physical distance and the frequency of face-to-face communication. The amount of contact among co-workers drops sharply when they are located at a distance of more than 100 feet (Allen 1977). Being located in the presence of others is also associated with increases in attention, social impact and familiarity (Kiesler and Cummings 2002). In this research, survey results showed executive recruiters believe they receive proportionately more value than time spent when they are engaged in face-to-face interaction. This result was statistically significant across all three executive recruiting firms.[3] This perception is consistent with a summary of research findings that suggests face-to-face is the most powerful medium known for coordinating work within interdependent groups (Kiesler and Cummings 2002).

While physical proximity is likely to be associated with differences in communication patterns in this setting, it is less clear whether collocation with teammates will be related to performance. Strong relationships between proximity and performance have been identified with respect to certain tasks such as software development (Teasley, Covi et al. 2000). At the same time, development of the Linux operating system provides a counterexample of a successful software project conducted almost entirely through distributed work (Moon and Sproull 2002). Factors that help predict the potential for successful distributed work include loose coupling, common ground, collaboration readiness and collaboration technology readiness (Olson and Olson 2000). These factors

[3] I focus my dissertation on results from a single firm. Two other firms took part in some aspects of this research.

all appear to be present in this setting. In addition, the high percentage of non collocated searches, approximately 50 percent, suggests an evolutionary argument. It seems unlikely that this percentage would be as high as it is if a statistically significant negative relationship existed between distance from teammates and performance.

Findings from the literature on collocation were too inconsistent to suggest clear hypotheses regarding collocation effects on either email patterns or performance measures. However, because the literature suggested physical proximity might matter I conducted a number of analyses. I report analyses related to collocation in Appendix D.

Email content

Because I used email data in which the words were encoded to preserve privacy, I have to infer how email was likely to be used in this setting from interviews and accounts of email use in other white collar settings. Prior research suggests that information exchanged over email can play a diversity of roles. Most of these could be linked theoretically to performance. Examples include the transmission of news and opportunities through the "grapevine," routine patterns of workflow and coordination, social support and advice, and the exchange of "how to" information that supports learning (Mackay 1989; Monge and Contractor 1999; Ducheneaut and Bellotti 2001; Monge and Contractor 2003).

Empirical studies in organizations have led to both a greater awareness of subtleties regarding the application of information richness theory to email as well as general support for elements of social definition theories. With respect to information richness theory, Markus (1994) found that although managers perceived email to be a relatively lean medium when answering survey questions about appropriate use, their behaviors were consistent with a greater than expected use of email in equivocal situations.[4] Rice, Grant et. al (1990) found that lower task analyzability was associated with higher levels of email adoption and use, which is the opposite of what information richness theory would predict. In a detailed analysis of communication on computer programming teams, McKenny, Zack et. al (1992) reported communication patterns that

[4] I also found evidence suggesting that perceived media substitution effects involving email may be stronger than measured effects (Appendix D, Analysis D.6).

were strongly consistent with media richness theory. They found programmers relied heavily on face-to-face for problem solving and email for messages involving task status, coordination and the exchange of facts.

To summarize, consistent with media richness theory, in organizations in which email is universally used, it is often used heavily for the type of tasks media richness theory would predict. These include routine coordination, status updates and exchange of facts. However, researchers have also found email may often be used as one of a number of channels in more equivocal contexts.

Research on email adoption and use has generally supported social definition theory interpretations. For example, Rice et. al (1990) found critical mass to be a strong predictor of both email adoption and use. Markus (1994) suggests social norms provided a better fit to observed patterns of email use than media richness theory, even if characterizations of email as a lean medium were relaxed to incorporate phenomena like "channel-switching." Markus characterizes the individual level decision process as one aimed at "behaving appropriately" as opposed to rational choice based on media characteristics. For example, she suggests that the CEO's role as an early proponent of widespread email use was likely to be related to a general perception that email was appropriate for all work related communication except personnel matters. Telephone as opposed to email was seen as the preferred medium when a "personal connection" was required. Markus also provides anecdotal evidence that email use declined after the CEO was replaced by a successor who did not use email, a development that clearly suggests the relevance of social definition theories.

Email and changing organizational communication patterns

The rapid adoption of email and the Internet in the 1990s spurred predictions of changes in organizational communication patterns. Recurrent themes include the flattening of hierarchies and increases in communication directed towards communities defined by interest as opposed to physical proximity. The first theme is rooted in contingency theory, particularly Galbraith's work (1973; 1974). It predicts organizations will increase specialization and lateral communication links as a response to increasing environmental complexity. Hinds and Kiesler (1995) explored choices between email, telephone and voicemail in the context of communication patterns among technical and administrative staff in a large telecommunications firm. They found technical employees had more lateral communication than administrators and were also proportionately more likely to use email as opposed to voice mail for asynchronous messages. They also found that lateral and out-of-chain communication was disproportionately by telephone, which they interpret as suggesting that when employees connect weak ties they must exchange social as well as substantive information. In light of findings from the more general literature on email usage and adoption, it seems likely that the balance between telephone and email communication at a distance differs across organizations. Consistent with social definition theory interpretations, organizational culture and task differentiation may be important explanatory factors.

Theoretical Motivation for Hypotheses

My hypotheses relating email patterns to individual performance were motivated by classic theories. Taken together, they consider effects at multiple of levels of analyses. They include perspectives drawn from literature in sociology, organizational learning, economics and coordination theory.

In the first hypothesis group, I apply resource dependency theory to examine relationships between position in an email communication network and performance. In hypotheses group two, I consider potential job level differences in relationships between communication patterns and performance. I develop the rationale for these differences from an intra-organizational network interpretation of the tradeoff between exploration and exploitation (March 1991). In hypothesis group three, I consider co-specialization effects, which may appear at the level of team assignment. In hypotheses group four, I consider potential efficiencies in email communication related to response time and message size. These may be most likely to appear within the context of communication between team members.

Merits of approaches that use multiple theories and multiple levels of analyses to analyze communication networks have been advocated by other researchers (Monge and Contractor 2003). My specific choice of theories and levels of analysis was motivated by characteristics of the research setting.

Hypotheses Group One – Network Centrality

The importance of position in a network is among the most extensively covered topics in social network research. Most explanations of associations between centrality, power and influence in social networks are rooted in exchange and dependency frameworks (Homans 1950; Blau 1964; Homans 1974). The basic argument is that an actor in the center of a communications network has the greatest access to information and is also potentially able to exert the most control over the access of others. One of the main contributions of social network theorists has been to formalize measures that express different dimensions of centrality (Freeman 1977; Freeman 1979; Friedkin 1991; Wasserman and Faust 1994).

Evidence supporting the application of resource dependency theory to communication networks appears consistently in laboratory studies of small groups from the 1950s. Researchers generally concluded that individuals in central positions were more likely to emerge as leaders (for a review see Shaw 1964). Field studies have generally found positive relationships between centrality and perceptions of leadership, power and influence in larger group structures (Brass and Burkhardt 1992; Krackhardt and Brass 1994). However, some studies have found negative relationships between specific centrality measures and performance. For example, Cummings' (2004) found that innovation was negatively associated with structural holes in the networks of group leaders. Because most of the work has been cross sectional, the direction of causality has only been examined in a limited number of contexts (e.g. Burkhardt and Brass 1990).

Podolney and Baron's (1997) study of relationships between structural holes and intraorganizational job mobility helped motivate my multi-measure approach to formulating hypotheses involving relationships between centrality and performance.

They considered four types of ties: task advice, strategic information, social support and mentorship. They found that not all relationships between structural holes and performance were equal and some were negative. Interpretation of the differences within their theoretical framework provides a richer understanding of how ties can both enable and diminish workplace mobility within the setting of a high tech firm. I borrow a key element of their approach, the idea of testing centrality across multiple measures. I do this through measures that include variation in networks, tie strengths, centrality metrics and performance dimensions.

Variation in networks compares relationships between centrality in the formal network, in which ties are defined by search contracts, and the informal network of email communications. Comparisons between email and formal networks in other settings have yielded somewhat conflicting results. In R&D settings these include close correspondence (Bizot, Smith et al. 1991), evidence that email networks augment and complement formal networks (Eveland and Bikson 1986) and initial correspondence with similarities that diminished over time (Rice 1994). Social definition theories suggest that differences across organizations might be expected based on organizational culture, with more formal or bureaucratic organizations exhibiting a stronger correspondence. Other research suggests network position in informal communication networks is likely to be a better predictor of performance than position in formal networks. The explanation is that because people often get help from colleagues outside the formal chain of command, position in an informal network will often be a better predictor of performance (Krackhardt and Hanson 1993; Monge and Contractor 2003). Other researchers have described similar effects associated with peer networks and other learning communities within organizations (Brown and Duguid 1991; Wenger 1998; Brown and Duguid 2000).

Social network researchers typically characterize variation in tie strength in terms of weak and strong ties. Weak ties represent interactions characterized by lower levels of time spent, emotional intensity, intimacy (mutual confiding) and reciprocal services (Granovetter 1973). Weak ties often serve as bridges, linking parts of a social system that would otherwise be disconnected. As a result, they are theoretically more likely to provide new information beyond that readily available in a local community. Strong ties represent the opposite end of the continuum. Theoretically, individuals connected by strong ties have greater motivation to be of assistance and are more readily available. Strong ties are more likely to be characterized by trust relationships. They can be important for sharing complex or tacit information that relies on shared understanding that tends to develop over time (Granovetter 1983; Krackhardt 1992; Hansen 1999). In this research, I examine variation in tie strength along a continuum by choosing different cutoff points for the number of messages above which a relationship is coded as a tie. In contrast to survey measures, which may use assessments of affect to differentiate between weak and strong ties, my measures are based on communication frequency. I discuss implications of this distinction in the methodology chapter.

I consider variation in centrality metrics using the measures of betweenness centrality, structural holes, indegree and outdegree. I also considered, but did not select closeness centrality and the rank index of prestige. I cover definitions of these measures, theoretical interpretations and my selection criteria in the methodology chapter.

Variation in performance metrics is an empirical distinction. Different information needs may be associated with the performance metrics of billings (contract execution) and bookings (landing contracts). I further subdivide bookings into bookings from new and existing clients. I explain these distinctions in greater detail in the methodology chapter.

<u>Hypothesis Group 2 – Exploration vs. Exploitation</u>

I investigate potential job level differences in relationships between communication patterns and performance through an intra-organizational network interpretation of the tradeoff between exploration and exploitation (March 1991). March conceptualizes the tradeoff between the exploration of new possibilities and the exploitation of old certainties in organizational learning as a choice between high variance and low variance strategies. March uses terms such as search and innovation to describe higher variance exploration strategies and terms such as selection and efficiency describe lower variance exploitation strategies. In March's paper, exploitation strategies are associated with routines that have already been incorporated into the organizational code, while exploration strategies lie outside the code. Organizational theorists have often interpreted these distinctions in terms of the exploitation of internal capabilities and the exploration of external opportunities, including interactions between the two (e.g. Crossan, Lane et al. 1999; Siggelkow and Levinthal 2003; He and Wong 2004; Homqvist 2004).

Organizational theorists have focused most extensively on large corporate bureaucracies (March and Simon 1958; Chandler 1962). In contrast, many recruiting firms function more like loosely coupled federations of individuals (Finlay and Coverdill 2002). Given the difference in setting, I believe that conceptualizing individuals as managing social and intellectual capital as an asset may be a more appropriate metaphor for learning than March's organizational code.

In developing an intra-organizational interpretation more suited to recruiting as a setting, I shift the reference point from the organizational code to the formal/informal boundary. I equate internal email communication within hierarchical team relationships with the locus of organizational routines associated with exploitation strategies. Communication outside the formal search team relationship may be less directly related to current production. I equate this communication with exploration strategies. I also re-interpret the process of individuals learning from and contributing to the organizational code in terms of individual practices associated with accumulating and exercising social and intellectual capital.

Theories of social capital focus on the investments people make in developing relationships from which they hope to profit (Coleman 1988). Researchers have demonstrated the relevance of social capital across numerous social contexts (Kadushin 2004). Theories of social capital often combine the assumption that individuals are motivated by rational self-interest with the observation that economic actions are "embedded" in social structure (Granovetter 1985). Definitions vary in the degree to which social capital is considered a joint resource along the lines of a public good. Although theorists recognize liabilities of social capital (Putnam 2000), they tend to focus more on benefits and applications of social capital as opposed to costs or tradeoffs.

I observe that the investment time horizon may define a central tradeoff between building and exercising social capital. Economists have incorporated the investment time horizon into lifecycle models of relationships between learning and earnings (e.g. Heckman 1976). By definition, the time horizon over which gains from networking and learning can be appropriated is shorter for junior than senior employees. Longer time horizons favor exploration by investing in capital; shorter time horizons favor exploitation by exercising capital. This suggests that optimal strategies for managing these assets may shift over the course of a career. Since the movement of social and intellectual capital occurs through communication, it may be possible to measure this evolution through email patterns. Hypothesized changes in optimal strategies may appear as job level differences in relationships between communication patterns and performance.

I hypothesize that one way these job level differences will appear is in relationships between proportional information flows measured over email and performance in landing contracts. At the junior level, consultant performance may be positively related to measures of communication directed towards relationship building and learning. At the senior level, partner performance may be positively related to the proportion of communication exchanged within the organizational hierarchy.

I also hypothesize that job level differences may appear in the form of relationships between self-reported information related behaviors and network centrality. My focus on the investment time horizon suggests a prediction regarding the type of information exchanged that follows from theory on the value of information. While procedural or "how to" information has value in re-use, the value of declarative information or facts is dependent on the context of the decision problem (Blackwell 1953; Van Alstyne 1999). Other things being equal, a longer time horizon favors investment in procedural information; a shorter time horizon favors the acquisition of declarative information. A student studying for a test provides a familiar illustration. If the student perceives material to be learned represents a technique with repeated value in application, the investment required to internalize it as procedural knowledge may be optimal. Alternatively, if the student perceives the material is likely to have little value beyond the score on a test (an isolated decision problem), treating it as a fact to be memorized may be optimal.

Applied to internal communication within the recruiting firm, consultants may exchange more procedural information while partners may exchange more declarative information. Recruiters whose inclinations align with the theoretically optimal strategy regarding information type may invest more in developing relationships with colleagues, leading to a more central position. I hypothesize that among consultants the exchange of information perceived as more procedural in nature will be positively related to centrality. Among partners, the exchange of information that is perceived as more declarative will be positively related to centrality.

These theoretical predictions may also be interpreted as stylized facts. At the junior level, the exchange of procedural information through communication outside the chain of command is often observed in peer networks, where it is characterized as participation in communities of practice or learning (Brown and Duguid 1991; Wenger 1998; Brown and Duguid 2000). In addition, a finding from the careers literature suggests promotions are positively associated with the existence of multiple mentors (Seibert, Kraimer et al. 2001). To cultivate multiple mentors, junior employees may be more likely to build relationships with superiors outside the chain of command.

At the senior level, economic and contingency theory theorists generalize communication patterns in the form of a stereotypical executive decision maker. This figure uses subordinates as information filters to obtain the best facts and status updates which serve as inputs into existing routines (Galbraith 1973; Radner 1992; Bolton and Dewatripont 1994).

So far, my theoretical arguments have proceeded from the assumption that behaviors of recruiters enable higher performance or more central positions. However, my regression models do not address the causal direction of these relationships. If exploitation strategies are pursued by higher performing senior recruiters, as my argument suggests, then these recruiters are less likely to be making investments in building their internal network. However, they could occupy more central positions in the organizational network if colleagues are more likely to communicate with them because they are higher performers. This may be mediated by their willingness to help colleagues. This observation leads to the hypothesis that self-reported mentoring and information sharing behaviors will be positively associated with centrality at the senior, but not junior level. One reason these associations might not appear at the junior level is that the intellectual and social capital assets of junior recruiters may not have appreciated to the point where they would be actively sought out by others.

It is also possible that junior recruiters have a disincentive to share information with colleagues. Compensation practices that emphasize relative over absolute performance can create disincentives to share information (Orlikowski 1992). In the recruiting context, only a fraction of the junior consultants make partner. Consultants essentially face up or out competition which places them on a relative yardstick. In economic terminology, yardstick competition is exactly a comparison that rewards only the relatively higher performer. For consultants, sharing useful information with another consultant could tip the balance in that colleague's favor reducing your own chances of success. In contrast, partners are residual claimants on the assets of the whole firm. Their incentive is growth in absolute assets. This incentive scheme moves partners away from direct competition. For partners, telling others useful information grows your assets. Following this argument, I hypothesize that to the extent positive relationships between information hoarding and performance exist, they would appear only among consultants.

In framing this group of hypotheses, I use the tradeoff between exploration and exploitation as an organizing framework. Differences in the investment time horizon provide a rationale for why exploration strategies may be related to higher performance at the junior level and exploitation strategies may be related to higher performance at the senior level. I believe a valid criticism is that this is more of an explanation for why certain communication pattern might exist than a theory that addresses how they develop. My interpretation of the tradeoff suggests an organizational tension. But this tension plays a descriptive role. A stronger theory might predict differences in communication patterns across settings on the basis of how this tension is resolved. This raises the question of whether an alternative theoretical framework might better capture key tensions that explain job level differences in relationships between communication patterns and performance.

Economic literature on team production captures some relevant aspects. For example, Alchian and Demsetz (1972) focus on the role inseparabilities in production play in creating a potential free-rider problem among team members. Their solution involves making a third party a residual claimant, which creates an incentive for monitoring effort. Recruiting firms resolve this potential problem by assigning the role of residual claimant to partners in two ways. A partner "owns" the client, creating an incentive to monitor the consultant's work. A partner is also a residual claimant to the assets of the firm, creating an incentive to invest in the consultant's development. However, time spent investing in a consultant's development is also likely to represent time spent away from landing more contracts. This additional tension present in recruiting is not captured by the theory.

Agency theory also has parallels with the recruiting context (Jensen and Meckling 1976; Eisenhardt 1989). In most professional services contexts, partners are principals or part owners of the firm who face the problem of structuring incentives to motivate effort from lower level agents (consultants). In these contexts, monitoring effort is typically difficult. A common practice is to use the opportunity to make partner as an incentive. In recruiting, promotion to partner is determined primarily by a recruiter's success at developing clients. Successful investments in social and intellectual capital help consulants achieve this goal. This suggests that the central tradeoff for the agent may involve the choice of investing through the principal or others. Given this incentive structure, effort an agent does not contribute to the principal's project is not necessarily "shirking", as assumed in agency theory, since he or she could be investing elsewhere. Investment is not a standard option in agency theory. In the recruiting context, the agent's choice of strategy could be measured empirically through email patterns. This suggests a potentially promising direction for future work. However, it also entails significant extensions to existing theory.

Hypothesis Group 3 – Co-specialization

Specialization has the longest academic lineage of the theories that motivate my hypotheses, dating back at least as far as Adam Smith's description of the pin factory in the *Wealth of Nations* (Smith 1776). Theoretical relationships between specialization and communication continue to be revisited by economists and organizational theorists (e.g. Lawrence and Lorsch 1967; Bolton and Farrell 1990).

Pin making as described by Adam Smith is a modular process. The person shaping the head of the pin needs at most an occasional sentence to coordinate effort with the person stretching the wire that forms the body of the pin. In contrast, executive recruiting is an iterative process. Clients frequently update their desires as the capabilities of available candidates become better known. The process typically entails extensive communication between search team members. For this reason, I consider co-specialization to be more relevant within the context of executive recruiting. In contrast to the modular form of specialization described by Adam Smith, co-specialization is characterized by greater interdependence and demands for coordination.

In hypothesis testing, I focus on hierarchical co-specialization in the performance dimensions of executing and landing contracts. Higher levels of individual performance may be linked to interactions with others who have complementary skills.

If performance effects related to interactions with others who possess complementary skills are bi-directional, then the resulting effect at the organizational level could be characterized as a division into higher and lower performing cliques. Clique membership as an explanation for individual performance differences has been observed in other settings. For example, Rice (1994) found the performance of interns in an R&D group was related to the performance of the permanent employees they communicated with over email at the beginning of their internships. Guimera, Uzzi et. al. (2005) found positive relationships between diversity, experience and team performance in the production of Broadway musicals and the publishing of journal articles in the fields of economics, social psychology and ecology. While their work measures team assignment as opposed to communication patterns, their findings could be interpreted as evidence of both co-specialization and separation into higher and lower performing cliques.

The empirical setting of executive recruiting motivates my focus on co-specialization in a hierarchical relationship. In other settings, other forms of specialists might be hypothesized to be higher performers. For example, contingency theory suggests boundary spanners can attain considerable influence and prestige in uncertain environments (Thompson 1967). The importance of individual networks that consist of a high number of boundary spanning ties has been empirically verified in contexts such as biotechnology (Liebeskind, Oliver et al. 1996). However, in the context of executive recruiting, performance effects associated with boundary spanning are difficult to test because recruiters engage in extensive internal and external communication, making boundary spanning more the norm than the exception. Boundary spanners could potentially be identified on the basis of metrics such as external email and the self-reported proportion of time spent and value received from communications with people outside the organization. However, in practice the construct validity of these measures with respect to boundary spanning appears doubtful.

I consider specialization in information technology use in Appendix D under mediating variables. Direct measures of email and survey measures of the time spent, value received and self-reported proficiencies with the technologies of phone and databases were included in the data set. An affinity for information technology could be associated with a higher proportion of communications via email in comparison to other media or more email. It could also involve technological complementarities (Brynjolfsson, Renshaw et al. 1997). For example, recruiters might use databases and external email to process more communications with candidates. Alternatively, an affinity for information technology could be associated with greater isolation, an effect analogous to the "Internet paradox" effect observed among teenagers (Kraut, Patterson et al. 1998). However, I did not formulate speculations about these effects into hypotheses because of difficulties associated with developing measures of technological specialization.[5]

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[5] For example, as I describe subsequently in Appendix D, variables that correlate with responses to survey question "information technology has increased my ability to handle more projects at the same time,"

Hypothesis Group 4 – Efficiencies in Network Use

My last hypothesis considers the efficient movement of information through a network. I propose frequent short email communication will outperform infrequent lengthy communication.

My hypothesis invokes a human analogy to load balancing models of queuing and network flow that imply short jobs can be swapped in and attended to more quickly than long jobs of the same priority. Long jobs are more likely to cause a processor to block on a given task and so, given stochastic arrivals, may be attended to during periods of lower utilization. A human analog involving email might be a tendency of people to postpone or defer long messages until they have free time.

My hypothesis applies primarily to email communication between team members. It conceptualizes the amount of information team members exchange during a search as a single quantity, focusing on how it is divided into chunks in the form of messages. In executing searches recruiters have an incentive to choose the most efficient allocation scheme because they bill by the job not by the hour.

Media richness and organizational contingency theory suggest additional reasons why shorter, more frequent patterns of messages may be more efficient. Media richness theory suggests more equivocal information is better conveyed through richer media such as face-to-face and phone that offer more contextual cues to aid interpretation (Daft and Lengel 1984; Daft and Weick 1984; Daft and Lengel 1986). This suggests text messages can become too long when the sender feels the need to supply detailed context. While some researchers have argued that email does not fit well within the media richness taxonomy, the reasoning may still be consistent with the hypotheses. For example, Markus (1994) disputes the characterization of email as a lean medium, while suggesting that an iterative series of brief, frequent email exchanges is a potentially efficient way of exchanging equivocal information through email. She reasons that providing clarifications and refinements asynchronously can promote convergence between problems and solutions. Contingency theory suggests shorter response times could be

reveal a pattern that may reflect self-efficacy bias. In addition, underlying traits associated with the technology measures found in the survey may be highly multidimensional.

related to efficiency by reducing bottlenecks (Galbraith 1973; 1974; Thompson 1967). Bottlenecks may occur when one party is delayed awaiting another's response. More frequent communication may also promote the earlier identification and correction of problems.

An alternative hypothesis suggests that email message sizes and response times may be related to differences in status (Owens, Neale et al. 2000). High status individuals may send the shortest emails because they prefer to resolve issues in forums such as meetings in which they have access to a wider variety of strategies for exerting control. Mid-status individuals may send the longest emails because they perceive email as an open forum in which they can make their expertise, knowledge or skills more visible. Owens, Neale et. al. also suggest email response times will be inversely proportional to status. High status types may have the longest response times because they are more likely to be (or want to appear to be) busy. Low status types may respond more quickly to messages, the greater the status difference the more rapid the response.

Not all researchers agree on the extent to which status cues are present in email. Sproull and Kiesler (1995) suggests email promotes more equal participation, so status cues may be less prevalent in email than richer media. In contrast, Ducheneaut and Bellotti (2001) identify email power games as an important theme in their research.

Linguistic analysis would presumably be useful for better understanding the extent to which status dynamics play out over email. However, because the words in the email messages used in this research were encoded using a hash function to preserve privacy, this is not possible in this setting. This also makes it difficult to rule out task variation across searches as an alternative hypothesis for differences in email response times and size. Finally, the best way to operationalize measures of status in this setting given the existing data is unclear. For these reasons, I did not formulate the status based theory regarding email response times and size in the form of hypotheses to be tested. Instead, I consider status as a potential alternative to efficiency in interpreting results involving hypothesis group four.[6]

[6] In Appendix B, I provide plots of response time and email size differences between partners and consultants in team and non team contexts. These results may be the most relevant for assessing correspondence between the status-based theory and the recruiter data.

Chapter 3
Methodology

In this chapter, I describe the methodology I developed for evaluating relationships between communication patterns and individual performance. This includes the development and definition of measures and the instrumentation of hypotheses.

I begin by outlining my motivation for using network methodology to study relational aspects of performance. This includes my rationale for using email data in contrast to the more common technique of network surveys. A description of the data and research setting follows.

Given the scarcity of prior work based on email measures of communication, I had to develop many of my own measures. In this chapter, I define my measures and outline key steps I followed in assessing their validity and reliability. This is followed by descriptions of the regression models I used to test specific hypotheses.

My research design is an econometric case study in which I seek to explain variation in individual performance as a combination of individual specific controls and relational factors. The case study approach represents a first step towards defining, validating and testing relational measures based on email data. My goal is to set the stage for future work aimed at multi-site testing and the development of a more complete body of theory.

A. Motivation for Applying Network Methodology to Email Data

Prior work suggests ways network methodologies and representations have proven useful for addressing research questions that involve structural attributes of relationships. The proper selection of networks, metrics and values can lead to significant insights. For instance, the historical development of cities as economic centers has been illustrated through network representations, such as work tracing Moscow's development to patterns of Russian trade routes in the Middle Ages (Pitts 1979). A key insight in Internet search engine design involved the application of an eigenvector measure of centrality, which led to the creation of the Google PageRank algorithm (Bonacich 1987; Brin and Page 1998). Similarly, organizational researchers have used network analysis to study ways in which relationships with others are in turn related to dependent variables such as measures of promotions, power, leadership, job satisfaction and unethical behavior (Borgatti and Foster 2003; Brass 2005).

I seek a better understanding of relationships between organizational communication patterns and performance in a white-collar setting. My research design relates attributes of relationships between individuals to accounting measures of individual performance. My interest in topological attributes of relationships motivates the application of network analysis methodology. Awareness that attributes of relationships exist at multiple levels motivates further inquiry into non-topological characteristics. I refer to non-topological features as dyadic characteristics, since these measures represent communication patterns measured in the context of dyadic exchanges. Dyadic characteristics of email exchanges include information flows, assessed as proportions of messages sent to different types of individuals, message size and response times. I developed all of these dyadic measures as part of my dissertation.

Network surveys vs. Direct Measurement

The most common method of gathering network data on communication is to ask people who they communicate with, typically through a paper or online survey. An important advantage of network surveys is that the methodology is well developed. In particular, the evolution of social network metrics reflects an emphasis on binary and interval values along a limited scale, which are the types of values typically generated through surveys. Network surveys can also be used to gather perceptual information on ties. For example, researchers may ask subjects to distinguish between ties that are related to workflow, trust, advice seeking or effects on personal energy levels (e.g. Krackhardt and Hanson 1993; Cross, Baker et al. 2003).

However, network surveys have at least two important limitations. The first is the problem of informant inaccuracy, which I describe in greater detail in my literature review. Information inaccuracy issues include biases related to inaccurate self-perceptions, such as popularity biases, and framing effects that lead to situations in which minute changes in survey wording significantly alter responses. Network surveys have also been found to exhibit general biases towards routine structures and problems with recall biases that mirror those well-documented by cognitive scientists (Tversky and Kahneman 1981; Bernard, Killworth et al. 1984; Freeman, Romney et al. 1987; Marsden 1990; Anderson 1995; Feld and Carter 2002). Recognition of informant inaccuracy issues has led to strategies that may lessen their effects, such as using reciprocated reports and awareness that self-reported network data is generally able to capture strong ties more accurately than distant or weak ones (Hammer 1985; Marsden 1990). However, the literature still suggests that conclusions drawn from network survey data alone should be viewed with a healthy degree of skepticism.

A second limitation of network surveys is that they are time consuming for respondents. This restricts the range of settings in which adequate response rates can be achieved. This is particularly true if data are gathered at repeated intervals for longitudinal analysis, which is generally recommended, although not the norm for network studies. The validity of social network studies requires very high response rates, without which networks will be measured inaccurately.

These limitations of network surveys motivate interest in the use of archival data sources, such as email data. Email is considered a particularly promising data source for network researchers because of its near ubiquity and frequent use in modern organizations. Recent surveys report that all but 2 percent of employed Americans have e-mail access at work, while the time business users devote to managing e-mail averages nearly an hour a day (Grey 2001; Fallows 2002). However, for email to be used reliably as a social network data source specific challenges must be overcome.

The initial challenge for outside researchers is to convince others to provide full access to email logs, given serious concerns regarding data security and privacy. For this dissertation, privacy issues were addressed by encoding individual email messages using a hash function and giving participants the opportunity to opt-out of the email collection process. More information regarding the implementation of email data collection associated with the data set used in this dissertation can be found in Zhang and Van Alstyne (2003).

As a result of challenges associated with obtaining email data, published research using email as a social network data source has only recently begun to extend beyond the efforts of corporate researchers using in-house data and work conducted on the Enron email dataset that was made public through legal proceedings. This lack of pre-existing research poses a challenge because it means researchers operate in an environment characterized by a general lack of knowledge regarding properties of email as a social network data source (Kossinets and Watts 2006).

Of course, this challenge presents an opportunity for the development of knowledge that advances the use of email as a social network data source. These possibilities motivate a series of analyses assessing the construct validity and intertemporal reliability of email measures, as well as the potential for email patterns to serve as general proxies for intra-organizational communication patterns. Since good proxies for organizational communication patterns are hard to come by, work analyzing the viability of email data represents a contribution to existing knowledge.

B. Data description

My dissertation is based on the analysis of a three-part dataset consisting of nine months of e-mail traffic, an online survey and accounting data on search contracts. Participation rates for each of the three parts were over 80 percent. Results are based on the analysis of one firm (n= 71) in which a total of 29 consultants, 27 partners, 13 researchers and 2 information technology staffers participated in at least one of the parts. Because I used survey results primarily for interpretation of email measures, I conducted the majority of my analyses on the 22 partners and 25 consultants for whom I had complete accounting and email data (n=47). Data that also include survey responses were obtained for 21 consultants and 19 partners. I provide a more detailed breakdown of the selection criteria in the subsection on entry and exit.

Accounting Data

I calculated individual level measures of output from accounting data on search contracts. The raw accounting data include revenues generated for both bookings (ie. landing a search contract) and billings (ie. executing the contracts) and counts of the number of successfully completed and failed searches. For each contract, accounting records also provide individual share allocations of booking and billing credit. The firm determines share allocations on the basis of tasks performed. These allocations follow a standard formula. Billing categories include candidate identification, interviewing candidates, reference checks, coordination of candidate meetings and candidate negotiations. The firm assigns fifty percent of the booking credit on the basis of control over the client relationship that led to the sale of the search contract. Contributions to a sale, such as fielding a lead or sales opportunity and referring it to a supervisor, are eligible for the remaining 20 to 50 percent of the booking credit allocated on a contract. Accounting data distinguishes between contracts with new and existing clients and provides information on the industry sector and level of placed candidates that will be used to normalize for search quality. The accounting data I obtained encompasses several thousand contracts, with full coverage over the period from Jan. 1, 1999 – Nov. 18, 2003. I also obtained accounting data that includes all fields except bookings revenue, search status (eg. completed, failed) and search location for the period from Nov. 19, 2003 - Apr. 20, 2005.

Email data

I obtained full email logs for a period of nine months. Six of these months overlap with the accounting data that includes a full set of data fields. For each email, "to", "from," "cc," timestamp and size fields were recorded, while the subject line and body of the text (with stop words omitted) were encoded. For emails collected after the second month, the number of attachments and name of attachments were recorded (unencoded). Participation was voluntary on an opt-out basis and several mechanisms were used to protect individual privacy, ensure consistency of data, and retain both firm and individual consent. Briefly, email header and body information was encrypted using one-way hash functions that permit comparisons of similar tokens but not semantic interpretation of content (Zhang and Alstyne 2003). Incentive payments of $100 in Amazon gift certificates per person were given for consent.

I cross-referenced email addresses with human resource records to identify the roles of staff members who were not directly involved in the study. I identified email sent to internal email lists using the “to” field. I did not include email sent to internal distribution lists in my analyses. I coded all email not specifically identified as internal as external. I coded external email into three categories: spam, news and other. I identified spam and news on the basis of the “from:” address. I identified more than 14,000 unique spam addresses and 1,300 unique news addresses. The category of “other” external email consists primarily of communication between real people.

Email activity covers the periods Aug. 23, 2002 – Feb. 19, 2003 and Nov. 17, 2003 – Feb. 11, 2004. While email was collected in the interval between Feb. 20 – Nov. 16, 2003,these data were corrupted and are not used in the analysis.

Survey data

The online survey developed for this research consists of 52 questions covering aspects of information management including information sharing, type of information exchanged (i.e. procedural vs. declarative), database use, compensation practices and proportions of time spent and value gained from both information sources and modes of information gathering. The survey was administered in April 2002.

Missing values

All three data sources exhibit some problems with missing or potentially missing values. I describe these problems and the steps I took to address them below. This is followed by descriptions of the steps I took to address the entry and exit of recruiters from the firm during the study and individual cases that exhibit distinctive or unusual characteristics. I made the latter identifications to guide subsequent interpretation of results should any of these cases appear as outliers.

Unresolved gaps in accounting data

There are two sources of unresolved gaps in the accounting data: billing records for which I was unable to identify corresponding bookings credits and gaps in the sequential ordering of search IDs. These are potential gaps in the data. The data may be complete, however I flagged these situations because they could reflect gaps in the records kept by the firm. As I received successive rounds of accounting data, some information on previous searches not identified in earlier records appeared in the data, suggesting imperfections in the firm's accounting records.

In the study period, there are 10 searches for which billing records were supplied, but no booking figures were given. One case has a recorded salary of 0 and another is classified as a "redo." Two recruiters participated in two of the remaining 8 cases. Nine recruiters participated in only one case. The firm kept booking and billing records separately and used blanks as opposed to zeros to indicate no bookings for a particular recruiter. As a result, I did not identify this discrepancy until late in the analysis process when I performed a direct search-by-search comparison of different versions of the accounting records.

For reasons that will be explained shortly, I believe the most likely explanation for this gap is that the firm did not assign booking credit for some searches. If that is the case, the data I used were correctly recorded. However, I cannot rule out the alternative explanation that the booking records I used were incomplete. Since the recruiters involved are identified, a sensitivity analysis of key results to different interpretations regarding the cause of the missing values could be performed in future work.

Similar discrepancies involving incomplete bookings records appear in the historical data. The overall rate at which the firm gave billing but not booking information for searches is slightly over 5 percent.[7] While the billing credits on searches generally sum to 100 percent, booking credits summing to less than 100 percent are not uncommon. The overall rate for which booking credits failed to sum to 100 percent was 18.7 percent. However, in only 1.4 percent of these cases, booking totals summed to less

[7] The figure for searches with billing records for which no corresponding booking credit is given was calculated as (161 – 41 redos / 2207 billing records = 5.5%).

than 50 percent, which is the share automatically given to the recruiter credited with the client relationship.[8]

For solo searches, I used ANOVA and regression analysis to compare the duration of searches for which booking credit was given with those for which no credit was given. On average, searches for which no booking credit was given were completed in 56 percent of the time of searches for which credit was given.[9] These analyses strongly suggested a difference in the populations consistent with an interpretation that searches for which no credit is given involve less work than those for which credit is given. On the basis of this result, I believe that the most likely reason booking credit was not awarded for some searches is that an element of the booking process was not applicable.

The second source of potentially missing values in the accounting data are unexplained gaps in the sequential numbers the firm uses to identify searches. Slightly more than 2 percent of the numbers are missing from the sequence over the period Jan. 1, 1999 – Apr. 20, 2005. Since search numbers do not correspond perfectly with a strict chronological ordering of the official start dates of searches, it is possible that these gaps represent searches that were anticipated but never materialized. However, it is also possible that gaps represent actual searches for which records were somehow lost. The number of gaps in the ID records is considerably less than the number of searches classified as "dropped" or "hold." While I have no way to conclusively determine whether records of searches that are dropped or held might be less complete than records of searches that were successfully completed, I believe this explanation is unlikely to be correct.[10] I believe the most likely explanation is that the gaps in sequence numbers are simply an idiosyncrasy in the accounting practice that does not reflect missing data.

[8] The respective calculations are (383 / 2044 search records) with booking credits that fail to sum to 100 percent and (29/2044 search records) with booking credits below 50 percent but greater than 0.

[9] When outlying searches (greater than 400 days) are excluded, searches for which no booking credit is given are clearly shorter in duration ($F = 35.26$, $p < 0.001$). A regression model that controls for the type of search gives similar results ($B_{nocredit} = -73.3$ days, $t = -5.96$, $p < 0.001$). The average search duration in this population is 165.91 days, the average search time for nocredit searches is 92.63 days, 92.63 / 165.91 = 55.8 %. Results are still significant ($p < 0.05$) when outliers are included.

[10] Over the period in which records on dropped searches was supplied (12.7% - 233/1822) of searches were classified as dropped and an additional (1.1 % - 20/1822) were classified as "hold."

Missing Email Data

The one serious problem with email data loss I encountered during this research was a data recording error that caused more than nine months of email data to be corrupted. Although some emails from this period remain, I did not include any of the emails from this period in my analyses. I regard other situations that resulted in missing email values as minor, but describe them in detail below.

Most of the emails from Thursday, Oct. 3 – Monday, Oct. 7, 2002 and Wednesday Oct. 9 – Sunday, Oct. 13 are missing. A failure of the email capture software caused the data loss. Since my regression models use aggregations of email data over a six month period and this data loss can be considered random, I believe it does not pose a problem for results in my dissertation. However, in future work involving temporal analyses, this problem needs to be considered.

A total of five recruiters, 2 consultants and 3 partners, opted out of the email capture section of the study. In accordance with the wishes of the subjects, the email activity of these recruiters was not directly recorded. However, records of these recruiters email activity with others who voluntarily participated in the study were obtained and used in the analysis. As a result, the only internal email data involving recruiters that was not obtained from those who opted out involves emails that were only sent among the recruiters who opted out. In addition, only one search took place in the study period that exclusively involved recruiters who had opted out of email capture. Since 50 revenue generating consultants and partners initially opted in, the initial number of unobserved dyads was less than 1 percent.[11] The specific instance in which two recruiters who opted out worked on the same search may have contributed to an outlying value in models that assess co-specialization. Another potential area of concern involves email sent between staff members who were not solicited to be participants and recruiters who opted out. With respect to measures used in subsequent regression models, the effect would be to understate the proportion of email recruiters who opted out exchanged with staff members and to overstate the proportions they exchanged with consultants, partners and researchers. With these minor exceptions, which I considered in interpreting

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[11] The percentage of missing dyads as a result of recruiters opting out of the email capture portion of the study was calculated as ((5 * 4) / (55 * 54) = 0.67 %).

results of regression models involving these measures, I do not believe gaps in the internal email record that occur as a result of recruiters opting out of the email portion are likely to influence the results.

On the other hand, the external email record of recruiters who opted out of the email capture portion is clearly incomplete. I did not use any external email metrics in my regression models. If external metrics were to be used in future work recruiters who opted out of the email portion of the study should be dropped and an analysis of potential sample selection bias should be conducted.

A more serious source of gaps in email data that current and future studies are likely to face involves the use of instant messaging or wireless handheld devices (eg. BlackBerries). In the current study, only one revenue generating recruiter self-reported any proportion of media use (time) associated with instant messaging (3 percent). Because that recruiter had among the highest email volumes, I do not believe that the omission of instant messaging data is likely to influence the results. In addition, one researcher shows an email pattern that appears to indicate the use of a wireless device (my2way.com). However, I only used researcher emails in the calculation of the proportion of messages sent to recruiters in different job types, so I believe this is unlikely to influence results. Finally, one consultant, one partner and two researchers exhibit an unusually high number of very short emails (< 250 bytes). In these four cases, the percentages of very short emails exceed 15 percent, while the average percentage in the rest of the population is slightly below one percent. While this could be consistent with the use of a handheld device, it is not conclusive evidence. For example, sending email in which the full message is contained in the subject line would produce a similar result. I identified the two revenue generating recruiters in this category so that I could include this information in the interpretation of results should these recruiters appear as outliers in models involving sent email size.

Survey Response

The effective response rate among revenue generating consultants and partners included in the models was 85 percent (40/47). Recruiters not included in this figure consist of 10 researchers who took the survey and revenue generating recruiters who either left the firm before the conclusion of the study period or were recent entrants not given the survey because they were not known to the researchers at the beginning of the study.

I used survey data primarily for the interpretation of measures as opposed to treatments in the performance models. I did use years of experience and years of education as controls in all models. The small sample size makes it undesirable to drop observations on the basis of not reporting these values alone. In addition, survey non-response is not necessarily random. In fact, non-respondents were statistically more likely than respondents to be among those who left the firm before the conclusion of the study period. As a result, I believe the potential risk of introducing sample selection bias by dropping observations on the basis of survey non-response alone outweighs the risk of error from imperfect techniques for filling in the missing values.

The ideal solution would be to obtain missing values directly from the firm. Although this has not been possible to date, the possibility of obtaining estimated values from a recruiter is currently being pursued. Current analyses substitute group means for missing years of experience and years of education values. Although imputation techniques are generally favored over group means, the challenge lies in finding values that could be used to impute the missing values that are not subsequently used in the regression models. For imputing years of experience, a leading candidate is salary, which I do not use in any of my regression analyses. Although the formula the firm uses to compute salaries was not provided, it appears that it can be closely approximated using existing data.[12] Years of education exhibited little variation and had minimal explanatory power in this context with the exception of recruiters who have an M.D. This distinction is picked up by a control variable for industry sector.

Entry and Exit

[12] For example, an estimate of salary using the independent variables of booking revenue (2002), number of completed searches (2002), Percentage of CEO and Med. Exec searches (2002), years of experience (sqrt) and a dummy variable for practice group leaders has Adj. $R^2 = 0.914$ (n=39). The data strongly suggest that a substantial portion of variation in salary can be explained by prior year revenues.

The firm did not supply official entry and exit dates of recruiters. However, I was able to infer entry and exit dates from the email and accounting data. In general, I believe records of email activity provide a more accurate data source for inferring entry and exit. My assessment is based on observing cases in which email activity stopped months before the conclusion of the last search on which a recruiter officially participated.

I identified five consultants and one partner who were members of the firm when the survey was given in April 2002, but had either left or were clearly on the way out by the time email collection began. I did not include any of these recruiters in my regression analyses. I included email sent by these recruiters when calculating email measures.

I dropped three additional recruiters from analyses in regression models because of problems associated with normalizing output in a way that would be comparable to that of others active over the full duration of the study. One recruiter worked only part-time during the study period. One recruiter recorded the start of his/her last new search on Sept. 16, 2002 and sent his/her last email on Jan. 22, 2003. Another recruiter received his/her last email on Dec. 15, 2003, but did not start any new searches after July 25, 2002. The average date of email sent from this recruiter was Sept. 26, 2002. On the basis of this information, I believe the most likely explanations are either that this recruiter left the firm during the study period or moved from a consultant to researcher position.

Three revenue generating recruiters not identified by the firm when the survey was administered were subsequently identified through my analysis of the email data. Since the start dates of these recruiter's first searches all precede the period of email collection, I could potentially include these recruiters in future work. However, the rule of thumb that it takes six months to a year to ramp up in a new job combined with issues associated with measuring output (e.g. completed searches are likely to be lower because these recruiters had no or fewer searches in the pipeline at the beginning of the study) contributed to my decision not to include these recruiters in the analysis.

At least one recruiter was promoted from consultant to partner during the course of the study. I classified recruiters by job level on the basis of their job level at the beginning of the study.

Unusual cases

Two partners and three consultants included in the models represent unusual cases because I have reason to believe their output during the study period may not accurately reflect their output during earlier periods. I included these recruiters in the regression analyses, but have identified them in case any results turn out to be sensitive to these outliers. Two consultants can be considered potential "lame ducks." Although they were active throughout the study period, they left the firm within the next six months.[13] One additional consultant recorded a conclusion of a last search within a year of the end of the study period. Since analysis of email patterns suggests exit from the firm often precedes the official conclusion of the last search for which a recruiter is given credit, interpretation of results in which this recruiter appears as an outlier also deserve attention. Two senior partners and may have lower output because they may have performed in more of an administrative role.

Other distinctive cases

As I subsequently describe in the appendices, five partners accounted for a significant majority of cases in which lower than expected email activity occurred between recruiters who worked together on a search contract for more than half of the study. I identified six other partners as practice group leaders. While it is possible that administrative overhead associated with this role could lead to lower output, my analysis of the data suggests otherwise. When I evaluated practice group leaders as a group, I found these recruiters actually had higher booking output during the study period than other partners. ANOVA identified a statistically significant difference with respect to new bookings ($F = 6.02$, $p < 0.05$). In general, the practice group leader designation appears to be associated with greater support from consultants. This factor may outweigh reductions in output that might be brought on by any potential additional administrative responsibilities.

Heterogeneity in the specific roles of individuals is common in white-collar settings. In the data description above I identified 16 percent of the consultants and 55

[13] I know that the end of the last search these recruiters received credit for occurred less than six months after the study period ended. The date a recruiter leaves the firm typically occurs before the end of the last search for which a recruiter receives credit, so this can be considered an outer bound. This happens because recruiters who leave the firm often receive some credit for searches that others finish.

percent of the partners as cases that exhibited some distinctive qualities. In the final section of Appendix D, I consider additional ways in which some recruiters may specialize. Heterogeneity exists in this setting despite the fact that all recruiters perform similar activities, landing and executing searches, and their specific tasks are similar enough that the firm applies a standardized formula to assign credit.

This implies that "one-size fits all" models are unlikely to work in white-collar settings. Researchers need to pay careful attention to specialization or task differentiation in developing models and interpreting results. As subsequently described in section E, I included a job level dummy variable in the base model to account for differences between consultants and partners.[14] Whether other forms of heterogeneity might influence relationships between communication patterns and performance was less clear. As a result, I did not control for these factors, but examined individual cases in residual plots for evidence that known differences, such as those identified above, may partially explain results.

C. Empirical Setting: Uses of E-mail in Executive Recruiting

Relationships between communication patterns and performance depend on characteristics of the work (Hansen 1999). Like many professional services organizations, the firm involved in this research is organized in a hierarchy. Senior partners have primary responsibility for landing contracts and junior consultants focus primarily on executing contracts.

Recruiters are compensated primarily on the basis of revenues associated with landing (booking) and executing (billing) contracts. Partners are selected primarily on the basis of prior success in landing contracts with occasional exceptions made for recruiters who enter the firm with a high probability of expected success based on achievements in their previous position. Approximately 80 percent of the contracts involved existing as opposed to new clients.

[14] Formal job level differences provide a reasonable starting point for controls. However, in research design, it is also worth considering opportunities to collect data that could be used to develop finer grained measures that reflect how individuals actually do their work. I describe examples such as a proxy for external social capital, the percentage of revenues from bookings and the percentage of solo searches in the section on limitations of the base model and in appendices D and E.

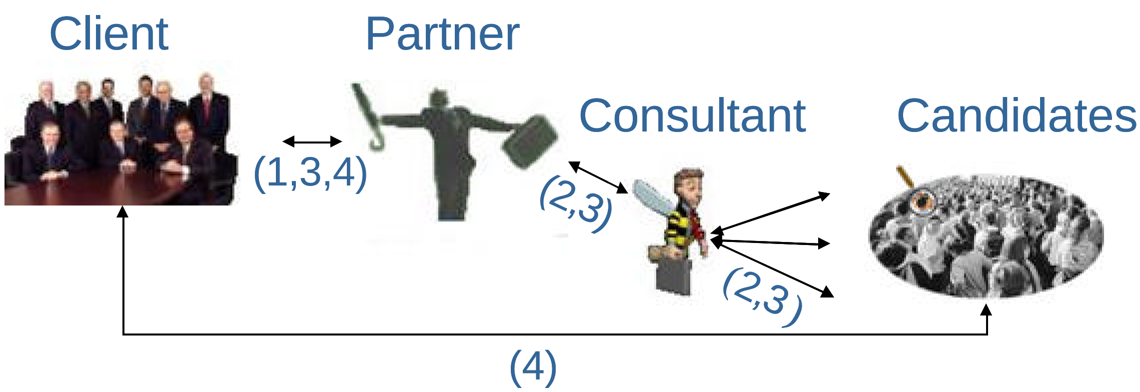

Fig. 3.1 A simplified schematic of communication patterns in the executive recruiting process. Partners focus primarily on client relations, while consultants focus primarily on screening candidates. At any given time, each partner will work with a number of consultants on different searches and each consultant will work with a number of partners. Researchers and administrative staff also support partners and consultants.

The executive recruiting process can be divided into four stages in rough chronological order: (1) landing contracts; (2) screening candidates; (3) coordinating client interviews with "short list" candidates; and (4) closing the deal. In landing contracts and closing the deal (1 and 4), recruiters generally prefer the richer media of phone and face-to-face to e-mail. A single recruiter usually acts as the point person between the client and the firm, minimizing coordination demands.[15]

In contrast, search execution (2 and 3) is generally a team based activity. Sixty percent of internal e-mails exchanged between revenue generating recruiters (ie. partners and consultants, not researchers or staff) are between those who have one or more active searches in common. This suggests e-mail is used extensively in the coordination of searches.[16]

The modal team is composed of a partner and a consultant. Two person teams conducted sixty percent of the searches, slightly under a third were solo searches and three or more person teams conducted the remainder.

After a contract is landed, a list of approximately 100-200 potential candidates is generated, typically by the research staff. In the screening process, recruiters narrow this

[15] In some cases, one recruiter fields or develops a lead, while another completes the sale. Opportunities for associating email activity with the landing of search contracts may be greatest in these situations. These could be identified on the basis of share allocations of bookings associated with specific contracts.

[16] Results from a model that predicts the number of emails sent between any two recruiters further support this claim (Appendix D). Variables related to the number of weeks recruiters worked together on searches are the most significant predictors of the number of messages exchanged.

list down to roughly a dozen candidates that are given formal interviews. While the elapsed time needed to complete a search has changed little over the five years for which I have contract data (on average about 180 days), technology has made it possible for recruiters, particularly consultants screening candidates, to juggle more simultaneous searches. Analysis of the historical contract data also reveals that the ratio of consultants to partners in the firm has been declining. One possibility is that technological efficiencies, particularly those related to the screening stage of the search process, have led to a reduction in consultant jobs. This conjecture is developed further in the section on intertemporal reliability of performance measures (Appendix C).

Deal closing is the stage least amenable to separate analysis. Clients make the final decisions on the selection of candidates. E-mail is not likely to play a significant role in closing deals on either the client or candidate side. Failure to close a deal may be related to difficulties in any of the previous stages. In some cases, email activity may reveal indicators related to the closing of searches. For example, messages with attachment names that suggest contractual documents. But this remains a subject for future work.

D. Development and Assessment of Email Measures

I study relationships between communication patterns and performance by using email patterns as proxies for general communication patterns. Email measures are aggregations of behavior observed at the level of interactions. In defining measures, I am interested in summarizing aspects of these interactions that have meaningful theoretical interpretations with respect to my hypotheses. In conjunction with perceptual data from the online survey, I use these measures to help define the nature of relationships in the workplace.

To use email measures in this way, I have to address a number of validity and reliability issues. I give an overview of my analyses in this chapter and provide step-by-step descriptions and results in the appendices. I summarize perceived threats and my responses in the following table.

Treats to validity	Response
(1) Results may be dependent on the way in which raw email is coded for use in calculating network metrics	I derive measures using multiple ways of calculating email ties. Analyses assess convergent and discriminant validity (Appendix A).
(2) Properties of novel measures such as email flows, size and response times are unknown. As a result, the choice of summary metrics might not coincide with theoretical concepts being evaluated.	I evaluate distributional properties of measures and related them to the theoretical concepts they represent. When one measure is not found to be clearly superior, I evaluate multiple measures. Analyses assess convergent and discriminant validity (Appendix B).
(3) Statistically significant results may be better explained by mediating factors.	I address media preferences, proximity and specialization, three factors that could affect communication patterns, performance or both in the analysis (Appendix D).
(4) Low or idiosyncratic email use may produce signals that are too weak for meaningful interpretation of organizational communication patterns.	I construct a predictive model of email frequency between any two recruiters. I use this model to identify lower than expected email activity. I examine individual cases falling into the lower 20^{th} percentile to identify underlying patterns that may be associated with low email outliers. This analysis also provides an alternative strategy for assessing the influence of potential mediating factors (Appendix D).
Threats to reliability	
(5) Relationships between email patterns and performance may hold in a certain time period but not generally.	I calculate measures separately on a division of emails into three segments (3-4 months each). I assess reliability in terms of the level of agreement between measures in different time periods (Appendix C). I compare performance measures to historical values to determine the extent to which individual levels of performance during the study may differ from historical norms. In addition, I assess potential seasonality in performance measures (Appendix C)

Table 3.1 Summary of threats to validity and reliability.

<u>Email Measures</u>

Centrality Measures

From the perspective of graph theory, an email network is equivalent to a network constructed through survey measures. As a result, I can use existing social network metrics to summarize an individual's position in a network. However, I have to select criteria for representing raw email data as network ties. I summarize implications of this choice after introducing the centrality metrics used in this dissertation.

<u>Centrality Metrics</u>

I selected four measures of centrality: structural holes, betweenness, indegree and outdegree. The effective size of **structural holes** is defined as a count of the number of links in an actor's ego-network with a discount applied to links to nodes that are linked to each other (Burt 1992). The rationale for discounting links that are connected to each other is that these are theoretically more likely to exhibit overlapping information. **Betweenness centrality** is defined as a count of the number of times an actor appears on the shortest path between any two others in a network. When multiple shortest paths exist, shares are allocated in equal proportions summing to one (Wasserman and Faust 1994). An individual that lies on the shortest path between two others can function as an intermediary, leading to the theoretical interpretation of betweenness centrality as a measure of control over information flows. **Indegree** is defined as a count of the number of incoming links, which I interpreted as the number of individuals who send email to an actor. **Outdegree** is defined as a count of outgoing links, which I interpreted as the number of individuals to whom an actor sends email.

I considered, but did not select, two additional topological measures: closeness centrality and the rank index of prestige. In both cases, the measures I derived from email data did not appear to represent distinctive theoretical network properties. Network researchers frequently use closeness centrality, which is defined as a sum of the minimum number of links needed to reach all others in a network (normalized in some definitions). However, within the email network, almost all pairs of individuals are connected by at most one intermediary. This results in a measure that is roughly equivalent to a non-directional degree measure.[17] In addition, in practice, all individuals can directly reach all others through email. If the email network had a lower density, closeness centrality could have a more theoretically meaningful interpretation.

While less frequently used, the rank index of prestige has the potentially desirable quality of fully incorporating information on differences in tie strength. However, when I used the number of messages exchanged as tie strength values, the rank index of prestige provided roughly the same information as the total number of messages exchanged.[18]

Measuring Tie Strength

In social network surveys, respondents typically assign tie strength values in completing the survey. These values are usually either binary or based on a limited interval scale such as a Likert scale. In contrast, when using email, the researcher decides how to aggregate the raw data recorded at the level of messages into tie strength values.

One implication is that email data provide measures of tie strength that are all typically related to communication frequency.[19] In Appendix A, I describe differences in representations of frequency that had little influence over centrality measures. For example, I measured frequency as the number of weeks email activity is present vs. the number of messages exchanged. I also considered whether measures were influenced by messages sent to more than two recipients, which may be of a broadcast nature.[20]

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[17] While the value of a degree measure is incremented with each additional link, closeness centrality can be thought of as being de-incremented with each additional link when the range of values is limited to 1 and 2.

[18] I could potentially use content analysis techniques to estimate a value of information exchanged over each link as opposed to raw message counts. In that case, the rank index of prestige could potentially have a more meaningful interpretation, although this is a subject for future work.

[19] Researchers can make inferences about types of links through the use of content analysis. However, content analysis could not be used in this research because the actual words were encoded to preserve privacy. In future work, some inferences regarding types of ties could potentially be based on observable characteristics such as message size.

[20] These analyses do reveal some empirical regularities, which could lead to the identification of useful summary metrics for future work. Historically, the identification empirical regularities in communication patterns led to innovations in the design of physical space (Allen 1977). Whether innovations the design of virtual space might also result from the identification of empirical regularities in communication patterns is a subject for future research.

However, I also found that finer grained distinctions regarding tie strength result in empirically distinct measures. I conducted these analyses by varying the cutoff for the number of messages above which a link is recorded.

In contrast to email data, survey data typically provide a more limited range of values, often characterized as weak and strong ties. But these values can express dimensions of communication other than frequency. For example, Granovetter's (1973) original definition of a weak tie included the dimensions of emotional intensity, intimacy (mutual confiding) and reciprocal services, as well as time spent. Subsequent studies have found that different characterizations of relationships, such as ties based on trust, advice, workflow or energy, can lead to different relationships between network position and dependent variables of interest, including performance measures (Krackhardt and Hanson 1993; Podolney and Baron 1997; Cross, Baker et al. 2003). Given current techniques, email data does not reveal psychological dimensions of interactions. Whether relationships might exist between interaction patterns in email and psychological dimensions of interactions is a question for future research.

While existing work has focused largely on the weak/strong tie distinction, email data enables exploration of whether intermediate tie strength values may lead to different results. I did not find literature offering methodological guidance around the question of using email data to represent tie strength. In recent studies of search through email networks, researchers have selected cutpoints of 5 or 6 emails to derive a binary classification of links (Adamic and Adar 2005; Zhang and Ackerman 2005). The apparent justification was to set the threshold low enough so that weak ties would be captured, but not so low that occasional announcements would be construed as links. While there is no reason to believe that these assumptions were unreasonable, existing work does not provide a basis for evaluating potential tradeoffs involved in the selection of one cutoff point over another. Cutoff points clearly influence social network metrics. It can easily be shown that increasing the threshold reduces the density of the graph.

To explore this question, I tested multiple measures of centrality in regression models. This provides evidence regarding substantive implications of these differences in the context of relationships between network position and performance within a specific setting.

I selected measures that express the following sources of variation in metrics and tie strength:

- Centrality metrics: betweenness, structural holes, indegree and outdegree.
- Cutoff values expressed in terms of the number of emails above which a link is recorded: 1, 5, 10, 20 and 40.

Dyadic Measures

It is quite possible that performance is related to aspects of how a person communicates as well as his or her position in a network. I used email data to assess non-topological features of communication regarding the flow of information over a network. My dyadic measures include response time, message size and proportional information flows. These dyadic measures complement the emphasis of traditional social network metrics on properties of network topology.

Such measures are rarely included in social network surveys. Research on informant accuracy in social network surveys suggests a potential reason why. This research has found that people are better at describing overall communication tendencies (eg. do you talk with John often, rarely or never) than specifics of interactions (eg. how many times did you talk with John last week?) (Bernard, Killworth et al. 1984; Marsden 1990). This suggests that if researchers were to ask respondents to estimate parameters such as communication response times and size (which could interpreted in some media as duration) the resulting data would probably be even less reliable than structural measures. However, email data offers the opportunity to accurately measure these parameters of communication. This enables me to test hypotheses that extend beyond network topology to consider how information flows through a network may influence performance.

<u>Proportions of email as message flows</u>

Relative emphases of communication across different types of relationships may correspond with differences in how individuals conduct their work. Measures based on these characteristics provide indirect evidence of task specialization, since different divisions of labor are likely to involve different proportions of communication across types of individuals. For example, consider hypothetical differences in the strategies three partners might use for handling research tasks. One might delegate to consultants who then interact with researchers; a second might delegate directly to researchers; and a third might handle the tasks himself. Such differences would be likely to appear as differences in these three individual's email patterns when communications are segmented by job level.

In contrast to message counts, proportional flow measures normalize communication activity with respect to the number of messages exchanged by an individual. This has useful properties as a way of controlling for individual behavioral differences in sending email. For example, two individuals might communicate the same information over email; yet one might choose to send fewer long emails, while another might choose to send more short emails. Similarly, two individuals might spend the same time on email; yet one prefers to send fewer presumably more thoughtful messages, while another sends a greater number of rapidly composed messages. Measures of email flows based on proportions of communication would control for these differences. In preliminary analyses of segmented email data, proportional measures generally explained more variation in performance than measures based on message counts. The property of proportions as a control for differences in individual email style may be one reason why.

Measures of email flows indicate the proportion of messages exchanged with others. Flow measures are bidirectional, so the numerators and denominators for sent and received email are distinct. I used two sets of proportional measures , which are outlined in the table below:

	Numerators	**Denominator**
Job level	Partner, Consultant, Researcher, Staff	Internal email
Relationship	Active teammate, former teammate, never teammates	Email exchanged among revenue generating consultants and partners

Table 3.2 Definition of proportional email measures.

My proportional information flow measures have the following attributes:

- While partner, consultant and researcher correspond to specific job titles, staff is a composite category. Staff includes administrative assistants, accounting and information technology support.
- Flow by relationship indicates the relative emphasis of email communication among revenue generating consultants and partners. I recorded the values with respect to the status of their relationship when the message was sent. Three mutually exclusive categories are possible: (1) recruiters actively pursuing a search contract; (2) recruiters not actively pursing who have worked together on a contract in the past; and (3) recruiters who have never worked together on a contract (since Jan 1, 1999).
- Proportional measures are directional. The total number of measures I created are (4 by job level + 3 by relationship type) * 2 directions = 14.

An additional attribute of information flows involves the extent to which communication is focused on a small number of individuals or spread across many. I used the Herfindahl index to calculate the diversity of message shares. I created the message share index by summing the squared values of the proportion of messages sent to or received from each individual. A value of one indicates communication focused on a single individual. The Herfindahl approaches 0 as the distribution of messages across individuals becomes more diffuse.

Theory Regarding Response Times and Size

In developing email response time and size measures I sought to create summaries of the underlying distributions that would have meaningful theoretical interpretations within the context of my hypotheses. These hypotheses are based on a coordination theory perspective that suggests shorter, more frequent communication will be positively related to performance in executing search contracts (billings). As I explain in the literature review, status cues and task-related differences provide the basis for two alternative explanations for why individual differences in email response times and size might appear in the data.

In the context of my hypotheses, I believe the distinction between email communication that occurs within and outside active search teams is likely to be relevant. I make this distinction for all response time and size measures. Hierarchical differences may also be important. The status based hypothesis emphasizes vertical relationships (Owens, Neale et al. 2000). Other organizational theory literature suggests differences in communication patterns may occur in comparisons of peer level communication. This motivates subpopulation level comparisons of email response time and size patterns in both vertical directions and across consultant and partner peer networks. I describe results of these analyses in Appendix B.

Many potential differences in task differentiation or situational context may be difficult to predict *a priori*. I conducted some analyses that could suggest differences along these lines. I describe these results in Appendix D, under the section on validity and reliability analyses dealing with specialization. However, the possibility that additional unidentified differences could significantly influence results is difficult to rule out completely when using encoded email.

Email Response Times

In this section, I summarize elements of the process that I used to define email response time measures. I provide a detailed step-by-step description of this process and other analyses related to response times in Appendix B.

I created an email response time measure that adjusts for daily periodicity by defining a measure of time spanning the typical workday. I estimated the span of the workday through analysis of the email data. Daily and weekly periodicity in email has been observed in other settings, reflecting a tendency to send fewer messages outside of working hours (e.g. Begole, Tang et al. 2002). The adjusted response times provided a better fit to a log normal distribution.

I defined response times on the basis of time intervals between messages independent of content. Preliminary analysis did not suggest a strategy for distinguishing between replies and new threads on the basis of content that would not involve considerable effort.[21]

At the message level, I defined response times in following way:

- The "sent email response time [to others]" reflects the time it takes an individual to respond to others. For individual A, I calculated the sent email response time of a message by subtracting the time of the most recently received previous message from individual B from the time individual A sent a message.
- The "received email response time [from others]" reflects the time it takes for others to respond to the individual. For individual A, I calculated the received email response time of a message by subtracting the time a message is sent from the time at which the next message from individual B was received.
- If one party never responded over the course of the study, I considered the response times to be undefined. I dropped these emails from the analyses involving response times. No responses among colleagues were rare, but were more common in external email.

After calculating response times at the message level, I selected two strategies for aggregating response distributions into individual level measures. I used the mean of the adjusted response times involving an individual as a summary metric over the whole distribution. However, within the context of the theory to be tested it is unclear whether the mean is an appropriate measure. I created an alternative set of measures based on the percentage of responses within a certain time periods. This can be thought of as the probability of giving or receiving a response within a given amount of time. It can be compared to subjective probability estimates people make in deciding whether or not it is

[21] I was able to identify use of the reply function ("Re:") in the subject line in the hashed data because of its high frequency. However, I also found considerable individual idiosyncrasies in the way recruiters use the reply function. While similarity metrics can be computed on the basis of the hashed words, this shifts the problem from one of distinguishing between replies and new threads on the basis of time alone to one of distinguishing on the basis of a similarity threshold. It could be argued that a similarity based metric would be superior, but the time cost of developing such a metric and justifying the choice of cutoff also needs to be considered. In light of the hypotheses to be explored, I consider the definition of an email response on the basis of time interval alone adequate in light of these alternatives.

worth sending a message, when the value depends on how soon they are likely to hear back. Email research from a social definition theory perspective suggests people also make similar estimates when deciding how long they can safely ignore messages. The social calculus typically involves a subjective estimate of normative expectations regarding "reasonable" reply times. My initial selection of the time intervals that served as cutoffs was based on a sense of what seemed reasonable because I could not identify prior work to guide the selection process. I simplified my initial set of time intervals following a process described in Appendix B.

Prior research has identified context as a statistically significant explanatory factor in email response patterns (Dabbish, Kraut et al. 2005). My theory suggested that whether recruiters exchanged emails within or outside the context of an active search team was a potentially relevant contextual factor. I made this distinction by cross referencing contract and email data. My ability to further evaluate context was limited by the prior decision to encode messages with a hash function to preserve privacy.

I selected the following individual response time measures for use in subsequent regression models:

- Mean response time and mean logged response time
- Percentage of responses within 30 minutes, one day and one week

I grouped measures to distinguish between:

- Responses in the sent and received direction
- Messages exchanged within and outside the context of participation on an active search team

Email Size

In this section, I briefly summarize the process that I used to define email size measures. I provide a detailed step-by-step description of this process and other analyses related to email size in Appendix B.

After I separated emails into two groups based on the presence or absence of attachments raw email size distributions (measured in bytes) were approximately log normal. Based on this observation, I selected the following email size measures expressed in bytes:

- The mean size of all messages
- The mean size of messages with attachments
- The mean size of messages without attachments
- The percentage of messages without attachments

I grouped messages to distinguish between:

- Responses in the sent and received direction
- Messages exchanged within and outside the context of participation on an active search team.

Intertemporal Reliability of Measures

My regression models are cross-sectional. However, I still consider intertemporal reliability analyses of the measures important. For email measures, exploratory analyses of temporal variation provide information that is useful for interpreting results and may suggest valuable opportunities for future work. For performance measures, I based the time interval over which performance is measured on temporal analyses of the data. In addition, I conducted temporal analyses of the performance data to assess external factors that lie outside the theories of interest but could threaten validity through a form of omitted variable bias. This threat occurs because variation in individual performance may be related to external variation in economic conditions that is not incorporated into my regression models. By assessing variation in the performance measures over the full five years for which I have contract data, I am better able to make judgments to regarding the extent to which these external factors are likely to influence individual performance.

Measures that exhibit a high level of intertemporal reliability or stability are often characterized as "trait measures," while those that exhibit low levels of stability are referred to as "state measures," although the distinction is a continuum. A third possibility is a measure that trends over time. For example, cognitive ability in adults tends to be trait-like, mood tends to be state-like and cognitive ability in children tends to trend upwards with respect to age. These high level distinctions are useful for evaluating intertemporal properties of the measures I use in subsequent regression models.

Intertemporal Reliability of Email Measures

Researchers have long recognized that that properties of social networks change over time (Suitor, Wellman et al. 1997; Burt 2000). However, most network studies are cross-sectional. For example, Burt (2000) surveyed papers in the two leading social network journals published through 1998 and found less than 5 percent used true longitudinal data. Researchers have only very recently begun to analyze temporal properties of email measures (Kossinets and Watts 2006).

My longest continuous interval of email data was six months. This is unlikely to be long enough to clearly observe trends in relationships or performance. However, considerable "state-like" variation may be observed as a result of relationships between email and contract activity. Unfortunately, the most popular statistical software for longitudinal social network analysis, StOCNET, is unsuitable for distinguishing potential regularities in state-like properties. The limitation is tied to an estimation strategy based on approximations to a Markov model. Given the nascent state of existing methods for estimating intertemporal parameters with respect to email data, I left this as a subject for future work.

Instead, I employ a modest two-stage strategy for evaluating the intertemporal reliability of email measures. The first stage focuses on whether or not measures appear to be stable over the length of the study period. I use Cronbach's alpha to compare the level of agreement between measures calculated across three periods of approximately three months. This can be thought of as a heuristic confirmatory analysis strategy. It assess whether or not measures appear to converge to a stable state over the study period. I subject measures that do not appear to be stable to a second stage correlation analysis. This involved measuring correlations between email measures and contract activity at weekly intervals. These analyses, detailed in Appendix C, can be considered exploratory. I conducted them primarily to identify opportunities for future work.

Intertemporal Reliability and Definition of Performance Measures

Meyer's (1994) survey of economic and sociological studies of performance in organizations highlights common problems associated with intertemporal instability. Variables that best explain past performance are not guaranteed to explain future performance, as environments change and individuals become proficient at gaming performance metrics over time. The gaming problem may be less of an issue in this setting because individual performance metrics are directly measured as revenues. Opportunities for gaming may be limited to haggling over the credit assignment formula involving the share of revenues. In addition, the effects of external conditions on individual performance are directly incorporated into the performance measures.

However, a potential problem still exists because variation in external economic conditions is not identified by the measures used in my regression models. This is a data limitation. Some variation is likely to be picked up by controls for the different industry sectors, but these proxies are imperfect. If the remaining effects are randomly distributed, then they can be safely incorporated into the error term. My assessment of intertemporal reliability of performance measures focuses on assessing situations in which this assumption may be violated.

Two plausible sources of non-random variation are seasonal effects in hiring and longer term cyclical patterns of labor investments. In addition, individual performance measures are determined in part by the arrival rate of contracts. In the limit, as the period over which performance is assessed approaches the arrival rate of contracts, measures of individual performance become random. This is because such a measure would pick up only whether or not a contract arrived or was completed in a short interval, not the tendency to land or complete a quantity of contracts over a reasonable period of time. As the length of the period over which performance is assessed increases, individual performance measures become less sensitive to volatility in the arrival rate of contracts. However, trends in individual performance may also accumulate as the time interval increases. An ideal interval would be long enough to smooth volatility in the arrival rate of contracts, but not so long as to preclude measurement over several time periods, which could be used to detect individual trends.

In the existing data, the longest continuous span of email activity is six months. This is likely to be too short a period for long term trends in individual performance to appear. As a result, my analysis focuses on the length of time needed to smooth volatility in the arrival rate of search contracts. If volatility can be smoothed in less time, this would suggest that performance measures could be calculated over multiple periods. I could then use a panel model. If volatility cannot be not sufficiently smoothed over six months, this would suggest that it may be better to calculate individual performance measures over a longer time interval.

In Appendix C, I report results of analyses concerning seasonal and cyclical variation in contract activity, as well as the level of agreement between measures calculated over different time windows. Performance is measured in two dimensions. Bookings involve performance at landing contracts; I assigned booking credit at the start of contract activity. Billings involve performance in executing contracts; I assigned billing credit at the end date of a contract. Temporal analyses suggested that it is not possible to reliably measure individual performance in this setting over a period of less than six months. The six-month window appears to be adequate for bookings, but not billings. A potential explanation for this finding may be that seasonal patterns of hiring are more pronounced in some sectors than others. For example, in academe, postings appear throughout the year, while hiring decisions for faculty positions occur predominately in the spring.

I address this problem by using an annual measure of billings in which the measurement period begins with the start of the contract data and extends for a full year. Because the average length of a search is approximately six months, this conveniently corresponds with a measure of throughput involving both contracts that were in a recruiter's portfolio when the study began as well as those added during the study and completed within a reasonable period of time thereafter. In addition to revenue measures, I also created corresponding measures of project counts by summing shares of billing and booking credit.

On the basis of these analyses, the measures of individual performance I selected for use in subsequent regression models are:

- Booking revenue and booking shares measured over the period that directly overlaps with the email data.
- Billing revenue and billing shares measured over a one year period that begins on the date email data were first recorded.

<u>Temporal relationships between email and performance measures</u>

Relationships between contract and email activity are likely to exist in the data. I consider further analyses of these relationships to be a promising area for future work. This type of analysis could lead to strategies for testing causal relationships between email patterns and performance measures.

One of the main reasons I did not pursue this direction more actively involves the perceived investment of time needed to develop proficiency in methodological techniques that I do not use elsewhere in my dissertation. For example, relationships between email patterns and contract activity are complicated by the fact that search teams often pursued multiple simultaneous searches. One implication is that it would be desirable to differentiate between messages associated with different searches. This could potentially be done by applying strategies for content analysis to the hashed data. In addition, my preliminary analysis of the data suggested that while start and end dates of contracts approximate email activity on specific searches they do not always coincide directly. For example, email activity on a search may precede the start date, potentially indicating communication that led up to the signing of a contract. This suggests that models that directly relate contract to email activity at the level of individual searches may need to incorporate lags that may vary by search. Search level analysis involves significant challenges, although it represents a promising direction for future work. I conducted preliminary exploratory analyses of temporal relationships between email and contract activity. I describe this work in Appendix C.

<u>Additional Validity Analyses</u>

Validity of Email as a Proxy for General Communication Patterns

Email analysis and other techniques involving direct measurement of communication can address many of the validity and reliability issues raised in the literature on respondent inaccuracy in social network surveys. At the same time, direct measurement techniques raise other validity and reliability issues. In particular, mono-method bias has received less attention than informant inaccuracy in the social network literature, but it is clearly a relevant concern for a study that relies on email as its sole source of social network data (Cook and Campbell 1979). A fundamental question for interpreting hypothesis tests is whether results suggest the importance of email as a mode of communication or the importance of general communication patterns for which email serves as a proxy.

This distinction can be thought of as a continuum. In this setting, a series of empirical analyses lead me to conclude that email patterns are more reasonably interpreted as proxies for general communication patterns. My data are not sufficient to directly compare the content of email communication with that of communication in other media, so my argument is indirect.

However, an accumulation of evidence suggests email is likely to be a reasonably good proxy for general internal communication patterns in this setting. The data suggest recruiters are very responsive to colleagues over email -- the modal response time to colleagues for all recruiters except one is 0 to 30 minutes. Measured numbers of email messages are strongly correlated with self-reported communication volume across other media. In addition to these positive findings, I failed to find evidence regarding a number of potential problems. When I identified and classified dyads in which email activity was lower than expected I found evidence that suggests five partners may prefer other media. However, four of these partners are still very responsive to the email of colleagues.[22] I also used ANOVA and correlation analyses to specifically investigate potential problems with collocation and media preferences as mediating variables. I did not find evidence of systematic effects attributable to collocation. I found evidence that media preferences do vary with respect to differences in the tasks recruiters perform. For example, consultants who perform more bookings reported devoting a greater proportion of time to face-to-

[22] A combination of low email and responsiveness to colleagues could be consistent with either a preference for other media or low communication overall. Given this ambiguity, I did not control for these cases in the base model, but examine the influence of these cases in residual plots and note any situations in which they may influence results in the interpretation.

face communication. This is important to consider in interpreting results. However, I did not find clear evidence of substitution effects involving internal email. I describe the results of these analyses in detail in Appendix D.

Specialization and Task Differentiation

Specialization and task differentiation could lead to statistically significant relationships between email patterns and individual performance. In such instances, results could reflect unmeasured features of the setting as opposed to features described in the development of hypotheses. Awareness of this problem helped motivate the development of the survey as a third data source. I used the survey to develop ANOVA and correlation analyses that help suggest other factors that may be related to communication patterns and performance in this setting.

In Appendix D, I describe analyses I conducted to assess relationships between potential forms of specialization and email and performance measures. For example, I constructed a finer grained measure of hierarchical specialization by creating an individual level revenue based measure of the balance between landing (booking) and executing (billing) contracts. I considered one form of horizontal specialization by using ANOVA to compare survey, email and performance measures across the two largest practice areas of the firm. I was not able to create measures of specialization for all of the categories I would have liked. For example, I found it difficult to characterize and identify a boundary spanning role in this setting. I was also unable to construct a measure of technological specialization from the survey measures. I suspect the reason is that technological specialization in the recruiting context is multidimensional. Results of analyses related to specialization serve as a source of data for interpreting results and as a source of motivation for future work aimed at addressing some of these issues.

Given my reliance on OLS regression models and the potential influence of specialization and task differentiation, I am unable to make causal claims without further evidence. However, I can make the weaker claim of interpreting statistically significant results as evidence that email patterns serve as indicators or predictors of performance.

Some evidence that suggests a particular causal direction can come from measures that include temporal and directional dimensions. In future work, stronger evidence could come from applying modeling frameworks that provide specific tests of causal claims.

Email vs. Network Surveys as Social Network Data Sources

One of my motivations for using email, a form of direct measurement, followed from the literature on informant inaccuracy in social network surveys. The findings of the seminal BKS studies were based on comparisons between direct measurement and respondent's reports of communication (Bernard, Killworth et al. 1984). My data included one question I used to make a similar direct comparison. The level of agreement between respondent perceptions of the number of people they communicated with per day over email and the actual number of unique email contacts per day during the study was reasonable, but not stellar (Cronbach's alpha ~ 0.80).

This result is generally consistent with the BKS studies and subsequent research on informant inaccuracy. It suggests that when researchers seek objective measures of communication, direct measurement is better because it reduces measurement error. On the other hand, when direct measurement is costly or impractical, network surveys accompanied by techniques used to improve accuracy, such as reciprocated reports, may be sufficiently reliable. Factors that constitute "sufficient" reliability are likely to depend in large part on the context and research objectives.

The section in the appendices covering a direct comparison of email and direct report also includes correlation analyses between direct measurement and distinct, but related measures of email usage. Not unexpectedly, these relationships generally exhibited lower levels of reliability. In addition, relationships between technology and performance measures exhibited some evidence of self-efficacy biases. I revisit the topic of direct measurement through email versus network surveys in the discussion chapter.

E. Regression Models

My regression models consist of a base model composed of control variables, one or more relational treatments and a dependent variable that measures individual performance. Variables in the base model include demographic characteristics of individuals, controls for industry sector and a dummy variable that indicates whether a recruiter has made partner. Treatments measure relational characteristics, which I derive primarily from email data. Dependent variables measure individual performance in landing (booking) and executing (billing) searches. I use these models to test the null hypothesis that a specific relational measure is not related to performance. I do this by using a t- or F-test to evaluate whether the addition of a treatment(s) to the base model is statistically significant. My objective is to evaluate whether characteristics of relationships between recruiters explain variation in individual performance.

Relational characteristics are rarely included in models that assess performance or productivity. For white-collar studies, the most likely explanation involves difficulties associated with measurement, as opposed to a lack of relevant theory. Statistically significant results would suggest the value of including similar measures in future studies of white-collar performance to address potential problems with omitted variable bias.

Dependent variables

I calculated individual performance measures from raw data at the level of search contracts. On each contract record, the firm assigns shares of booking and billing credit to individual recruiters on the basis of tasks performed. Booking refers to landing contracts. Billing refers to executing contracts. Each contract record also contains the revenue received by the firm. This amount is usually, but not always, equivalent to one-third of a new hire's first year salary.

I created measures I refer to as **billing shares** and **booking shares** by adding the shares of credit accumulated by an individual. I also created measures I refer to as **billing revenues** and **booking revenues** by summing the products of each contract share multiplied by the corresponding contract revenue.

I use these performance measures to run sets of models that differ only in the choice of dependent variable. In the first set of models, I measure performance as shares of billing and booking credit. The results can be interpreted as relationships with the number of projects completed. In the second set of models, I measure performance as billing and booking revenue.

In most cases, the two models give nearly identical results. In these cases, I have evidence that my results are not sensitive to whether performance is measured as revenues or projects. In a few cases, the results are sensitive to the choice of performance measure. The percentage of searches recruiters conduct for CEO level positions, which generate significantly higher revenues than other types of searches, is one factor that may help explain some of the differences (See Appendix E).

Base model overview

To test my hypotheses, I want to control for factors that may theoretically influence individual performance, but are unrelated to relationships between recruiters within the firm. My constraints include a small sample size (n=47), available data, and the limits of my understanding regarding factors that might theoretically influence individual performance in the context of executive recruiting. Operating within these constraints, I selected six control variables representing non-relational factors. After describing the theoretical rationale for the control variables I selected, I discuss limitations of the base model. These involve omitted variables that are theoretically unrelated to relationships among consultants and partners within the firm but may influence individual performance. These limitations are important for interpreting results. I focus this discussion on ways that these factors could potentially be measured as motivation for future work.

General human capital controls

I included three demographic measures in my base model to control for individual variation in human capital: years of experience, years of education and gender. The first two are self-reported values from a survey. I determined gender primarily on the basis of first names, using conversations with members of the firm to resolve ambiguities (e.g.

Pat).

Economic and sociological researchers studying human performance in organizations frequently use this set of controls. I followed suit because I do not believe I have sufficiently addressed the burden of proof needed to deviate from standard practice. While I believe more extensive knowledge of executive recruiting as a research setting is likely to lead to the identification of a better set of human capital controls, these measures provide a reasonable starting point.

I believe the number of years a recruiter has worked in the industry influences performance in both theory and practice. However, I use years of education and gender reluctantly. I explain my position with the goal of identifying a better set of controls for future work.

I believe the number of years of education is a poor proxy for individual human capital in this setting. All of the recruiters attended college, so variation in the measure is limited to years of graduate education. However, few people pursue graduate education with the intention of becoming an executive recruiter. Few, if any, schools market graduate course offerings to attract students who want to become recruiters. While the number of years of education is likely to be a reasonable human capital proxy in many professional service settings, I believe it may be significantly less relevant in recruiting. I find it difficult to identify a convincing theoretical argument for why a generic year of graduate school would be more or less likely to influence a recruiter's future performance than a year spent in a non-recruiting occupation.

While I accept arguments for using gender as a control in this setting because it might matter, and would be interesting if it did, I have not identified a convincing theoretical explanation for why it should matter. Some arguments supporting the inclusion of gender in models of performance that use salary or promotions as dependent variables may be less relevant when revenue or project based measures are used. Other common arguments involving gender can be spun in either direction. For example, communication skills used in recruiting involve both stereotypical male and female attributes (Tannen 1990).

Other controls in the base model

In addition to my general human capital controls, I included three dummy variables in my base model. These control for industry sector and differentiate between consultants and partners.

Each recruiter belongs to one of three practice areas within the firm that serve different industry sectors. I used this designation to create two dummy variables for industry sector. One recruiter served as an intermediate between two practice areas. In that instance, I allocated half a share to each.

A recruiter's focus on a particular sector may influence relationships between communication patterns and performance in a number of ways. Across industry sectors, the difficulty of landing and executing searches, as well as revenues, may vary. In addition, industry sector may influence internal communication patterns. More internal email communication occurs among recruiters within the practice area than across practice areas. Social definition theory perspectives suggest that communication patterns may vary within subgroups in an organization. In addition, the number of recruiters in each practice area was not distributed evenly, which could influence social network measures.

I also included a dummy variable for whether a recruiter had made partner based on the status at the beginning of the study period. Promotion to partner is typically based on past performance at landing search contracts. This constitutes a measure of individual human capital and external social capital specific to the research setting.

Limitations of the base model

The control variables I use are similar to those found in many other studies of human performance in organizations. At the same time, these basic models typically explain only a small proportion of the total variation. My base model is similar in this respect.

My ability to introduce additional control variables is restricted by my small sample size. However, the limitations of my base model and ways it might be improved are worth considering both for the interpretation of results and future work.

Potential improvements in general controls for individual human capital all involve the collection of additional data. Evidence of specific achievements or traits typically provide better human capital controls than generic measures of individual characteristics. For example, test scores or dummy variables that represent specific graduate degrees that are likely to have value in the context of executive recruiting could be better predictors. An example of the latter is an M.D. Interview data suggest candidates and clients with M.D.'s are more receptive to working with recruiters who also have the degree. Since candidates with M.D.'s often command relatively high salaries, an M.D. may help a recruiter generate more revenue.

I could also introduce additional measures of human capital that are specific to the research setting. For example, I could subdivide the job level distinction by introducing additional dummy variables for junior consultants and partners who act as practice group leaders. Recruiters may also have specific expertise that explains individual variation. For example, the value consultants place on the internal database (survey question, q26e) is statistically significant when added to the billing revenue base model. While this is not a measure of expertise *per se*, it suggests there may be relevant related measures in this context. Measures of performance that indicate progress along a career trajectory could also serve as proxies for human capital. The percentage of solo searches appears to play such a role in the recruiting context, although it may not be suitable as a human capital proxy because of confounding with internal social capital. I discuss the role of solo searches and the database in Appendix E.

I believe my control variables for industry sector are adequate to control for divisions within the firm. The largest practice area is divided geographically into practice groups. If I had more observations, I could use existing data to control for potential variation at the practice group level. A more limited, but potentially feasible strategy would be to include a dummy variable to control for the one practice group in which an ANOVA shows some statistically significant differences with respect to partner performance.

External social capital represents an omitted variable that is likely to explain a significant amount of variation in bookings. Measures derived from email data do not appear to make good proxies because the most important interactions with clients are likely to occur face-to-face or over the phone. However, I could create a proxy from contract data. Within the firm, recruiters have exclusive rights to existing clients. The owner of a client receives at least 0.5 booking shares on each contract. This suggests that lagged revenue on contracts for which recruiters receive more than 0.5 booking credits could be interpreted as a proxy for external social capital related to clients. When added to the base model, this measure is a significant predictor of booking revenue during the study period ($F = 12.7$, $p < 0.01$). The idea for this proxy came very late in the dissertation process, but using it as a replacement for the partner dummy in the base model is a promising idea for future work.

A difficult omitted variable problem involves detecting and controlling for potentially non-random influences on performance that could result from the selection of more favorable types of search contracts. In Appendix E, I discuss the issue of contract selection effects with respect to both geography and job level variation in search contracts. The challenge involves developing a way to estimate the expected difficulty of a search based on observable characteristics.

Potentially non-random effects involving heterogeneity in tasks could influence performance. However, I believe my data are significantly better than most in this respect. The firm allocates billing and booking credits based on a standard formula. The task descriptions in this formula appear to correspond with divisions of labor that recruiters follow in the search process. Situations in which search difficulty affects billing and booking differently are likely to be fairly common. However, the credit assignment process differentiates between these two dimensions of performance. A more likely problem is that heterogeneity in tasks could influence email communication patterns. I discuss this problem in reference to specialization in Appendix D.

While I focused this study on relationships involving partners and consultants, communication with researchers and staff could potentially influence performance. I discuss this further in Appendix E.

Hypotheses

My investigation of relationships between email patterns and individual performance provides opportunities to test hypotheses derived from classic theories using a novel data source. I identify the motivating literatures, main ideas and research questions to be tested in the following table.

Theoretical basis	**Main idea**	**Research question**
Resource dependency theory (sociology, political economy)	Individuals with better access to a key resource are likely to be higher performers. Recruiters who occupy central positions in the firm's email communication network are likely to have better access to the key resource of information.	Are measures of centrality in an organizational email network related to individual performance?
Exploration vs. exploitation tradeoffs (organizational learning)	Job level differences in the time horizon for realizing returns from investments in social and intellectual capital lead to the prediction that positive associations will be found between exploration strategies at the junior level and exploitation strategies at the senior level. These may be expressed as job level differences in information flows associated with landing contracts and job level differences in information related behaviors associated with email network centrality.	Do predictors of network centrality and performance in landing contracts differ between job levels?
Theories of co-specialization (economics) and clique formation (sociology)	Individuals with complementary skills may associate on the basis of performance expectations, leading to the formation of higher and lower performing cliques. Recruiters who are more successful at landing contracts may communicate more with recruiters who are more successful at executing contracts and visa versa.	Are individual measures of performance in one dimension associated with the past performance of colleagues in the alternate dimension?
Queuing models (coordination theory, computer science)	Individual performance may be related to communication strategies among team members that eliminate bottlenecks and minimize bad handoffs. In particular, sending smaller, more frequent messages to teammates may be associated with higher performance in executing search contracts.	On average, is a pattern of shorter, more frequent email communication among team members positively related to individual performance in executing search contracts?

Table 3.3 Theoretical sources, main ideas and research questions that motivate hypotheses testing.

Sociological Perspective: Resource Dependency Theory

From the perspective of sociological theory, individual performance is likely to be related to elements of social structure. More specifically, resource dependency theorists argue that individuals with the best access to key resources are more likely to be higher performers. Information is a key resource for executive recruiters. More central positions in a network often provide better access and control over information. These ideas motivate tests of the general hypothesis that recruiters who occupy more central positions in the organizational email network will be higher performers. While relationships between centrality and performance have been found in other settings, this hypothesis asks whether these effects may extend to email networks as well. Stated formally,

Hypothesis 1a: Centrality in a recruiter's internal email network will be positively related to performance.

Existing work on relationships between network centrality measures and performance has also established the precedent of using of multiple measures. These help researchers increase the specificity with which they can interpret results (Polodney and Baron 1997). I test my general hypothesis across multiple networks, centrality metrics and performance measures as a way of increasing the specificity with which I can interpret results. I outline relationships between measures and research questions in the table below.

Variation in Measures	**Question**
Email Tie Strength	Do relationships between centrality in an email network and performance vary by according to the frequency of communication?
Centrality Metrics	Do relationships between centrality in an email network and performance vary depending on structural characteristics of centrality, expressed in terms of distinctions between different centrality metrics?
Type of Network	Do relationships between network centrality and performance vary with respect to the type of network? In particular, how does centrality within the formal network defined by job assignments (i.e. search contracts) compare to centrality within the informal network defined by email communication?

Performance Measures	Do relationships between centrality in an email network and performance vary depending on the performance measure?

Table 3.4 Relationships between measures and research questions involving centrality.

Variation in Centrality Metrics and Tie Strengths

Social network theorists attribute different theoretical properties to different centrality indices and distinguish between weak and strong ties. Open questions remain regarding the mapping of these concepts to the use of email as a social network data source. In my previous discussion of email centrality measures in this chapter I developed the rationale for selecting the following metrics and tie strength cutoffs. Centrality metrics include: structural holes, betweenness centrality, indegree and outdegree. I assigned email ties on the basis of message counts at or above the following cutoff points: 1, 5, 10, 20 and 40 messages.[23] Gradations in tie strength that can be obtained using email data are typically finer in granularity than those obtained in response to social network surveys. This allows me to assess whether tie strength effects vary along a continuum or whether they can be sufficiently characterized by the standard weak/strong tie distinction.

I formulated the following hypotheses in reference to centrality measures that I define in two dimensions. The first dimension involves tie strength. The second dimension involves the specific metric (i.e. betweenness, structural holes, indegree or outdegree). Empirical results I obtained while defining and validating measures suggested that the resulting measures exhibited greater variation in the dimension of tie strength (see Appendix A). My interest lies in whether that variation leads to differences in the statistical significance of relationships between centrality measures and performance:

Hypothesis 1b: The statistical significance of relationships between centrality and performance will vary based on the way centrality is calculated. Changes in the tie strength cutoff will lead to greater variation in the statistical significance of results than changes in the centrality metric.

Variation in Networks: Email vs. Search Contracts

[23] I also used a threshold of more than 80 messages in some analyses. However, I do not report these results because I believe they lack a meaningful interpretation. This high threshold eliminated more than 90 percent of the possible ties. Relationships at this threshold might be characterized as strong ties between heavy emailers. I believe that the 40 message threshold, representing strong ties, is more meaningful.

From a theoretical perspective, the network defined by ties assigned on the basis of whether or not recruiters worked together on a search contract during the study period can be classified as a formal network. While organizational charts are more commonly used as formal network representations, given the fluid nature of task assignments in executive recruiting, the organizational network as it is defined by search contracts may be the best analogue. In organizational and communications theory, formal networks are typically contrasted with informal or emergent networks. Communications networks, such as email networks, are representative examples of informal or emergent networks. Communications and social network theorists have suggested that position in an informal or emergent network may often be a better predictor of performance than position in the formal network (Krackhardt and Hanson 1993; Monge and Contractor 2003). The explanation is that not all the resources someone needs to complete a project or perform a service are typically found within the direct chain of command. This suggests individuals who have better developed communication networks may be higher performers. It motivates the following hypothesis comparing centrality in the contract and email networks as predictors of individual performance:

Hypothesis 1c: Relationships between network centrality and performance will be stronger with respect to the email network than the contract network.

Variation in performance measures

Relationships between email network centrality and performance may also vary with respect to the nature of the task. Within the context of executive recruiting, the tasks of landing and executing contracts form the basis for performance measures. Interviews with recruiters also suggested differences in information needs associated with landing contracts from new as opposed to existing clients, a distinction that is also present in the raw contract data. In a new client context, competition with other firms on the basis of proposals and demonstrations of ability in tasks such as creating initial candidate lists may precede the landing of a contract. Within the industry, these competitions are sometimes referred to as “shootouts.” In an existing client context, the sales task is more likely to involve convincing the client to use the service of the firm as opposed to either promoting an internal candidate or having the company’s human resource department handle the search. I summarize potential relationships between performance measures, tasks and information needs in the following table.

Association with:	**Suggests benefits related to:**	**Such as:**
Billings Revenue	Search execution	Information that promotes efficiencies in screening candidates or in coordinating candidate-client matchmaking
Bookings Revenue from New Clients	New client development	Information that provides competitive intelligence leading to the development of new clients or procedural information regarding the new client development process.
Bookings Revenue from Existing Clients	Developing new opportunities with existing clients	Information that points to sales opportunities with existing clients or sales "scripts" that generate more repeat sales

Table 3.5 Relationships between output metrics, tasks and information needs.

Because search execution typically involves extensive communication between recruiters over an average period of slightly over six months, I hypothesize that billing revenue is more likely to be associated with strong ties. It is difficult to predict *a priori* what differences in email patterns if any might be associated with new client as opposed to existing client bookings. I speculate that they are likely to be equivalent and both will involve measures that include weak ties (Granovetter 1973; 1983). This motivates the following hypothesis:

Hypothesis 1d: Centrality measures based on strong ties will be positively associated with billing performance. Centrality measures that include weak ties will be positively associated with booking performance involving both new and existing clients.

Organizational Learning Perspective: Exploration vs. Exploitation

My second group of hypotheses considers the possibility that ego-networks with similar topologies may exhibit different patterns of information flow. In the preceding chapter, I outlined an intra-organizational network interpretation of the tradeoff between exploration and exploitation. It suggests information related behaviors and flows associated with centrality and performance may differ across job levels.

The investment time horizon is a key variable in the tradeoff between exploration and exploitation. Longer time horizons favor exploration since it offers the greatest potential payoffs; shorter time horizons favor immediate gains from exploitation. At the individual level, the investment time horizon can be equated to the timeline of a career. Exploration strategies would be favored among junior employees, while exploitation strategies would be favored at the senior level. The relevant investments can be thought of as investments in social and intellectual capital. Drawing on these metaphors, one would expect relationships between network variables and performance measures to change over the course of a career. Measures of investment in network building and learning would be positively associated with the performance at the junior level, while measures related to generating returns from existing social and intellectual assets would be positively associated with performance at the senior level.

My strategy for testing this hypothesis uses theory to predict ways in which information flow and use measures may differ across job levels. Booking is the relevant performance dimension in this context for the following reason. For consultants, it provides a measure of learning because making the progression from executing contracts to landing them involves acquiring a key set of skills they need to make partner. For partners, booking revenue is the primary metric upon which compensation is based.

I selected structural holes as the most relevant centrality measure because theoretical explanations for relationships with performance are more extensively developed (Burt 1992; Burt 2000; Burt 2004). A tie strength cutoff set at a relatively low number of messages is desirable because the empirical results suggest that relationships with booking revenue are statistically stronger when weak ties are included. I consider a cutoff of one or more messages too low, given a desire to rule out an occasional email announcement as an indication of a relationship. In this particular setting, relationships between booking revenue and structural holes are statistically stronger at the 10 or more email cutoff than 5, so I selected the former for my cutoff.

The theory predicts that the performance of early career employees, consultants in the recruiting context, will be positively associated with investments in developing their internal network. A higher proportion of e-mail messages sent to colleagues they have never formally worked with on searches suggests a strategy of investing in new relationships (March 1991). Another way of investing in relationships would be to communicate more broadly within senior colleagues. This can be expressed in terms of a more diverse message share of communications with partners calculated using the Herfindahl index. Stated as hypotheses:

Hypothesis 2a: Among consultants, but not partners, the proportion of messages sent to colleagues they have never worked with on projects will be positively related to bookings.

Hypothesis 2b: Among consultants, but not partners, the diversity of communication with partners will be positively related to bookings.

The theory predicts that the performance of late career employees, partners in the recruiting context, will be positively associated with the ability to capitalize on earlier investments in developing their networks. For partners, sending a greater proportion of messages to consultants may indicate a greater ability to offload lower valued work. Consultants are thought to represent the most desirable type to whom a partner can delegated work, because consultants can it turn call on researchers and staff for support. In other words, delegation to middle management may be more efficient than the alternatives of interacting directly with those at a lower level or spending one's time interacting with peers at the top who are unlikely to provide support for lower valued tasks. Stated as a hypothesis,

Hypothesis 2c: Among partners, but not consultants, bookings will be positively related to the proportion of email sent to consultants.

The exploration versus exploitation framework can also be applied to identify job level differences in information behaviors that may be associated with network centrality. For example, accumulated experience can be thought of as an asset. A recruiter may occupy a more central position either because he or she reaches out more to colleagues or because he or she receives communication from a greater number of colleagues. The latter possibility suggests centrality within an organizational email network could provide an indication of how the asset of social and intellectual capital is valued by others.

Valued information combined with a willingness to share may generate the most requests. Senior employees have had more time to develop the asset of accumulated experience, leading to the prediction that self-reported tendencies to share information are more likely to be associated with network centrality at the senior as opposed to junior level.

In the recruiting context, a disincentive to share information with others may also operate at the junior level. Compensation based on relative performance, as opposed to absolute benchmarks, can create a disincentive for sharing, since improving another's standing means hurting one's own (Orlikowski 1992). To the extent that consultants compete more with each other over assignments for executing contracts that have been landed by others, their compensation can thought of as based more on relative performance. A contract executed by one recruiter is one less contract to be executed by another. On the other hand, because client "ownership" is clearly delineated within the firm, a contract that is landed by one recruiter is not thought to influence opportunities for other recruiters to land contracts. In that sense, booking revenue can be thought of as an absolute metric, while billing revenue derived from contracts landed by others is more relative.

The opposite of information sharing is hoarding. Although the estimated contacts held in the private rolodex is not a direct measure of hoarding, it may be related, because the private rolodex may be considered to be an alternative to sharing contacts throughout the firm by placing them in the firm database. Consultants could be theorized to be more likely to hoard contacts as a way of improving their relative efficiency in executing contracts. This suggests also considering a measure of information hoarding to distinguish between reasons why information sharing might not be associated with centrality at the consultant level. In one case, information shared by a consultant is simply less valued. However, a positive relationship between contacts held in the private rolodex and centrality, would suggest an alternative explanation in which there may also be a strategic reason for not sharing information. I express these observations on potential relationships between measures of information sharing and centrality in the following hypotheses:

Hypothesis 2d: Among partners, but not consultants, structural holes will be positively related to information sharing.

Hypotheses 2e: Among consultants, but not partners, structural holes will be positively related to the number of contacts privately held in personal rolodexes.

The exploration versus exploration framework can also be combined with theory on the value of information to generate predictions regarding relationships between the type of information exchanged with others and centrality. Procedural or "how to" information has value in re-use, while the value of declarative information or "facts" is specific to the context of a decision problem (Blackwell 1953; Van Alstyne 1999). Other things being equal, a longer time horizon provides more opportunities for the re-use of procedural information. In relative terms, the acquisition of procedural information may be favored at the junior level, while the acquisition of declarative information may be favored at the senior level. At the junior level, a network optimized for learning may be more valuable; at the senior level, a network optimized for filtering facts that can be used as inputs to decisions may be more valuable. Recruiters who perceive the information they exchange with others is more closely aligned to the theoretically optimal type may have a greater incentive to invest in their networks, leading to a more central position. Perceptions regarding the extent to which information shared with others was perceived as being primarily declarative or procedural were elicited through the survey. Stated as a hypothesis:

Hypothesis 2f: Among consultants, procedural information sharing will be positively related to structural holes; among partners, declarative information sharing will be positively related to structural holes.

Economic Perspective: Co-Specialization

Centrality metrics capture differences in how people are connected to others, while implicitly assuming that the attributes of others are equivalent. In practice, factors unrelated to social structure often make communication with one person more valuable than communication with another. I develop a hypothesis for how a combination of individual attributes and interaction patterns may influence performance by drawing on theories of co-specialization.

The concept of co-specialization can be applied to executive recruiting at the level of the search team. The division of labor typically occurs between one recruiter focusing on the client side and a teammate focusing on the candidate side. Since searches involve an iterative matching process between client needs and the capabilities of available candidates, it is not possible to fully modularize tasks. As a result, the search process involves extensive communication between search team members.

Following the logic of co-specialization, I hypothesize that a recruiter's performance in the dimension in which he or she specializes will be higher during the study period when he or she communicates more with colleagues who are more highly skilled in the alternative dimension. At the organizational level, the resulting outcome may be a team assignment process that leads to the creation of higher and lower performing cliques.

Within the context of executive recruiting, performance is measured in the dimensions associated with landing and executing search contracts. The modal team size is two. A partner typically focuses more on landing contracts. A consultant typically focuses more on executing contracts. I use the proportions of email exchanged with each colleague as a measure of the informal strength of association and proportions of billing credit as a measure of the formal strength of association. I measure colleague skills by using lagged revenues, measured from the beginning of the contract data (Jan. 1, 1999) through the day before the start of the study (Aug. 22, 2002). I use these measures to construct a weighted average of the prior performance of the colleagues with whom a recruiter interacts. The weighting is proportional to the message share or contract share. For email interactions, two dimensions of performance and two directions of email flow give a total of four measures of colleague performance. Since the focal recruiter's performance is also measured in two dimensions, this yields a total of eight models. Formal interactions are not directional, so they are expressed in four models.

Regressions of interest for testing co-specialization effects involve split samples in which a recruiter's performance is compared to that of his or her peers. This leads to parallel hypotheses for consultants and partners. I hypothesize that one reason some consultants might execute more contracts is that they interact more with colleagues who are more successful at landing contracts. Likewise, among partners, I hypothesize that those who land more contracts may interact more with colleagues who are more successful at executing contracts. Stated formally:

Hypothesis 3a: Using email shares to weight interactions, partner bookings will be positively related to the lagged billing revenue of colleagues. Consultant billings will be positively related to the lagged booking revenue of colleagues.

A co-specialization effect could also show up directly in team assignment patterns. To test for this effect, I used billing shares as opposed to email patterns as weights. This leads to a similar hypothesis based on properties of the formal network:

Hypothesis 3b: Using billing shares to weight interactions, partner bookings will be positively related to the lagged billing revenue of colleagues. Consultant billings will be positively related to the lagged booking revenue of colleagues.

Coordination Theory Perspective: Email Response Times and Size

My last set of hypotheses considers the efficient movement of information through a network. I propose that frequent short communication outperforms infrequent lengthy communication. Load balancing models of queuing and network flow imply short jobs can be swapped in and attended to more quickly than long jobs of the same priority. Long jobs are more likely to cause a processor to block on a given task and so, given stochastic arrivals, may be attended to during periods of lower utilization. A human analog involving email may be a tendency of people to postpone or defer long messages until they have free time.

Media richness and organizational contingency theory offer additional reasons for why shorter, more frequent patterns of messages could be more efficient. Media richness theory suggests that as a relatively lean medium email is often most efficiently used for shorter communications, since more complex information could often be better conveyed through richer media such as face-to-face and phone that offer more interpretive cues

(Daft and Lengel 1984; Daft and Weick 1984; Daft and Lengel 1986). Contingency theory suggests shorter response times could be related to efficiency by reducing bottlenecks (Galbraith 1973; 1974; Thompson 1967).

I expect relationships between response times, messages sizes and performance will be most relevant in the context of search team activity. This suggests response times and message sizes in email exchanged between team members will on average be negatively associated with billing revenue. By adding the centrality measure that explains the most variation in billing revenues to the base model I am able to introduce a control for network structure. The hypotheses to be tested are:

Hypothesis 4a: Controlling for network structure, longer than average emails exchanged with team members will be negatively related to billings.

Hypothesis 4b: Controlling for network structure, longer than average response times in email communication with team members will be negatively related to billings.

Chapter 4

Results

In this chapter, I report regression results associated with my base model and hypothesis tests. I provide context and interpretation for these results in the discussion section of the next chapter. Results of analyses I conducted to develop my email measures can be found in the appendices.

Base Model

	Billing Shares (Full Year)						Booking Shares (Study)					
Parameter	B	Std. Error	Beta	t	Sig.	Adj. R^2	B	Std. Error	Beta	t	Sig.	Adj. R^2
Intercept	19.80 ***	6.96		2.84	0.01		4.59	5.52		0.83	0.41	
Yrs. of Exp.	-0.12 *	0.07	-0.33	-1.73	0.09		-0.05	0.05	-0.17	-1.01	0.32	
Yrs. of Ed.	-0.46	0.38	-0.20	-1.20	0.24		-0.09	0.30	-0.04	-0.30	0.77	
Gender (D)	-0.40	0.91	-0.07	-0.44	0.66		-0.04	0.72	-0.01	-0.06	0.95	
Partner (D)	-0.31	1.20	-0.05	-0.26	0.80		3.99 ***	0.95	0.73	4.20	0.00	
Sector A (D)	-2.09 *	1.21	-0.26	-1.73	0.09		-0.30	0.96	-0.04	-0.32	0.75	
Sector B (D)	-2.84	1.91	-0.23	-1.49	0.14		0.52	1.51	0.05	0.34	0.73	
						0.10						0.30

	Billing Revenue (Full Year)						Booking Revenue (Study)					
Parameter	B	Std. Error	Beta	t	Sig.	Adj. R^2	B	Std. Error	Beta	t	Sig.	Adj. R^2
Intercept	1,057,786 **	397,290		2.66	0.01		86,222	348,460		0.25	0.81	
Yrs. of Exp.	-6,718 *	3,876	-0.35	-1.73	0.09		-2,573	3,400	-0.12	-0.76	0.45	
Yrs. of Ed.	-22,818	21,755	-0.18	-1.05	0.30		3,510	19,081	0.03	0.18	0.85	
Gender (D)	-64,481	52,129	-0.19	-1.24	0.22		-9,188	45,722	-0.02	-0.20	0.84	
Partner (D)	66,404	68,539	0.20	0.97	0.34		273,033 ***	60,115	0.73	4.54	0.00	
Sector A (D)	-129,594 *	69,041	-0.29	-1.88	0.07		-16,204	60,555	-0.03	-0.27	0.79	
Sector B (D)	-9,587	108,700	-0.01	-0.09	0.93		124,594	95,340	0.16	1.31	0.20	
						0.03						0.40

N=47, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$
Table 4.1 Base model results

Values of coefficients in the base model are shown in the table above. As explained in the methodology chapter in the section on intertemporal reliability and definition of performance measures, I calculated bookings over the six month study period and billings over a full year beginning with the start of the study period. I used a longer period for billings to control for seasonal variation. Because the average length of a search is approximately six months, this corresponds with a measure of throughput involving both contracts that were in a recruiter's portfolio when the study began as well as those active during the study and completed within a reasonable period of time thereafter. I report the analyses that led to this choice of measures in Appendix C. Shares are shown in the top panels and refer to a count of the number of projects calculated by summing the shares of credit assigned by the firm. Revenues are shown in the bottom panels and reflect shares multiplied by contract revenues and then summed.

In models with billings as the dependent variable (left), the negative sign on years of experience reflects the influence of the dummy variable for partner. As recruiters gain more experience, they typically focus more on bookings as opposed to billings, so individual billings decline.[24] Recruiters in sector A accumulated fewer billing credits, which also corresponded with lower revenue. The opposite signs on the partner dummy in the billing shares and billing revenue regressions indicate that partners billed fewer searches, but generated more billing revenue. This implies that on average partners billed higher revenue contracts than consultants.

In models with bookings as the dependent variable (right), the partner dummy is highly significant. This is a selection effect. Recruiters are promoted to partner primarily on the basis of their ability to land contracts.

Years of education and gender are not significant in any of the regressions. For gender, male is coded as one, so the gender effect in all four models is towards higher performance among women. I used years of education as a human capital control while suggesting that it was likely to be a poor proxy in this setting. Theory predicts a positive sign. The sign is positive only with respect to booking revenue.

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[24] Surprisingly, the coefficient on years of experience was also negative for regressions involving booking revenue, although not significant. Plots show that recruiters with the most experience at each job level often have lower than expected performance. I tried fitting a quadratic and a quadratic with an interaction with the partner dummy, but these terms were not significant. Because of this I did not control for this effect in my base model. An interpretation is that performance may tail off at the end of a career. This effect appears to apply not only to partners, but also to consultants who do not make partner after an extended period of time.

Hypothesis 1 – Network Centrality

	Cutoff	Billing Shares B	S.E.	Beta	t	Sig.	Adj. R^2	Booking Shares B	S.E.	Beta	t	Sig.	Adj. R^2
Base Model							0.10						0.30
Structural Holes	1	0.17 **	0.07	0.39	2.21	0.03	0.18	0.14 **	0.06	0.37	2.36	0.02	0.38
	5	0.31 ***	0.08	0.59	4.03	0.00	0.35	0.12 *	0.07	0.25	1.70	0.10	0.34
	10	0.45 ***	0.11	0.54	3.95	0.00	0.34	0.24 **	0.10	0.31	2.38	0.02	0.38
	20	0.40 **	0.17	0.32	2.29	0.03	0.18	0.14	0.15	0.13	1.00	0.33	0.30
	40	0.52 **	0.22	0.32	2.33	0.03	0.19	0.24	0.19	0.17	1.32	0.19	0.32
Betweenness	1	1.08 **	0.51	0.31	2.11	0.04	0.17	0.28	0.43	0.09	0.65	0.52	0.29
	5	0.53 *	0.26	0.31	2.01	0.05	0.16	0.21	0.22	0.14	0.98	0.33	0.30
	10	0.38 *	0.19	0.29	1.95	0.06	0.16	0.22	0.16	0.19	1.40	0.17	0.32
	20	0.26 **	0.12	0.30	2.09	0.04	0.17	0.06	0.10	0.08	0.57	0.57	0.29
	40	0.12	0.09	0.19	1.30	0.20	0.11	0.00	0.08	0.01	0.04	0.97	0.29
Indegree	1	0.22 ***	0.07	0.51	2.95	0.01	0.24	0.15 **	0.06	0.40	2.56	0.01	0.39
	5	0.23 **	0.09	0.42	2.65	0.01	0.22	0.12	0.07	0.23	1.62	0.11	0.33
	10	0.35 **	0.13	0.41	2.70	0.01	0.22	0.22 **	0.10	0.29	2.10	0.04	0.36
	20	0.35 **	0.17	0.30	2.11	0.04	0.17	0.11	0.14	0.10	0.79	0.44	0.30
	40	0.52 **	0.26	0.29	2.03	0.05	0.16	0.22	0.21	0.14	1.05	0.30	0.31
Outdegree	1	0.20 ***	0.06	0.52	3.43	0.00	0.29	0.11 **	0.05	0.31	2.16	0.04	0.36
	5	0.26 ***	0.06	0.58	4.31	0.00	0.37	0.08	0.06	0.20	1.44	0.16	0.32
	10	0.39 ***	0.10	0.52	4.02	0.00	0.35	0.15 *	0.09	0.23	1.72	0.09	0.34
	20	0.36 **	0.15	0.35	2.45	0.02	0.20	0.19	0.12	0.20	1.57	0.13	0.33
	40	0.48 **	0.20	0.34	2.42	0.02	0.20	0.16	0.17	0.13	0.96	0.34	0.30
Contract Network													
Structural Holes	NA	0.16	0.18	0.15	0.90	0.37	0.09	0.16	0.14	0.16	1.12	0.27	0.31
Betweenness	NA	0.30	0.37	0.13	0.80	0.43	0.09	0.25	0.30	0.12	0.84	0.41	0.30
Degree	NA	0.13	0.16	0.14	0.82	0.42	0.09	0.15	0.13	0.17	1.16	0.25	0.31

N = 47 recruiters, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

	Cutoff	Billing Revenue B	S.E.	Beta	t	Sig.	Adj. R^2	Booking Revenue B	S.E.	Beta	t	Sig.	Adj. R^2
Base Model							0.03						0.40
Structural Holes	1	7,638 *	4,370	0.33	1.75	0.09	0.08	8,168 **	3,759	0.32	2.17	0.04	0.45
	5	12,473 **	4,736	0.44	2.63	0.01	0.16	4,648	4,446	0.15	1.05	0.30	0.40
	10	21,311 ***	6,900	0.46	3.09	0.00	0.20	10,609	6,534	0.21	1.62	0.11	0.42
	20	17,169	10,229	0.25	1.68	0.10	0.07	5,397	9,250	0.07	0.58	0.56	0.39
	40	19,141	13,303	0.22	1.44	0.16	0.06	8,933	11,888	0.09	0.75	0.46	0.39
Betweenness	1	41,929	30,229	0.22	1.39	0.17	0.05	13,068	27,079	0.06	0.48	0.63	0.39
	5	23,424	15,239	0.25	1.54	0.13	0.06	9,318	13,684	0.09	0.68	0.50	0.39
	10	20,795 *	11,046	0.29	1.88	0.07	0.09	11,354	9,954	0.14	1.14	0.26	0.40
	20	9,472	7,352	0.20	1.29	0.21	0.05	1,639	6,579	0.03	0.25	0.80	0.39
	40	4,800	5,448	0.14	0.88	0.38	0.03	-1,096	4,823	-0.03	-0.23	0.82	0.39
Indegree	1	9,794 **	4,361	0.42	2.25	0.03	0.12	7,994 **	3,858	0.31	2.07	0.04	0.45
	5	9,895 *	5,261	0.32	1.88	0.07	0.09	4,827	4,756	0.14	1.01	0.32	0.40
	10	15,995 **	7,530	0.34	2.12	0.04	0.11	10,195	6,783	0.20	1.50	0.14	0.42
	20	16,469 *	9,601	0.26	1.72	0.09	0.08	4,769	8,699	0.07	0.55	0.59	0.39
	40	19,512	15,034	0.20	1.30	0.20	0.05	7,187	13,418	0.07	0.54	0.60	0.39
Outdegree	1	8,713 **	3,495	0.41	2.49	0.02	0.14	5,269	3,191	0.22	1.65	0.11	0.42
	5	10,375 **	3,889	0.41	2.67	0.01	0.16	2,343	3,690	0.08	0.63	0.53	0.39
	10	17,366 ***	5,928	0.42	2.93	0.01	0.19	5,547	5,674	0.12	0.98	0.33	0.40
	20	14,005	8,761	0.24	1.60	0.12	0.07	6,799	7,857	0.11	0.87	0.39	0.40
	40	16,584	11,846	0.22	1.40	0.17	0.06	3,242	10,635	0.04	0.30	0.76	0.39
Contract Network													
Structural Holes	NA	15,063	10,227	0.25	1.47	0.15	0.06	15,931 *	8,856	0.23	1.80	0.08	0.43
Betweenness	NA	25,554	21,091	0.20	1.21	0.23	0.04	24,921	18,417	0.18	1.35	0.18	0.41
Degree	NA	13,608	9,028	0.26	1.51	0.14	0.06	14,626 *	7,802	0.25	1.87	0.07	0.44

N = 47 recruiters, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table 4.2 Hypothesis 1a-c results.

Hypothesis 1a: Centrality in a recruiter's internal email network will be positively related to performance.

Hypothesis 1b: The statistical significance of relationships between centrality and performance will vary based on the way centrality is calculated. Changes in the tie strength cutoff will lead to greater variation in the statistical significance of results than changes in the centrality metric.

In the presentation of results on the preceding page, dependent variables calculated as project shares are shown in the top panels and dependent variables calculated as revenues are shown in the bottom panels. Billings are on the left and billings are on the right. For a given email metric, the statistically strongest tie strength value is shaded. For contract measures, the statistically strongest metric is shaded.

Billing shares (top left) are positively associated with centrality in the organizational email network at statistically significant levels ($p < 0.10$) across all combinations of metrics and tie strengths except betweenness centrality using a cutoff of 40 or more emails ($p < 0.20$). Billing revenues (bottom left) are also positively associated with centrality, although the level of significance is consistently lower. The significance is generally marginal at cutoffs of 20 or more emails and above. The stronger effect in the direction of shares indicates that email network centrality is more strongly related to the number of searches than the revenue associated with those searches.

Although the sign of relationships between booking revenue and centrality in the email network is almost always positive, these relationships are only statistically significant when low tie strength cutoffs are used. As with billings, these relationships are statistically stronger when performance is measured in terms of shares than revenues. Only structural holes and indegree at the greater than one email cutoff are related to booking revenue at a statistically significant level (both $p < 0.05$). Betweenness centrality is not related to booking revenue at statistically significant levels.

Results vary in both the dimensions of tie strength and metrics. The relationship between centrality and billing shares is statistically significant across a wide range of tie strengths, while relationships with bookings are only significant when relatively weak ties are included. Of the four centrality metrics, the weakest relationships in terms of statistical significance are observed with respect to betweenness centrality. Some minor differences appear among the degree measures. Because these are directional, differences can potentially give some indication of the most likely direction of causality. With respect to bookings, coefficient values and significance levels associated with indegree are generally higher; with respect to billings, significance levels with respect to outdegree are generally higher.

Hypothesis 1c: The relationship between network centrality and revenue will be stronger with respect to the email network than the contract network.

The results suggest that centrality in the contract and email networks are related to performance in different ways. Relationships involving centrality in the contract network are only statistically significant with respect to booking revenue. The relationship with the contract network degree measure indicates that the number of teammates is positively related to booking revenue. It is not related to any of the other performance metrics.

Some statistically significant relationships exist between centrality in the email network and all four performance measures. Centrality in the email network is most strongly related to billing shares, which indicate the number of projects completed. At tie strength cutoffs of 10 emails and below, centrality in the email network is generally related to billing revenue and booking shares for all metrics except betweenness centrality. The only statistically significant relationships between email network centrality and booking revenue occur with respect to structural holes and indegree at the greater than or equal to one email cutoff.

In support of hypothesis 1c, the results suggest that ties present in the email network but the formal network explain some of the variation in individual performance measures. They most strongly suggest the number of colleagues a recruiter communicates with over email plays a role in executing contracts that extends beyond relationships found in the contract network. The relationship between booking revenue and activity in the email network is less clear. Booking revenue is related to centrality measures that count any email communication as a tie. But booking revenue is not related to the number of colleagues a recruiter frequently communicates with over email.

Hypothesis 1d: Centrality measures based on strong ties will be positively associated with billing performance. Centrality measures that include weak ties will be positively associated with booking performance involving both new and existing clients.

		Repeat Bookings Shares						New Booking Shares					
	Cutoff	B	S.E.	Beta	t	Sig.	Adj. R^2	B	S.E.	Beta	t	Sig.	Adj. R^2
Base Model							0.28						0.17
Structural Holes	1	0.14 ***	0.04	0.48	3.18	0.00	0.41	0.00	0.03	0.00	-0.03	0.98	0.15
	5	0.11 **	0.05	0.32	2.18	0.04	0.34	0.00	0.03	0.01	0.07	0.94	0.15
	10	0.19 **	0.08	0.32	2.39	0.02	0.36	0.05	0.05	0.17	1.11	0.28	0.17
	20	0.12	0.11	0.15	1.10	0.28	0.28	0.02	0.06	0.05	0.32	0.75	0.15
	40	0.17	0.15	0.15	1.17	0.25	0.29	0.07	0.08	0.13	0.90	0.37	0.16
Betweenness	1	0.42	0.33	0.17	1.26	0.21	0.29	-0.14	0.19	-0.11	-0.74	0.46	0.16
	5	0.21	0.17	0.18	1.28	0.21	0.29	0.00	0.10	0.00	-0.02	0.99	0.15
	10	0.19	0.12	0.21	1.56	0.13	0.31	0.03	0.07	0.06	0.41	0.69	0.15
	20	0.05	0.08	0.08	0.59	0.56	0.27	0.01	0.05	0.04	0.25	0.80	0.15
	40	0.01	0.06	0.02	0.18	0.86	0.26	-0.01	0.03	-0.03	-0.22	0.83	0.15
Indegree	1	0.15 ***	0.04	0.50	3.29	0.00	0.42	0.01	0.03	0.04	0.21	0.83	0.15
	5	0.10 *	0.06	0.25	1.72	0.09	0.31	0.02	0.03	0.10	0.62	0.54	0.16
	10	0.16 *	0.08	0.27	1.95	0.06	0.33	0.06	0.05	0.19	1.25	0.22	0.18
	20	0.12	0.11	0.15	1.11	0.27	0.29	-0.01	0.06	-0.03	-0.18	0.86	0.15
	40	0.19	0.16	0.15	1.14	0.26	0.29	0.03	0.09	0.05	0.37	0.72	0.15
Outdegree	1	0.10 **	0.04	0.37	2.65	0.01	0.38	0.01	0.02	0.05	0.31	0.76	0.15
	5	0.08 *	0.04	0.26	1.83	0.07	0.32	0.00	0.03	0.01	0.06	0.95	0.15
	10	0.12 *	0.07	0.24	1.82	0.08	0.32	0.03	0.04	0.10	0.67	0.51	0.16
	20	0.12	0.10	0.17	1.24	0.22	0.29	0.07	0.05	0.19	1.33	0.19	0.18
	40	0.09	0.13	0.09	0.69	0.50	0.27	0.07	0.07	0.14	0.96	0.34	0.17

N = 47 recruiters, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

		Repeat Bookings Revenue						New Booking Revenue					
	Cutoff	B	S.E.	Beta	t	Sig.	Adj. R^2	B	S.E.	Beta	t	Sig.	Adj. R^2
Base Model													
Structural Holes	1	6,980 **	2,626	0.38	2.66	0.01	0.46	662	1,871	0.06	0.35	0.73	0.21
	5	4,953	3,133	0.22	1.58	0.12	0.40	-582	2,121	-0.04	-0.27	0.79	0.21
	10	9,409 **	4,600	0.26	2.05	0.05	0.42	768	3,177	0.04	0.24	0.81	0.21
	20	6,700	6,574	0.13	1.02	0.31	0.38	-1,275	4,370	-0.04	-0.29	0.77	0.21
	40	6,259	8,526	0.09	0.73	0.47	0.37	3,186	5,615	0.08	0.57	0.57	0.22
Betweenness	1	17,928	19,260	0.12	0.93	0.36	0.37	-6,511	12,746	-0.07	-0.51	0.61	0.22
	5	10,167	9,734	0.14	1.04	0.30	0.38	-1,730	6,475	-0.04	-0.27	0.79	0.21
	10	10,965	7,039	0.20	1.56	0.13	0.40	-27	4,765	0.00	-0.01	1.00	0.21
	20	2,050	4,709	0.05	0.44	0.67	0.36	-131	3,100	-0.01	-0.04	0.97	0.21
	40	-409	3,459	-0.01	-0.12	0.91	0.36	-671	2,270	-0.04	-0.30	0.77	0.21
Indegree	1	7,428 ***	2,661	0.41	2.79	0.01	0.47	94	1,914	0.01	0.05	0.96	0.21
	5	4,345	3,384	0.18	1.28	0.21	0.39	143	2,269	0.01	0.06	0.95	0.21
	10	8,484 *	4,814	0.23	1.76	0.09	0.41	1,230	3,279	0.06	0.38	0.71	0.22
	20	6,586	6,172	0.13	1.07	0.29	0.38	-1,833	4,101	-0.06	-0.45	0.66	0.22
	40	8,425	9,561	0.11	0.88	0.38	0.37	-289	6,341	-0.01	-0.05	0.96	0.21
Outdegree	1	4,670 **	2,245	0.28	2.08	0.04	0.42	396	1,553	0.04	0.26	0.80	0.21
	5	2,970	2,617	0.15	1.13	0.26	0.38	-722	1,743	-0.06	-0.41	0.68	0.22
	10	5,566	4,020	0.17	1.38	0.17	0.39	-156	2,704	-0.01	-0.06	0.95	0.21
	20	5,002	5,630	0.11	0.89	0.38	0.37	2,027	3,721	0.08	0.54	0.59	0.22
	40	1,148	7,632	0.02	0.15	0.88	0.36	2,881	4,992	0.08	0.58	0.57	0.22

N = 47 recruiters, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table 4.3 Hypothesis 1d results

In table 4.3, dependent variables calculated as shares are shown in the top panel and dependent variables calculated as revenues are shown in the bottom panel. No statistically significant relationships were found between email centrality measures and revenue associated with new client bookings (right panels). Booking revenue from repeat clients is positively associated with some centrality measures at cutoffs of greater than or equal to one and 10 emails. As cutoffs increased, significance levels declined. In regressions that used booking revenue associated with repeat clients as the dependent variable, all centrality metrics except one have positive signs; in regressions that used booking revenue with new clients as the dependent variable, signs were mixed.

These results suggest a relationship between weak email ties and repeat client bookings. Significance levels are also slightly stronger with respect to indegree as opposed to outdegree, but because these differences are minor it not clear how much weight should be placed on them in interpreting results.

Although almost all email centrality measures in regressions involving repeat bookings had positive signs, they ceased to be statistically significant above cutoffs of 10 emails. In contrast, in regressions involving billing revenue, centrality measures at the 20 email cutoff were close to $p < 0.10$. In regressions involving billing shares, centrality measures with the exception of betweenness were significant at $p < 0.10$.

Consistent with the first part of hypothesis 1d, the results suggest that centrality involving strong ties is related to billings. Stronger ties are related the execution of more projects as opposed to the execution of projects involving more revenue. In contrast the second part of hypothesis 1d, centrality in the email network was not related to booking revenue associated with new clients.

Hypothesis 2 – Exploration and Exploitation

Booking Shares

	B	S.E.	SB	t	Sig.	Adj. R^2	Sig. F Change
Revenue base model						0.30	
Hypothesis 2a							
Proportion of messages to recruiters with no previous contracts in common	-4.19	3.56	-0.17	-1.18	0.25	0.31	0.245
" "	-11.21 ***	3.96	-0.45	-2.84	0.01		
" " * consultant dummy	19.17 ***	6.25	0.86	3.07	0.00	0.43	0.008
Hypothesis 2b							
Share of email communication sent to partners	-12.06 **	4.64	-0.38	-2.60	0.01	0.39	0.013
" "	-9.47	10.86	-0.30	-0.87	0.39		
" " * consultant dummy	-3.21	12.16	-0.14	-0.26	0.79	0.38	0.046
Hypothesis 2c							
Proportion of internal messages sent to consultants	9.94 ***	2.75	0.43	3.62	0.00	0.47	0.001
" "	9.21 **	4.83	0.40	1.91	0.06		
" " * partner dummy	1.15	6.23	0.07	0.19	0.85	0.45	0.004

N = 47 recruiters, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Booking Revenue

	B	S.E.	Beta	t	Sig.	Adj. R^2	Sig. F Change
Revenue base model							
Hypothesis 2a							
Proportion of messages to recruiters with no previous contracts in common	-211,291	225,988	-0.13	-0.93	0.36	0.40	0.36
" "	-625,010 **	255,645	-0.37	-2.44	0.02		
" " * consultant dummy	1,129,895 ***	404,032	0.74	2.80	0.01	0.49	0.02
Hypothesis 2b							
Share of email communication sent to partners	-699,539 **	296,603	-0.32	-2.36	0.02	0.46	0.02
" "	-1,034,953	693,220	-0.48	-1.49	0.14		
" " * consultant dummy	416,270	775,983	0.27	0.54	0.59	0.45	0.07
Hypothesis 2c							
Proportion of internal messages sent to consultants	595,244 ***	176,319	0.38	3.38	0.00	0.52	0.00
" "	624,055 *	310,129	0.39	2.01	0.05		
" " * partner dummy	-45,447	399,952	-0.04	-0.11	0.91	0.51	0.01

N = 47 recruiters, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table 4.4 Hypothesis 2a-2c results

Hypothesis 2a: Among consultants, but not partners, the proportion of messages sent to colleagues they have never worked with on projects will be positively related to bookings.

Hypothesis 2b: Among consultants, but not partners, the diversity of communication with partners will be positively related to bookings.

Hypothesis 2c: Among partners, but not consultants, bookings will be positively related to the proportion of email sent to consultants.

Hypothesis group 2 predicts job level differences in relationships between information flows and bookings (2a-c) and self-reported information behaviors and structural holes (2d-f). I tested each hypothesis by comparing two models. The first model included the base model and treatment with no distinction made between job level; the second model (below the dashed line) included the base model, treatment and an interaction between the treatment and a job level dummy variable. Shading indicates the relevant model for interpreting results. For hypotheses 2 a-c, results involving both booking revenue and shares were similar.

As shown above, for hypothesis 2a, both the treatment and the interaction term are significant when estimated together. For consultants, exchanging a greater proportion of emails with colleagues they have never formally worked with on contracts is positively related to booking revenue and shares ($p < 0.01$); for partners, it is negatively related.

For hypotheses 2b and 2c, the treatments are significant, but the interactions are insignificant. This is interpreted as a significant effect, but not one that differs by job level, indicating partial support for the respective hypotheses. A negative Herfindahl indicates a more diverse message share, so the interpretation of the hypotheses 2b result is that a more diffuse pattern of email communication to partners is positively related to booking revenue and shares.

Taken together, the hypothesized positive relationships between proportions of email activity and performance of consultants and partners were all found to be at least weakly significant. However, both the diversity of message share sent to partners and the proportion of email sent to consultants were found to be significant predictors for both groups.

However, the latter result can also be interpreted as a job level difference between recruiters in that higher performing consultants are communicating proportionally more with their peers over email, while higher performing partners are communicating more with subordinates.

Structural Holes (ge10)

	B	S.E.	Beta	t	Sig.	Adj. R^2	Sig. F Change
Controls							
Constant	13.59	8.56		1.59	0.12		
Yrs. of Experience	-0.26 ***	0.09	-0.58	-2.89	0.01		
Yrs. of Education	-0.18	0.47	-0.07	-0.40	0.69		
Gender	1.51	1.24	0.20	1.22	0.23		
Partner (Dummy)	2.19	1.53	0.29	1.43	0.16		
Sector A (Dummy)	-2.23	1.51	-0.24	-1.47	0.15		
Sector B (Dummy)	-3.52	2.36	-0.25	-1.49	0.15		
Base Model Total						0.10	
Hypothesis 2d							
I volunteer all relevant information to colleagues	-0.69	0.59	-0.19	-1.18	0.25	0.11	0.25
" "	-1.43 **	0.69	-0.39	-2.07	0.05		
" " * partner (dummy)	2.16 *	1.16	1.66	1.86	0.07	0.17	0.10
Hypothesis 2e							
Self-reported contacts in private rolodex (1000s)	1.23	1.26	0.18	0.98	0.34	0.13	0.34
" "	0.46	2.11	0.07	0.22	0.83		
" " * consultant (dummy)	1.15	2.48	0.15	0.46	0.65	0.11	0.57
Hypothesis 2f							
Type of information exchanged (Procedural vs. Declarative)	-0.10	0.48	-0.04	-0.20	0.84	0.11	0.84
" "	1.70 **	0.67	0.64	2.54	0.02		
" " * partner (dummy)	-2.86 ***	0.83	-1.57	-3.45	0.00	0.34	0.01

N = 40 recruiters, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table 4.5 Hypothesis 2d-2f results.

Hypothesis 2d: Among partners, but not consultants, structural holes will be positively related to information sharing.

Hypotheses 2e: Among consultants, but not partners, structural holes will be positively related to the number of contacts privately held in personal rolodexes.

Hypothesis 2f: Among consultants, procedural information sharing will be positively related to structural holes; among partners, declarative information sharing will be positively related to structural holes.

Hypotheses 2d-2f involve relationships with network position, measured as the value of structural holes using a cutoff of greater than or equal to 10 emails (ge10). Hypothesis 2d, predicting that among partners the self-reported willingness to share information would be positively related to structural holes, was supported ($p < 0.10$). However, the result is very sensitive to a single outlier. If the outlier is removed, then the interaction is not significant and the relationship between structural holes and information sharing is marginally positive ($p < 0.20$). Since structural holes were strongly correlated with the number of colleagues in a recruiter's email network (degree measures), this is weak evidence that information sharing may be positively related to the size of recruiters' internal email networks. Hypothesis 2e, predicting that for consultants, the number of contacts in private rolodexes would be positively associated with structural holes was not supported.[25]

Relationships between the type of information shared and structural holes were significant for both groups with opposite signs, consistent with hypothesis 3f. For consultants, exchanging a greater proportion of procedural information was positively associated with structural holes, while for partners exchanging a greater proportion of declarative information was positively associated with structural holes.[26]

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[25] The survey question asked: "how many people are in your personal Rolodex, DayTimer or PalmPilot?" The sample size for this question was slightly smaller, N=37 recruiters (base model Adj. R^2=0.13) because of survey non-response.

[26] The survey question was: "the information content I share with others is typically: declarative…procedural." This was explained with the further clarification: Declarative means factual data such as "Bob has 1995 MBA from Wharton." Procedural means a know-how tip such as how to let a candidate down gracefully when he/she did not get the job.

Hypothesis 3 – Co-Specialization Effects

Relationships between recruiter performance and that of colleagues with whom they communicate

	Billing Shares						Booking Shares					
	B	S.E.	Beta	t	Sig.	Adj. R^2	B	S.E.	Beta	t	Sig.	Adj. R^2
All												
Base Model						0.10						0.30
Email In * Billings	0.29	0.27	0.24	1.09	0.28	0.10	-0.19	0.21	-0.17	-0.89	0.38	0.30
Email Out * Billings	-0.12	0.29	-0.09	-0.43	0.67	0.08	-0.33	0.22	-0.27	-1.50	0.14	0.32
Email In * Bookings	-0.04	0.14	-0.05	-0.30	0.77	0.08	-0.31 ***	0.10	-0.38	-3.00	0.00	0.42
Email Out * Bookings	-0.14	0.14	-0.16	-1.04	0.31	0.10	-0.38 ***	0.09	-0.48	-4.13	0.00	0.50
Consultants Only												
Base Model						-0.01						-0.24
Email In * Billings	0.35	0.33	0.39	1.08	0.29	0.00	-0.10	0.25	-0.17	-0.41	0.68	-0.27
Email Out * Billings	0.06	0.38	0.06	0.16	0.88	-0.07	-0.43	0.26	-0.61	-1.67	0.11	-0.11
Email In * Bookings	0.29	0.19	0.35	1.54	0.14	0.06	-0.15	0.14	-0.27	-1.07	0.30	-0.21
Email Out * Bookings	0.29	0.22	0.32	1.34	0.20	0.03	-0.34 **	0.15	-0.54	-2.26	0.04	0.00
Partners Only												
Base Model						-0.06						0.03
Email In * Billings	0.28	0.53	0.18	0.53	0.60	-0.11	-0.32	0.41	-0.25	-0.79	0.44	0.00
Email Out * Billings	-0.39	0.60	-0.20	-0.65	0.53	-0.10	-0.26	0.47	-0.16	-0.55	0.59	-0.02
Email In * Bookings	-0.40	0.30	-0.42	-1.33	0.20	-0.01	-0.48 **	0.21	-0.62	-2.22	0.04	0.22
Email Out * Bookings	-0.41 *	0.21	-0.50	-1.99	0.06	0.10	-0.40 **	0.15	-0.59	-2.71	0.02	0.30

Past revenues in 100,000s
N = 47 recruiters, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

	Billing Revenue						Booking Revenue					
	B	S.E.	Beta	t	Sig.	Adj. R^2	B	S.E.	Beta	t	Sig.	Adj. R^2
All												
Base Model						0.03						0.40
Email In * Billings	0.14	0.15	0.22	0.95	0.35	0.03	-0.15	0.13	-0.20	-1.10	0.28	0.40
Email Out * Billings	-0.06	0.16	-0.08	-0.38	0.71	0.01	-0.17	0.14	-0.21	-1.23	0.23	0.41
Email In * Bookings	0.02	0.08	0.04	0.24	0.81	0.01	-0.15 **	0.07	-0.27	-2.21	0.03	0.45
Email Out * Bookings	-0.04	0.08	-0.09	-0.56	0.58	0.02	-0.17 **	0.06	-0.31	-2.65	0.01	0.48
Consultants Only												
Base Model						-0.01						-0.24
Email In * Billings	0.34	0.18	0.66	1.95	0.07	0.11	-0.03	0.13	-0.08	-0.21	0.84	-0.31
Email Out * Billings	0.17	0.21	0.28	0.80	0.44	-0.05	-0.18	0.14	-0.47	-1.21	0.24	-0.21
Email In * Bookings	0.20 *	0.11	0.42	1.89	0.07	0.10	-0.07	0.08	-0.24	-0.92	0.37	-0.25
Email Out * Bookings	0.18	0.12	0.34	1.46	0.16	0.03	-0.16 *	0.08	-0.47	-1.89	0.08	-0.09
Partners Only												
Base Model						-0.06						0.14
Email In * Billings	-0.08	0.30	-0.09	-0.27	0.79	-0.07	-0.30	0.26	-0.34	-1.16	0.26	0.16
Email Out * Billings	-0.32	0.33	-0.28	-0.95	0.36	-0.02	-0.13	0.31	-0.12	-0.43	0.67	0.09
Email In * Bookings	-0.08	0.18	-0.15	-0.47	0.65	-0.06	-0.13	0.16	-0.25	-0.84	0.41	0.12
Email Out * Bookings	-0.14	0.13	-0.28	-1.08	0.30	0.00	-0.12	0.11	-0.25	-1.05	0.31	0.15

N = 47 recruiters, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table 4.6 Hypothesis 3a results.

Hypothesis 3a: Using email shares to weight interactions, partner bookings will be positively related to the lagged billing revenue of colleagues. Consultant billings will be positively related to the lagged booking revenue of colleagues.

	Billing Shares						Booking Shares					
	B	S.E.	Beta	t	Sig.	Adj. R^2	B	S.E.	Beta	t	Sig.	Adj. R^2
All												
Base Model						0.10						0.30
Contracts * Billings	-0.13	0.17	-0.13	-0.78	0.44	0.09	-0.29 **	0.12	-0.32	-2.38	0.02	0.38
Contracts * Bookings	0.05	0.07	0.16	0.76	0.45	0.09	-0.14 ***	0.05	-0.48	-2.79	0.01	0.41
Consultants Only												
Base Model						-0.01						-0.24
Contracts * Billings	0.00	0.22	0.00	0.00	1.00	-0.70	-0.30 **	0.14	-0.52	-2.11	0.05	-0.03
Contracts * Bookings	0.07	0.08	0.18	0.81	0.43	-0.03	-0.07	0.06	-0.30	-1.24	0.23	-0.19
Partners Only												
Base Model						-0.06						0.03
Contracts * Billings	-0.34	0.29	-0.28	-1.17	0.26	-0.04	-0.29	0.22	-0.29	-1.30	0.21	0.07
Contracts * Bookings	0.06	0.15	0.10	0.39	0.71	-0.12	-0.28 ***	0.10	-0.56	-2.96	0.01	0.34

Past revenues in 100,000s
N = 47 recruiters, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

	Billing Revenue						Booking Revenue					
	B	S.E.	Beta	t	Sig.	Adj. R^2	B	S.E.	Beta	t	Sig.	Adj. R^2
All												
Base Model						0.03						0.40
Contracts * Billings	0.00	0.09	0.00	-0.01	0.99	0.01	-0.10	0.08	-0.17	-1.28	0.21	0.41
Contracts * Bookings	0.01	0.04	0.07	0.33	0.74	0.01	-0.10 ***	0.03	-0.48	-3.05	0.00	0.50
Consultants Only												
Base Model						-0.01						-0.24
Contracts * Billings	0.06	0.12	0.11	0.45	0.66	-0.07	-0.15 *	0.08	-0.49	-1.95	0.07	-0.08
Contracts * Bookings	0.04	0.05	0.18	0.81	0.43	-0.04	-0.05	0.03	-0.39	-1.66	0.12	-0.14
Partners Only												
Base Model						-0.06						0.14
Contracts * Billings	-0.08	0.17	-0.11	-0.48	0.64	-0.06	-0.03	0.15	-0.04	-0.19	0.85	0.09
Contracts * Bookings	-0.02	0.09	-0.06	-0.23	0.82	-0.07	-0.18 **	0.06	-0.52	-2.93	0.01	0.42

N = 47 recruiters, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table 4.7 Hypothesis 3b results.

Hypothesis 3b: Using billing shares to weight interactions, partner bookings will be positively related to the lagged billing revenue of colleagues. Consultant billings will be positively related to the lagged booking revenue of colleagues.

Hypothesis 3 predicts that a recruiter's performance in one dimension will be positively related to the performance of colleagues in the alternate dimension. The two parts differ in weights I used to represent interactions between a recruiter and his or her colleagues. In part a, I used proportions of email communication as weights. In part b, I used billing credits. The latter measure reflects formal team assignment. The former measure reflects all interactions that occurred among consultants and partners over email, including those outside the project team. In the tables, I shaded results that pertain directly to hypothesized co-specialization effects.

Among consultants, the results have the predicted sign, but only one is statistically significant. The relationship between billing revenue and received email is significant ($p < 0.10$). The other three e-mail based measures relating consultant billings to the bookings of colleagues are marginally significant ($p < 0.20$). Neither of the contract weighted measures is significant. Among partners, the sign of the results is opposite the prediction of hypothesis 3. None of my hypothesized results involving partners are significant. The results suggest consultants who have higher billing revenue receive more email from colleagues who had more booking revenue in the past. But they do not suggest co-specialization as I intended to measure it. Instead, a recruiter's booking performance appears to be negatively related to the previous booking performance of the colleagues with whom a recruiter interacts.

In the full population, I expected to find a strong negative relationship between a recruiter's booking performance and the past booking revenues of colleagues. This effect is significant for interactions measured using both email and contract data (at least $p < 0.05$). This reflects the hierarchical composition of a typical search team. Partners usually generate more booking revenue than consultants. Since the majority of emails were exchanged within search teams, I expected that email exchanges would also follow this hierarchical pattern.

I split the sample to perform a peer level comparison as a way of controlling for this effect. Associations between a recruiter's booking revenue and the lagged bookings of colleagues were also negative in both split samples. Among partners, results that used contract shares to represent interactions were significant ($p < 0.01$). When I used email to represent interactions with colleagues, partner performance was significant when measured in terms of booking shares ($p < 0.05$), but not booking revenue. Among consultants, results involving email sent to colleagues were significant, at $p < 0.05$ for booking shares and $p < 0.10$ for booking revenue. These results suggest a team assignment process in which recruiters with higher bookings were more likely to work and communicate over email with colleagues who had lower bookings, as opposed to higher billings. I can push my interpretation further by considering nuances in the data and results.

To further interpret results involving contract shares in terms of team assignment effects, I believe it may be useful to consider a tradeoff between availability and experience. The lagged booking revenue of an individual recruiter may be interpreted as a proxy for availability. Recruiters who have landed fewer contracts in the past are likely to land fewer contracts during the study period. They are therefore more likely to be available to provide assistance in search execution. The lagged billing revenue of an individual recruiter may be interpreted as a proxy for experience. Support from a more experienced colleague would presumably be more desirable, subject to the constraint that a potential teammate must also be available and not working on his or her own contracts. Among consultants, bookings are negatively related to the lagged billings of colleagues, a potential experience proxy, at statistically significant levels ($p < 0.05$ for shares, $p < 0.10$ for revenues). This suggests that among consultants, those with the highest bookings have the least experienced teammates. Among partners, booking shares are negatively related to lagged billings of colleagues at $p < 0.20$, but booking revenues are almost completely unrelated. This difference suggests partners who pursue higher revenue contracts may be able to select teammates who have relatively more experience. From the perspective of a more experienced colleague, the opportunity to join a partner on a higher revenue search would also presumably be more attractive. These interpretations of differences across performance measures and job levels are consistent with the results. They suggest a fairly subtle team assignment effect that I might be able to identify more clearly in future work.

To further interpret the results involving email shares, I believe it is important to consider the roles played by two outliers. One outlier involves probable measurement error in the email share values of a consultant. The consultant opted out of the email portion of the study. She also participated on the only search in which both team members opted out. Only one email is recorded for this search, almost certainly an underestimate. This recruiter's teammate had a relatively low level of lagged booking revenue. Correcting this missing data error would increase the significance of the consultant results. Further evidence that measurement error may affect this observation comes from considering the contract share weighted results, for which I have no reason to believe there is measurement error. This consultant does not appear as an outlier in these results. The other outlier is the CEO of the firm, who is an outlier in both email and performance dimensions.

If I exclude both of these outliers, Email Out * Bookings is significant for both consultants and partners ($p < 0.10$ for partner booking revenue, $p < 0.01$ for the other three combinations of email and performance measures). Email In * Bookings is significant for partner booking shares ($p < 0.05$) and consultant booking revenue ($p < 0.10$). It is marginally significant for consultant booking shares ($p < 0.15$) and not significant for partner booking revenue ($p < 0.30$). All of the signs are negative. All of the results are stronger in the direction of outgoing email than incoming email. The interpretation of this potential directional effect is unclear. However, there is a potential interpretation for the one result that is not significant. If partners with the highest booking revenue also received the most unsolicited email from colleagues outside the search team that effect would be consistent with this pattern of results.

My motivation for hypothesis 3 came from a desire to consider potential implications of the team selection process on individual performance. Consultant billing revenues are positively related to the booking revenues of colleagues from whom consultants receive email. However, I also observed a negative relationship between a recruiter's booking revenue and booking revenues of colleagues with whom he or she interacts at both job levels. One potential explanation is a team assignment process in which recruiters who land the most contracts seek billing assistance from colleagues primarily on the basis of availability as opposed to complementary skills.

Hypothesis 4 – Network Efficiencies: Email Size and Response Times

	Billing Shares						Booking Shares					
	B	S.E.	Beta	t	Sig.	Adj. R^2	B	S.E.	Beta	t	Sig.	Adj. R^2
Base Model + Structural holes (GE10)						0.34						0.38
Team												
Sent												
All	-0.74	0.82	-0.12	-0.90	0.37	0.34	0.50	0.72	0.09	0.70	0.49	0.37
No Attachments	-0.24	0.87	-0.04	-0.28	0.78	0.32	0.67	0.76	0.11	0.89	0.38	0.37
Attachments Only	0.21	0.96	0.03	0.22	0.83	0.23	0.78	0.85	0.12	0.91	0.37	0.40
% Attachments	-0.07 *	0.04	-0.23	-1.74	0.09	0.37	0.00	0.04	0.02	0.13	0.90	0.36
Received												
All	-0.18	0.95	-0.03	-0.19	0.85	0.32	0.99	0.82	0.16	1.21	0.23	0.38
No Attachments	0.78	0.96	0.11	0.81	0.42	0.33	1.38	0.82	0.22	1.68	0.10	0.40
Attachments Only	1.83	1.76	0.15	1.04	0.31	0.30	1.35	1.55	0.12	0.87	0.39	0.40
% Attachments	-0.01	0.04	-0.05	-0.38	0.70	0.32	0.03	0.03	0.11	0.88	0.38	0.37
Nonteam												
Sent												
All	-0.47	0.83	-0.08	-0.57	0.57	0.33	-0.14	0.73	-0.02	-0.19	0.85	0.36
No Attachments	0.19	0.85	0.03	0.22	0.82	0.32	0.25	0.75	0.04	0.33	0.74	0.36
Attachments Only	0.36	0.76	0.07	0.47	0.64	0.27	-0.03	0.67	-0.01	-0.05	0.96	0.33
% Attachments	-0.10 **	0.05	-0.26	-2.05	0.05	0.39	-0.06	0.05	-0.15	-1.23	0.23	0.38
Received												
All	1.15	1.18	0.14	0.97	0.34	0.34	2.63 ***	0.96	0.35	2.74	0.01	0.47
No Attachments	0.85	1.17	0.10	0.72	0.48	0.33	1.72 **	1.00	0.22	1.73	0.09	0.41
Attachments Only	-1.14	1.17	-0.13	-0.98	0.34	0.34	-0.16	1.03	-0.02	-0.15	0.88	0.34
% Attachments	0.01	0.07	0.03	0.19	0.85	0.32	0.09	0.06	0.23	1.63	0.11	0.40

N = 47 recruiters, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

	Billing Revenue						Booking Revenue					
	B	S.E.	Beta	t	Sig.	Adj. R^2	B	S.E.	Beta	t	Sig.	Adj. R^2
Base Model + Structural holes (GE10)						0.20						0.42
Team												
Sent												
All	-63,220	49,203	-0.18	-1.28	0.21	0.22	27,142	47,393	0.07	0.57	0.57	0.41
No Attachments	-26,270	52,608	-0.07	-0.50	0.62	0.19	48,085	49,372	0.12	0.97	0.34	0.42
Attachments Only	114,517 **	55,547	0.31	2.06	0.05	0.19	119,196 **	51,984	0.27	2.29	0.03	0.51
% Attachments	-4,656 *	2,324	-0.28	-2.00	0.05	0.26	-180	2,314	-0.01	-0.08	0.94	0.41
Received												
All	46,168	56,887	0.12	0.81	0.42	0.20	83,772	52,612	0.20	1.59	0.12	0.45
No Attachments	71,818	57,448	0.19	1.25	0.22	0.21	101,540 *	53,011	0.24	1.92	0.06	0.46
Attachments Only	137,902	104,762	0.21	1.32	0.20	0.17	53,628	101,529	0.07	0.53	0.60	0.45
% Attachments	87	2,190	0.01	0.04	0.97	0.18	1,850	2,052	0.11	0.90	0.37	0.42
Nonteam												
Sent												
All	-68,760	49,112	-0.21	-1.40	0.17	0.22	-8,187	47,676	-0.02	-0.17	0.86	0.41
No Attachments	-40,552	51,189	-0.11	-0.79	0.43	0.20	1,898	48,874	0.00	0.04	0.97	0.41
Attachments Only	37,310	46,025	0.12	0.81	0.42	0.15	-16,009	43,235	-0.05	-0.37	0.71	0.38
% Attachments	-7,899 **	2,980	-0.35	-2.65	0.01	0.31	-3,854	3,008	-0.15	-1.28	0.21	0.43
Received												
All	22,663	72,274	0.05	0.31	0.76	0.18	130,625 *	65,175	0.26	2.00	0.05	0.47
No Attachments	6,448	71,451	0.01	0.09	0.93	0.18	97,402	65,803	0.18	1.48	0.15	0.44
Attachments Only	-39,071	71,089	-0.08	-0.55	0.59	0.18	16,881	67,505	0.03	0.25	0.80	0.40
% Attachments	2,308	4,098	0.09	0.56	0.58	0.19	6,133	3,768	0.22	1.63	0.11	0.45

N = 47 recruiters, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table 4.8 Hypothesis 4a results.

	Billing Shares						Booking Shares					
	B	S.E.	Beta	t	Sig.	Adj. R^2	B	S.E.	Beta	t	Sig.	Adj. R^2
Base Model + Structural holes (GE10)						0.34						0.38
Team												
Sent												
Ave. Response Time	-0.09	0.13	-0.11	-0.66	0.51	0.33	0.07	0.11	0.09	0.59	0.56	0.37
Ave. Ln (Response Time)	-1.04 **	0.49	-0.32	-2.14	0.04	0.40	0.35	0.45	0.12	0.77	0.44	0.37
% Responses wi/30 min	0.06	0.04	0.22	1.67	0.10	0.37	-0.04	0.03	-0.15	-1.18	0.25	0.38
"" 1 day	0.06 *	0.03	0.29	2.02	0.05	0.39	0.00	0.03	0.01	0.04	0.96	0.36
"" 1 week	0.05 *	0.03	0.29	1.79	0.08	0.37	0.01	0.03	0.04	0.24	0.81	0.36
Received												
Ave. Response Time	0.03	0.13	0.03	0.24	0.81	0.32	0.03	0.12	0.04	0.29	0.78	0.36
Ave. Ln (Response Time)	0.29	0.57	0.07	0.51	0.61	0.33	-0.59	0.49	-0.15	-1.20	0.24	0.38
% Responses wi/30 min	0.03	0.04	0.08	0.62	0.54	0.33	0.04	0.04	0.13	1.05	0.30	0.38
"" 1 day	-0.02	0.03	-0.11	-0.85	0.40	0.33	0.00	0.02	0.02	0.20	0.84	0.36
"" 1 week	-0.05	0.03	-0.19	-1.47	0.15	0.36	-0.01	0.03	-0.06	-0.43	0.67	0.36
NonTeam												
Sent												
Ave. Response Time	-0.08	0.09	-0.13	-0.91	0.37	0.34	0.06	0.08	0.11	0.78	0.44	0.37
Ave. Ln (Response Time)	-0.75 *	0.43	-0.24	-1.74	0.09	0.37	0.68 *	0.38	0.24	1.79	0.08	0.41
% Responses wi/30 min	0.05	0.04	0.18	1.30	0.20	0.35	-0.07 **	0.03	-0.32	-2.48	0.02	0.45
"" 1 day	0.02	0.03	0.12	0.82	0.42	0.33	-0.04	0.03	-0.20	-1.52	0.14	0.40
"" 1 week	0.03	0.03	0.14	1.01	0.32	0.34	-0.01	0.02	-0.08	-0.62	0.54	0.37
Received												
Ave. Response Time	-0.08	0.11	-0.09	-0.67	0.51	0.33	0.19 *	0.10	0.25	1.97	0.06	0.42
Ave. Ln (Response Time)	-0.25	0.58	-0.06	-0.43	0.67	0.33	1.15 **	0.47	0.29	2.43	0.02	0.45
% Responses wi/30 min	0.01	0.04	0.03	0.18	0.86	0.32	-0.09 **	0.03	-0.32	-2.57	0.01	0.45
"" 1 day	0.00	0.03	0.00	0.03	0.97	0.32	-0.05 *	0.03	-0.24	-2.01	0.05	0.42
"" 1 week	0.00	0.04	0.00	0.03	0.97	0.32	-0.06 **	0.03	-0.25	-2.13	0.04	0.43

N = 47 recruiters, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

	Billing Revenue						Booking Revenue					
	B	S.E.	Beta	t	Sig.	Adj. R^2	B	S.E.	Beta	t	Sig.	Adj. R^2
Base Model + Structural holes (GE10)						0.20						0.42
Team												
Sent												
Ave. Response Time	-6,591	7,849	-0.15	-0.84	0.41	0.20	4,832	7,461	0.10	0.65	0.52	0.42
Ave. Ln (Response Time)	-41,953	30,371	-0.23	-1.38	0.18	0.22	33,749	28,962	0.17	1.17	0.25	0.43
% Responses wi/30 min	2,508	2,177	0.17	1.15	0.26	0.21	-3,247	2,030	-0.19	-1.60	0.12	0.45
"" 1 day	3,474 **	1,706	0.32	2.04	0.05	0.26	-109	1,702	-0.01	-0.06	0.95	0.41
"" 1 week	2,978	1,872	0.28	1.59	0.12	0.23	-421	1,830	-0.04	-0.23	0.82	0.41
Received												
Ave. Response Time	2,588	8,133	0.05	0.32	0.75	0.18	5,284	7,665	0.09	0.69	0.49	0.42
Ave. Ln (Response Time)	-5,900	34,659	-0.02	-0.17	0.87	0.18	-38,494	32,236	-0.14	-1.19	0.24	0.43
% Responses wi/30 min	2,511	2,534	0.13	0.99	0.33	0.20	2,298	2,401	0.11	0.96	0.34	0.42
"" 1 day	-323	1,681	-0.03	-0.19	0.85	0.18	830	1,587	0.06	0.52	0.60	0.41
"" 1 week	-2,161	2,049	-0.16	-1.05	0.30	0.21	-167	1,969	-0.01	-0.08	0.93	0.41
NonTeam												
Sent												
Ave. Response Time	2,519	5,242	0.07	0.48	0.63	0.19	6,938	4,851	0.18	1.43	0.16	0.44
Ave. Ln (Response Time)	-19,247	26,895	-0.11	-0.72	0.48	0.19	54,623 **	24,061	0.29	2.27	0.03	0.48
% Responses wi/30 min	1,890	2,162	0.13	0.87	0.39	0.20	-5,026 **	1,901	-0.32	-2.64	0.01	0.50
"" 1 day	238	1,798	0.02	0.13	0.90	0.18	-3,182 *	1,623	-0.25	-1.96	0.06	0.46
"" 1 week	-249	1,633	-0.02	-0.15	0.88	0.18	-2,256	1,503	-0.19	-1.50	0.14	0.44
Received												
Ave. Response Time	-2,684	6,903	-0.06	-0.39	0.70	0.19	15,663 **	6,037	0.30	2.59	0.01	0.50
Ave. Ln (Response Time)	-9,315	35,136	-0.04	-0.27	0.79	0.18	90,874 ***	29,865	0.34	3.04	0.00	0.52
% Responses wi/30 min	-271	2,499	-0.02	-0.11	0.91	0.18	-6,864 ***	2,088	-0.38	-3.29	0.00	0.54
"" 1 day	-1,012	1,951	-0.07	-0.52	0.61	0.19	-4,992 ***	1,668	-0.33	-2.99	0.00	0.52
"" 1 week	-1,134	2,140	-0.07	-0.53	0.60	0.19	-5,535 ***	1,825	-0.33	-3.03	0.00	0.52

N = 47 recruiters, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table 4.9 Hypothesis 4b results.

Hypothesis 4a: Controlling for network structure, longer than average emails exchanged with team members will be negatively related to billings.

Hypothesis 4b: Controlling for network structure, longer than average response times in email communication with team members will be negatively related to billings.

As shown in the tables on the preceding two pages, results were generally consistent with the direction of hypotheses 4a and 4b, which suggested smaller messages and more frequent responses to team members would be positively associated with billings. However, the effects were not always statistically significant. In addition, they suggest that the relationship between email size and billings may involve sending a lower percentage of emails as attachments, as opposed to smaller text messages.

The strength of relationships between response times to teammates and billings varied with the time interval. The strongest relationships involved the percentage of messages sent within one day ($p < 0.05$). Percentages of responses within 30 minutes and one week were not as strongly related, although the differences were minor. For responses to teammates, relationships with performance measures based on billing shares were at least as strong as those with measures based on billing revenue.[27]

Relationships between the size of email sent to teammates and billings depended on whether messages included attachments. For messages with attachments, larger messages were positively associated with billing revenue ($p < 0.05$). Results involving both types of messages pointed in the direction of an association between smaller messages sent to teammates and billing revenue. However, the size of text messages was not significant. Instead, sending a lower percentage of messages as attachments appears to account for the difference ($p < 0.10$).

While my hypotheses do not predict relationships with respect to bookings, statistically significant relationships were observed with respect to non team email. In particular, longer response times from non-teammates are associated with more bookings.

[27] Average response times and the percentage of responses within a specific time interval usually have opposite signs. For average response time measures, a positive sign coincides with slower responses. For the percentage of responses within a specific time interval, a positive sign coincides with more frequent responses.

The results were stronger when bookings were measures as revenues as opposed to shares. Most relationships involving booking revenue were significant at $p < 0.01$.

In interpreting these results, it is important to recall that I measured response times as time intervals between emails. My measure of response times does not differentiate between responses to specific messages. It seems reasonable to assume that responses that follow more than a one week gap are more likely to represent the initiation of new threads as opposed to specific responses to previous messages. If I make this assumption, I can interpret a lower percentage of responses to non teammates within a week as evidence of a higher percentage of email threads being initiated by non teammates. This suggests that recruiters who generated more booking revenue may receive more unsolicited email from colleagues outside their project teams.

Chapter 5
Discussion and Conclusion

In my final chapter I position my findings within the broader context of existing work. My discussion provides context and interpretation for results. I begin with results from tests of my four hypotheses, surfacing themes and comparing my findings to those of other researchers. I devote the second half of my discussion to the use of email as a data source in social network research. I begin by comparing the strengths and weaknesses of email and network survey data in light of my experience. I then explain my rationale for interpreting email measures as proxies for more general communication patterns in this setting. My discussion of email as a network data source targets opportunities to further develop methodological practices. Limitations and suggestions for future work follow my discussion. I conclude this chapter with a summary of contributions.

Discussion of Regression Model Results

My email measures can be thought of as aggregations of interaction patterns expressed in different dimensions. This dimensionality allowed me to define and evaluate hypotheses involving relationships between communication patterns and performance at multiple levels of analysis. Hypothesis one represents a direct adaptation of traditional social network metrics to email data. It addresses relationships between an individual's position within the topology of a communication network and performance. My remaining hypotheses involve measures that are independent of the topology of the network. They represent application of theories that suggests the way people allocate the resources they devote to communication may also influence performance.

Hypotheses two and three involve measures of proportions of communication with different types of individuals. Differences in proportions of communications may reflect characteristics of how people do their work. Hypothesis two considers communication patterns with different types of individuals. Hypothesis three considers the attributes of specific individuals. Hypothesis four considers decisions involving the allocation of information in the form of messages. I now discuss specific results that followed from applying these measures to test theories relating communication patterns to performance within the setting of an executive recruiting firm.

<u>Hypothesis 1: Network Centrality</u>

My general finding of positive relationships between network centrality and performance is consistent with findings of most, but not all, researchers who have used network surveys in other settings. My tests used multiple measures that included variation in networks, ties strength cutoffs, centrality metrics and performance metrics. As I varied features of the models, results also varied. My interpretation focuses on relating these differences to aspects of the research setting.

My finding that centrality in the organizational email network was generally as strong and often a stronger predictor than centrality in the formal network of search contracts was not unexpected. The result is consistent with theory that suggests position in an informal as opposed to formal network is likely to be a better predictor of performance because the former includes relationships outside the formal chain of command that play a role in getting work done (Krackhardt and Hanson 1993; Monge and Contractor 2003). The finding helps motivate subsequent hypotheses as a way of better identifying some of these internal communication effects.

Centrality measures that included weak ties were positively related to booking revenue, while measures at all tie strengths were positively related to billing revenue. This difference may be related to differences in the nature of the tasks. While the task of executing a search contract typically involves communication with colleagues over a long duration (the average length of a search is approximately 180 days), the task of landing a search contract does not. Consistent communication over a long duration is one attribute used to define a strong tie.

Ties involving 20 or more emails were more strongly related to the number of searches executed than the revenue generated by those searches. Interview data suggest productivity effects associated with information technology in search are likely to be associated with the ability to conduct multiple simultaneous searches or multitask. The results indicate that recruiters who execute the most searches also maintain high frequency email communications with the greatest number of colleagues. This may reflect one element of a multitasking strategy. Recruiters who generate the most revenue from search execution also communicate with more colleagues over email but do so at more moderate levels.

Recruiters who landed the most searches communicated with more colleagues over email, but on a less frequent basis. This could reflect a tradeoff between internal and external communication. Recruiters who generated the most booking revenue can be thought of as those with the most valuable external networks. I suggest this interpretation because approximately 80 percent of clients are repeat clients. By communicating less frequently with colleagues over email, they may have more time to pursue clients.

The direction of causality cannot be inferred from the regression model. The results do not indicate whether more internal weak ties help recruiters land contracts. It is possible that recruiters who land the most contracts are more central because they are more sought after by colleagues. In the methodology section, I speculated that recruiters might use the internal email network to share competitive intelligence that could help them land more contracts with new clients. But I did not find any relationship between new client bookings and centrality. Repeat client bookings were related to email network centrality, but this could reflect a tendency of recruiters to seek out more successful colleagues.

These results suggest differences between the formal network defined by search contract relationships and the email network. Recruiters who generate the most booking revenue have the most teammates. Formal topology appears to reflect the value of contracts landed. Email traffic among consultants and partners is more strongly related to contract execution. Recruiters who execute the most contracts have the most strong email ties.

The results did not appear to be sensitive to the choice of centrality metric, with the partial exception of betweenness centrality. In general, as network density increases variation among the four centrality metrics used in this study will decrease. The recruiter network would generally be considered a relatively dense organizational network, so it is not surprising that the four metrics tended to give similar results.

The weaker relationship between performance measures and betweenness centrality, which measures the number of times an individual falls on the shortest path connecting all possible combinations of dyads, suggests the following interpretation. The theoretical advantage of positions that exhibit high betweenness scores is often expressed in terms of gatekeeping. Characteristics of the recruiter population that would presumably mitigate benefits from gatekeeping include small team sizes, high internal network density and individuals with extensive external networks. The statistically weaker relationship also suggests that some aspect of betweenness centrality may make it less desirable than other forms of centrality in this context. High betweenness scores are also characteristic of individuals who perform centralized functions in organizations. In the case of recruiters, high betweenness scores may sometimes indicate a person others in the work group rely on more for research support. This suggests that betweenness may be more weakly related to performance in this context because the network structure offers fewer opportunities for benefits associated with exerting control over the information flow and may entail costs associated with being a broker of fairly routine information (eg. candidate as opposed to client leads). Among consultants, some of the recruiters with performance measures lower than would be expected on the basis of betweenness scores alone also responded very quickly (eg. less than 10 minutes) to a higher proportion of messages than their peers, which suggests a more routine function. However, since the signs on the centrality measures are almost always positive, this suggests that on the whole it is still better to be perceived by others as one that is likely to have information than not.

Finally, it is worth noting that other researchers have occasionally found negative relationships between the centrality metrics used in this study and performance measures.

In relating social networks to performance in the context of knowledge sharing among structurally diverse work groups performing complex, non-routine tasks, Cummings (2004) found innovation to be negatively associated with structural holes in the networks of group leaders. In the context of executive search, structural holes were found to be positively associated with individual performance. Such differences may well hinge on questions of context. More closed networks, in which the size of structural holes is smaller, are often associated with establishing trust and the ability to elicit specific capabilities from individuals in a complex, non-routine setting. On the other hand, more open networks may be advantageous in the recruiting context because deliverables are better understood, teams are smaller with a modal size of two, and network breadth facilitates finding the right person quickly. Correlations with other social network metrics also confirm centrality is important, while suggesting distinctions regarding the level at which networks are open or closed may be less important in this context.

Hypothesis 2: Exploration and Exploitation

Hypotheses motivated by the tradeoff between exploration and exploitation reflect a social network interpretation of March's (1991) classic work applied to communication patterns within an organization. The tradeoff provides a useful framework for organizing results that suggest job level differences in relationships between information flows and performance and information related behaviors and network centrality.

Other researchers have frequently interpreted March's work with respect to organizational level tradeoffs involving exploitation of internal resources and exploration of external opportunities (e.g. Crossan, Lane et al. 1999; Siggelkow and Levinthal 2003; He and Wong 2004; Homqvist 2004). Yet frameworks that express the basic tradeoff are found across a wide range of literatures, since the problem of striking the proper balance between new investment and capitalizing on existing assets as a function of factors such as uncertainty and the relevant time horizon is quite general.

At the junior level, results are consistent with the theoretical prediction that internal network of the firm would serve as a source of procedural know-how, socialization and new opportunities. Among consultants, a higher proportion of email exchanged with colleagues they had never formally worked with before on contracts and a greater diversity of email share exchanged with partners was positively related to booking revenue. These can be interpreted as investments in internal social capital.

The results also suggest that an important part of the answer to the question of how consultants move up may involve learning from their peers. The proportion of internal email consultants exchanged with peers was positively related to booking revenue. Interview data suggest that in seeking answers to questions, consultants were more likely to turn to their peers than admit ignorance to their superiors. Consultant perceptions that the information they exchanged with others was more procedural than declarative were positively related to email network size expressed in structural holes. In email response time plots, the greatest differences appeared between peer networks, with information moving move quickly in the consultant peer network.

Ethnographic studies in other settings suggest peer networks can play an important role in learning that promotes problem solving (Orr 1996; Brown and Duguid 1998). However, few studies have provided quantitative evidence of relationships between activity in peer networks and performance.

At the senior level, predictors of performance resemble those of a prototypical executive decision maker who seeks the best facts to make decisions following existing routines (e.g. Radner 1992). Relationships between declarative information sharing and network size expressed as structural holes and the proportion of email exchanged with consultants and booking revenue suggest partners may use their internal network as an information filter.

While relationships between two of the information flow measures and booking revenue were similar for consultants and partners, they have different implications. Most communication between partners and consultants occurs within the context of existing searches, while most peer communication occurs outside of search teams. For partners, a greater proportion of email communication with consultants represents communication within the chain of command. For consultants, a greater proportion of communication with consultants suggests investments within an informal network. Among partners, a more diverse communication share to other partners is associated with a lower proportion of email sent to colleagues they have never worked with previously (0.33, $p < 0.15$);

among consultants it is associated with a higher proportion (-0.35, $p < 0.10$).[28] This is consistent with an interpretation in which more successful partners are realizing returns from previous investments in relationships, while more successful consultants are investing in new relationships.

From a social network perspective, these findings suggest a new class of measures, dimensions of information flow, may explain individual variation in performance. This reflects the idea that how information flows over a network, as well as the network topology, may influence performance.

Dimensions of flow may have been largely absent from social network theory because they are typically difficult to measure through surveys. Using email data, the computation of information flow measures becomes fairly straightforward

Hypothesis 3: Co-Specialization

My hypothesis that individual performance would be associated with co-specialization was generally not supported. In other settings, such as scientific research and the arts, research suggests co-specialization and clique formation theories are likely to explain variation in individual performance. These contrasting findings can potentially be reconciled by considering how differences in incentive structures may influence communication and team assignment patterns. This interpretation suggests opportunities for future work aimed at testing revised hypotheses, while also illustrating how email patterns may be analyzed to assess organizational tensions.

Guimera, Uzzi et. al. (2005) found positive relationships between diversity, experience and team performance in the production of Broadway musicals and the publishing of journal articles in the fields of economics, social psychology and ecology. Their work measures team assignment. While they did not directly evaluate co-specialization, the combination of diversity and experience associated with higher performing teams suggests this interpretation. Rice (1994) used email data and found that the performance levels of interns in an R&D lab were positively associated with the performance levels of permanent employees they communicated with in the initial weeks

[28] A more diverse message share corresponds to a Herfindahl index closer to 0.

of their internships. This can be interpreted as evidence that exposure to higher and lower performing cliques was related to performance, but does not address co-specialization.

I found the billing revenue of consultants was positively associated with the lagged booking revenue of colleagues they communicated with most over email, but did not find any other evidence that suggested co-specialization. Among both consultants and partners, I found relationships between higher booking revenue and more interaction with colleagues who previously had lower booking revenue.

This pattern of results is consistent with an explanation that emphasizes the role of the firm's incentive structure. While almost all recruiters receive some credit for work in both performance dimensions, performance at landing contracts is valued more highly than performance in executing contracts. Given this rank ordering of value, recruiters are likely to strive for the higher valued work. Recruiters who are less successful at landing contracts are likely to settle for more of the lower valued work of executing contracts. An implication for team selection is that higher performers in the higher valued dimension are more likely to form teams with lower performers in that dimension, which is consistent with my results.

Rank orderings of value exist in other professional service settings such as law and consulting. In these contexts, pyramidal compensation structures are common. Incentives may be aligned at all levels towards moving up the value chain of information work performed, often expressed as "up or out." The top of the value chain is often associated with bringing revenue into the organization, but this does not necessarily have to be the case.

This finding can be related to job level differences in the networking strategies of recruiters I examined in my previous hypothesis involving the tradeoff between exploration and exploitation. At the top level of partner, it suggests a clear benefit to organizational membership. Partners are selected on the basis of proficiency at the higher valued work of landing contracts. Organizational membership makes it easier to find others to whom they can delegate the essential, but lower valued task of executing contracts. Freeing up time for higher valued work means that successful partners can create more value as firm members than they could if they operated on their own.

However, at the lower level, this incentive structure may create opposing organizational tensions that are theoretically likely to influence patterns of communication and information sharing. The first tension involves a choice in allocating effort towards supporting superiors versus investing in other relationships. While consultants who communicated more with colleagues who had higher booking revenues executed more searches, they also landed fewer searches than their peers. This suggests that this strategy could be useful for initial socialization, but consultants who continue to rely primarily on these relationships may find themselves facing an early ceiling with respect to prospects for advancement. In this context, "being a good solider" may not be the best long term strategy for advancement. Relationships between email patterns and performance suggest that successful consultants develop an alternative strategy that involves building a broad base at the top, while devoting a larger proportion of email communication to peer exchanges. Peer networks or communities of practice are likely to be favored to the extent that they create opportunities for learning that offer higher returns than those that can be found elsewhere. At the same time, when promotion is based on yardstick competition, reflected in the expression "up or out," incentives to participate in peer networks are reduced to the extent that improving the standing of another may harm one's chances of advancement (Orlikowski 1992). The recruiting setting suggests that it is possible for yardstick competition to co-exist with an active peer network. Theoretically, this outcome can occur when individuals perceive that participation in a peer network improves prospects for advancement more than the risk of losing relative standing by helping peers discourages it.

Differences in credit assignment suggest an additional way incentives may influence co-specialization. Expectations that credit will be shared may favor co-specialization, because mutual gains become more attractive. Expectations that credit will accrue to the leader may discourage co-specialization when higher performance involving lower valued skills goes unrewarded. In academia and the arts, the fields studied by Guimera, Uzzi et. al. (2005), the value of output is determined when audiences judge the finished project. Rewards for quality may take the form of prestige or monetary royalties. In either case, team members share benefits based on the success of the specific project. In recruiting, the value of output in recruiting is largely determined when the sale is made, which precedes project execution. Higher quality execution may generate more repeat business and more efficient execution allows recruiters to undertake more projects. But these benefits are generally not reflected in the compensation received for a specific project. In practice, recruiters who make the sales receive credit for most of the value. By equating bookings with sales, observations about recruiting may generalize to other white collar contexts involving professional services.

The result in contexts like recruiting is likely to be a tension. Co-specialization may lead to higher quality output, but establishing an environment that encourages it depend on mechanisms for assigning credit to those on the bottom of the hierarchy. The primary incentive is often the opportunity to ascend the hierarchy by making partner. The criteria on which evaluations for promotions are made may have significant implications for relationships between communication patterns and performance. However, the theoretically optimal way of structuring these incentives is unclear.

In future work, it may be possible to express these tensions in a theoretical model. For example, the relationship between partners and consultants could be interpreted as an agency problem. However, unlike traditional agency theory, a key incentive is the opportunity for the agent to become a principal. This is realized through investments in social capital that are reflected in a client base. As a result, agent effort not devoted to serving the principal may be channeled into investment in peer or potential client relationships as opposed to shirking. This is a more complicated dynamic, but may provide a more accurate reflection of key tensions observed in many white collar settings.

Hypotheses 4: Network Efficiencies Related to Response Times and Message Size

My results were generally consistent with my hypothesis that shorter more frequent communication would outperform infrequent lengthy communication in the context of team based activity. Because I included a control for network topology, my results suggest how information flows over a network may influence performance. However, implications for practice may be limited by the difficulty of ruling out an alternative explanation for results involving task differentiation, particularly with respect to the role of email size.

More frequent responses to teammates were positively associated with performance at executing contracts. My results also suggested that the frequency of response may be more important than rapidity in this context. The strongest relationships involved the percentage of messages sent within a day, as opposed to 30 minutes or a week.

My model does not address the direction of causality. For example, more frequent responses could serve as an indicator as opposed to an enabler of performance. Among consultants, but not partners, perceptions of information overload were negatively correlated with the percentage of responses to teammates. This relationship grew stronger as the time interval increased. The percentage of responses within one week was correlated at $\rho = -0.73$, $p < 0.001$. Among consultants, self-reported information overload was also correlated with longer emails (0.39, $p < 0.10$) and longer response times (0.49, $p < 0.05$) from teammates. The ability to juggle more simultaneous projects is positively related to consultant, but not partner performance. This suggests the asynchronous nature of email communication may play a role. These associations with overload suggest that among consultants email response times involving teammates could be indicators or enablers of a broader set of perceptions and behaviors that may be related to performance.

With respect to email size, I found that the percentage of messages sent with attachments was a statistically significant predictor of performance, while the size of text emails was not. In addition, when I consider only emails with attachments, sending longer messages to teammates was positively associated with billing revenue ($p < 0.05$). This suggests that relationships between email size and performance are more complicated than a tendency of human processors to block or defer action in the presence of long messages. In future work, analyses aimed at developing a more complete understanding of the role of attachments in this context could help better interpret relationships with email size. For example, in some cases attachments could involve contracts. In that case, an interpretation as an indicator as opposed to an enabler of performance would be more appropriate.

In my literature review, I described two alternative explanations for relationships between email size, response times and performance. I find it hard to rule out the possibility that some of the effects I observe could be related to task differentiation. This is particularly true with respect to email size. For example, some large emails with attachments could be related to search contracts. In that case, a correlation between email size and performance may reflect a task specific characteristic related to the contract itself as opposed to a more efficient pattern of communication among team members.

A second alternative explanation suggests differences in email size and response patterns may reflect differences in status. My results suggest some elements of Owens, Neale et.al's (2000) status based theory of email response times and size may come into play in this setting. However, the problem of ruling out the potential role of task differentiation as well as the difficulty of operationalizing status makes their theory difficult to test.

In this setting, I believe social definition theories generally provide better explanations for response time and size differences I observed across subgroups of the population. Owens, Neale et.al.'s theory draws heavily on arguments that power differentials between individuals vary across media. For example, they hypothesize that high status individuals prefer shorter emails because they prefer to resolve issues in face-to-face settings like meetings in which they control the agenda. They predict that mid-status challengers will send the longest emails because the medium gives them an open forum to challenge authority and display their expertise. This argument relies on drawing a contrast between formal face-to-face meetings and email activity that may restrict the application of their theory. In my study, approximately half of the searches were conducted by recruiters who were not physically collocated. In addition, full group meetings, particularly face-to-face ones, did not appear to be common. In settings that lack the contrast between formal face-to-face meetings and email as forums, the prerequisites for their theory may be lacking.

However, their status based theory may offer a useful perspective for assessing some features of my results. In the recruiting context, booking revenue may be a reasonable proxy for status. Booking revenue was positively related to the length of text email received from teammates ($p < 0.10$). This may reflect a tendency of subordinates to use the medium to try to impress high status individuals. Booking revenue was also positively related to the proportion of email received from non-teammates that was likely to be unsolicited (based on a time interval of more than one week between exchanges). Both status based and efficiency based interpretations of these results are plausible.

Owens, Neale et. al. also note that preferences of executives for shorter email have been found in other settings. Among partners, sending smaller emails to consultants is positively correlated with both self-reported tendencies to mentor others (0.43, $p < 0.10$) and less time reported on email (0.48, $p < 0.05$). One possibility is that, through mentoring, partners teach junior colleagues to better "fill in the holes" in email, enabling more efficient communication (Clark and Brennan 1991). My research model does not address the direction of causality, so it is worth considering what role might be played by unobserved behaviors that permit shorter emails to be effective.

My results generally did not support Owens, Neale et. al.'s prediction that response times would be inversely proportional to status. Instead, average response times varied by subgroup in ways that suggest a social definition theory interpretation. In Appendix B, I provide graphs of size and response time characteristics by job level. For vertical communication among consultants and partners, response times were closely matched in both directions. This contradicts the prediction that response times will be inversely proportional to status. Owens, Neale et. al. do not address peer level communication. However, in peer level comparisons I found consultant response times were significantly faster than partner response times. This suggests a social definition theory interpretation or task differentiation interpretation. The former suggests different norms may govern peer communication at different job levels. The latter suggests interaction patterns may vary by task.

I believe the peer level results are consistent with the job level differences I observed in the context of explore and exploit theory. Among consultants, the proportion of internal email exchanged with other consultants was correlated with perceptions that the type of information exchanged was primarily procedural. The exchange of procedural information in the context of problem solving has been associated with more frequent communications (Hansen 1999). Among partners, perceptions that the type of information exchanged with others was primarily declarative were positively related to structural holes. More sporadic communication is less likely to increase the difficulty of exchanging declarative information. This suggests an additional interpretation from an efficiency perspective. Faster response times in the consultant peer network and slower response times in the partner peer network could reflect differences in the type of information exchanged with colleagues. Response patterns in the two networks might be efficient given the respective differences in the type of information exchanged.

I believe the absence of information on content is a significant data limitation for differentiating between task differentiation and efficiency based explanations regarding relationships between email size, response times and performance. Other researchers have shown that content can be a significant predictor of response rates (Dabbish, Kraut et al. 2005). However, despite the difficulty involved in differentiating between alternative explanations for why email communication size and frequency effects may be related to performance, evidence of the relationship is still a contribution. It suggests a specific way in which information flows over a network, in addition to topology, may be related to performance.

Email Data in Social Network Research

The general prognosis for the application of email data in social network research appears bright. As I conducted this research, an email data set containing more than a half million messages associated with the Enron scandal was released by the Federal Energy Regulatory Commission and posted on the commission's Web site. The Enron data set has evolved into the *E. Coli* of email research, motivating both academic papers and the rapid growth of companies specializing in niche email applications, such as those associated with regulatory compliance (Kolata 2005). While work in information visualization and data mining spurred by the existence of the Enron data set is likely to have a significant influence on the application of email data in social network research, it had little direct influence on my work. The main reason is that while relationships between people and content are a natural focus of Enron email analysis, content analysis did not play a role in this research because the words in the messages were encoded to preserve privacy.

Another potential growth area for email network research involves physicists interested in network dynamics. After producing thousands of articles on properties of the World Wide Web, physicists have recently begun to investigate dynamics of email networks (Eckmann, Moses et al. 2003; Kossinets and Watts 2006). Further on the horizon, synergies between email network research and neuroscience research may exist. The movement of information through a network is recognized as an important research area in neuroscience (Tononi, Edelman et al. 1998; Sporns, Tononi et al. 2000). Neurons in the brain coordinate activities through patterns of electrical impulses, while people in organizations coordinate activities through patterns of email communication. Imperfections in the analogy aside, both are rapidly expanding research areas in which new methods have produced new data sources. The parallels suggest the potential for cross-fertilization involving data analysis methodology and measures.

The bright future for network research involving email has to be contrasted against the realization that researchers currently undertaking work in this area will be building the methodological foundations from the ground up. The community of researchers involved in the quantitative modeling of email patterns with the goal of better understanding some aspect of interpersonal or organizational behavior is still thought to be fairly small (e.g. Eveland and Bikson 1986; Begole, Tang et al. 2002; Eckmann, Moses et al. 2003; Fisher and Dourish 2004; Dabbish, Kraut et al. 2005; Tyler, Wilkinson et al. 2005; Gloor 2006; Kossinets and Watts 2006). However, it is also growing rapidly, as evidenced by annual increases in the number of presentations of work involving email data at the Sunbelt International Social Network Conference.

I began my research with the premise that I would be able to identify statistically significant relationships between email patterns and performance measures. At the same time, the sensemaking process involved in developing measures and methodology that relates traces of electronic communication to phenomena of interest to organizational researchers seemed formidable. I focus my reflections on that experience in two areas. I begin by discussing potential tradeoffs between email and network surveys as social network data sources, as well as benefits of using both. In the second section, I focus on evaluating the extent to which email and other electronic archival data sources can serve as proxies for more general communication patterns. My goal is to outline the beginnings of a framework that researchers can use to guide assessments in other settings.

Examples of results from the analyses I conducted also provide context for interpreting the email measures I used in my regression models.

Comparing Email and Network Surveys as Social Network Data Sources

While most current studies use only a single source of network data, multi-method studies are generally preferred on methodological grounds. In the next decade, I expect seminal studies of organizational networks will increasingly rely on combinations of archival and survey data. These data sources have complementary strengths. Network surveys capture perceptual measures, while electronic archival data such as email can accurately measure communication patterns at the level of interactions.

Network surveys are valuable for research questions involving relationships between people's actions and their perceptions of others. Other researchers have shown that perceptions can have performance implications. For example, perceptions of whether interactions with others leave people energized or de-energized have been linked to individual performance (Cross, Baker et al. 2003). As another example, perceptions are the focus of theories of transactive memory systems, which seek to link information search behavior to people's perceptions of what they think others know and how responsive they think others are likely to be to inquires (Palazzolo 2005; Palazzolo, Serb et al. In Press). In similar types of research, email and other electronic archival data sources are unlikely to displace survey methods. Advances in email methodologies may lead to multi-method designs that could address questions such as those associated with the influence of people's perceptions on actual communication patterns and visa versa.

Weaknesses of network survey methods become apparent when research questions depend on accurate measures of actual communication. Two sources of error should be considered. The problem of measurement error associated with respondent inaccuracy is well covered in the literature (Bernard, Killworth et al. 1984; Marsden 1990). A less frequently discussed problem occurs when researchers fail to consider parameters of communication that are difficult to estimate reliably though survey methods. The result of these errors of omission is that in many studies every social network effect is attributed to topological properties of the network. Networks with similar topological properties may differ significantly in other dimensions. The results of hypothesis 2 provide an example. A study focused on topology alone would overlook the role of job level differences in communication patterns. These differences involve relationships between information flows and performance and information behaviors and centrality. In such cases, explanations based on topology alone may fail to consider significant aspects of network use that have important theoretical and practical implications.

A fundamental difference between email data and network surveys is that raw email data provides a record at the level of interactions. Salancik's (1995) influential critique of social network analysis argues for the value of theorizing at the level of interactions. Salancik argues that network theorists should treat interactions as observations instead of taking them as givens. Treating email messages as observations suggests analogies with the axiom of revealed preference in microeconomic theory. Each message received prompts a small decision. The message sent is evidence of a decision made. In this way, people's email boxes provide records of revealed preferences. Given the right representations, the sum of all these micro decisions can potentially be interpreted in ways that reveal a great deal about the decisions individuals make regarding time allocations across relationships. Increasing use of archival data could lead to greater use of theories based on tradeoffs or allocation problems as opposed to those focused on enhancing or maximizing behaviors that are assumed to be beneficial.

Many of the questions involved in developing email measures revolve around how records of interactions can be aggregated to produce meaningful statistics. In network surveys, the respondent implicitly aggregates interactions when he or she classifies a relationship. In a clearly worded survey, this can be advantageous for focusing attention on perceptual qualities of communication that would be otherwise difficult to measure. For example, Granovetter's (1973) original definition of a weak tie included the dimensions of emotional intensity, intimacy (mutual confiding) and reciprocal services, as well as time spent. Subsequent studies have found that different characterizations of relationships, such as ties based on trust, advice or workflow, can lead to different relationships between network position and dependent variables of interest, including performance measures (Krackhardt and Hanson 1993; Podolney and Baron 1997).

In using email data alone, choices regarding the classification of relationships by tie strength are typically limited to variations on communication frequency. While frequency of interaction is often correlated with the "strength" of a relationship, they are not always the same (eg. a relationship between a rebellious teenager and an authority figure). On the other hand, email data makes it possible to distinguish between fine gradations of communication frequency. The ability to measure communication frequency with precision may lead to new classes of measures. For example, my hypotheses 2-4 all rely on measures that would be hard to justify on informant inaccuracy grounds if I had gathered them using network surveys.

It is also possible to identify at least three situations in which direct measurement is likely to be particularly valuable. The first occurs when subjects perceive a benefit to responding a certain way or may have a tendency to give responses that are better aligned with what people would ideally like to do as opposed to what they actually do. The second occurs when organizational members have competing hypotheses about more efficient or effective communication strategies. Anecdotally, I would observe most people have these opinions. They frequently surfaced when I discussed my dissertation findings with others. Direct measurement initially appealed to me as a way of telling who is right. Even if there are problems with measurement, the perceived objectivity of direct measurement is powerful. However, I believe direct measurement is most likely to be useful when used as artifact for sensemaking that leads to a greater understanding of why results came out the way they did. Direct observation rules out sources of survey measurement error as plausible alternative interpretations. Irrefutable evidence regarding what happened may make it easier to move to the next step of understanding why.

A third situation in which direct measurement has specific advantages occurs in situations in which people are prone to error associating cause and effect. One common class of problems occurs when people get stuck in nasty feedback loops because the temporary result is positive, but the long-term effect is bad. Addictive behaviors have this quality as do many examples from the systems dynamics literature (eg. the beer game or bullwhip effect in supply chains) (Sterman 1989; Sterman 2000). Many organizational learning tradeoffs can be presented as systems dynamics problems (Senge 1990). In the recruiting context, the pattern of consultants not going to partners for help may be worth noting. Although I would need more information to reach a normative conclusion, it presumably has delayed as well as immediate effects. Causal explanations in situations that involve delayed feedback often have counter-intuitive qualities. Or explanations that involve issues people would rather deny. In such cases, direct measurement of communication patterns may be particularly useful for helping people see traps for what they are as opposed to falling back on rationalizations.

Using email as a proxy for general organizational communication patterns

Email adoption and usage patterns are context specific, so interpretations of email measures of communication will vary across organizations (Rice, Grant et al. 1990; Rice 1994). At the same time, when electronic media are used in an "anytime, anywhere" fashion, they may generate archival data that offers a reasonable proxy for more general communication patterns. From a social network researcher's perspective, a key methodological issue involved in using archival electronic data sources is assessing the relationship between observed electronic communication and communication in other media.

This is a methods bias issue that is likely to receive more attention as studies based on email and other electronic archival data sources become more common (Cook and Campbell 1979). The strategy I followed in my dissertation can be divided into three phases. I began with a general assessment of email usage patterns. I then identified and classified low email users. I concluded with an assessment of relationships between email measures and variables that might mediate relationships between email patterns and performance. Because media usage patterns are context specific, I believe an assessment conducted in the specific research setting provides significantly more convincing support for later interpretation of results than arguments based on citations of research conducted in other settings. However, I was not able to find a guide to conducting such an assessment in the literature. I offer observations on how my approach could be generalized as a starting point for developing future methodology. Step by step results from my analyses can be found in Appendix D.

In making a general assessment of electronic media use, my goal was to identify data sources that provide sufficient coverage of communication to support the interpretation of subsequent measures. This suggests that it may be possible to develop a battery of useful strategies. For example, I considered measures of responsiveness to colleagues and correlations between measures of communication in email and other media. Both of these strategies generalize to other settings. I also gathered descriptive accounts of how email was used through interviews. More extensive qualitative research, ethnographic accounts for example, would presumably have been valuable for identifying and interpreting the signatures of different email patterns.

In my case, I was fortunate to find evidence supporting the use of email as a proxy for more general communication patterns. When I divided response times to colleagues into 30 minute increments, the modal response times for all recruiters except one was 0-30 minutes. This suggested that email was an actively monitored communication channel and that recruiters were generally highly responsive to messages from colleagues. Recruiters used internal email as if it were instant messaging. The second result involves statistically significant correlations between actual numbers of email messages and the number of people recruiters reported communicating with per day across all media. Strong relationships between email communication levels and communication levels in other media have been found in other settings (Haythornthwaite and Wellman 1998; Garton, Haythornthwaite et al. 1999). This suggests that email communication patterns may often track communication patterns in other media fairly well, although these studies were conducted before instant messaging became widely used in the workplace.

In my setting, only one revenue generating recruiter reported using instant messaging. In other settings, instant messaging may function as a command center for routing communication to various channels. Email may be used more to convey information than to facilitate coordination. Depending on the characteristics of media use in a particular setting, researchers may find they need to use more than one type of data to create a reasonable proxy. In the future, multi-method comparative studies of social networks in organizations could potentially be useful in this stage of research design if relationships with factors that are theoretically likely to lead to differences across settings could be identified.

Types of communication associated with various media are still likely to vary. The question of whether electronic archival data represents a reasonable proxy depends on the specific measures and research questions. I chose to focus on internal communication because I had evidence that email was not a reasonable proxy for external communication in my setting. Future studies could address the sensitivity of specific network measures to variation in media use. Existing research on missing data in social network studies has focused almost exclusively on topology, so researchers currently have little empirical evidence to draw on regarding the sensitivity of information flow measures.

Given favorable general evidence regarding the potential of email to serve as a communications proxy, I shifted my focus to identifying situations where methods bias might still cause problems. Individual media preferences are likely to vary. By relying on a single data source my measures were likely to over-represent communication of individuals who like using email and under-represent communication of those that prefer other media. I focused under-representation because I was concerned that in some cases email might provide too weak a signal to indicate more general communication tendencies.

To normalize communication activity across a standard context, I focused on recruiters who had worked together on searches for more than half the study period.[29,30] I chose the dyad as my unit of analysis because it was difficult to account for all the factors that might influence email frequency between search team members.[31] Through

[29] I developed a regression model that confirmed that search team membership was the best predictor of email frequency. The result in this setting is quite strong (See Appendix D).

[30] I chose recruiters who had worked together on searches for more than half the study period because I found it difficult to estimate an expected frequency of email communication at shorter time intervals, such as weeks on a search. Interview data suggested that email activity between team members peaked at the beginning and end of searches, as well as intermediate intervals involving client interaction. However, I found it difficult to estimate a typical communications profile of a search. Two factors made this more difficult. I had a limited number of complete searches because the length of an average search is close to the length of the study period. Teams often pursued multiple searches simultaneously, so this would also have required a strategy for disambiguating email communication by search.

[31] I chose dyads as opposed to individuals as the unit of analysis. This finer level of granularity could be useful if predictors involved interactions that varied across searches. For example, collocation might be relevant only in the context of searches between recruiters who preferred media other than email.

this analysis I was able to identify five partners with lower than expected levels of email activity. The effects were typically bi-directional. This suggests colleagues working with these recruiters may have recognized that email was not their teammate's preferred medium and adjusted their behavior. By using this strategy I was able to identify specific individuals for whom email measures might under-represent more general communication patterns in the context of search team activity.

My last set of analyses focused on variables that could potentially mediate relationships between email communication patterns and performance. I was particularly concerned about effects related to collocation and media preferences. I also considered a number of effects related to specialization, since task differentiation could explain variation in email patterns. Approximately 50 percent of the searches were conducted by recruiters who were not physically collocated. I used two measures of collocation, one based on collocated projects, the other based on location in a central or satellite office. I did not find evidence of biases related to collocation. Email communication frequency was strongly related to membership in the same workgroup, but within workgroups, there appeared to be little difference with respect to recruiters who were or were not collocated. My review of the literature suggests evidence from other studies regarding the influence of collocation on email patterns is inconclusive.

I examined media preference effects through correlation analyses between actual email and self reported measures of communication across the specific media that were most commonly used in the firm. My greatest area of concern involves potential substitution of phone for email. I found evidence suggesting this substitution effect with respect to external communication. This helped motivate my decision to focus on communication patterns within the firm. Analyses I conducted using self-reported email measures generally suggested stronger potential substitution effects than those in which I compared actual email to self-reported communication in other media. Although I did not find significant evidence that preferences for phone vs. email biased results, I consider these analyses inconclusive. In analyzing media preference effects, I did not have adequate controls for task differentiation effects. In this context, survey measures that distinguished between internal and external media usage patterns would have been desirable.

I believe unmeasured effects related to task differentiation represent the most serious threat to my claim that email serves as a reasonable general proxy for internal communication patterns in this setting. Some tasks are more email intensive than others and within my models I differentiate only between activities related to landing and executing contracts. While my analyses of specialization effects consider aspects of vertical and horizontal specialization, it is generally hard to control for all of the dimensions in which white collar workers might specialize. One potentially useful strategy for future work would be to collect data on measures that correlate with specific tasks. For example, database records accessed and expenses related to client visits are associated with different types of tasks in recruiting.

I base my conclusion that email represents a reasonable proxy for internal communication patterns in this setting on the evidence I gathered from these analyses. This includes a combination of positive results from general analyses and a failure to identify negative results when I probed further into areas of specific concern. As caveats, I make this claim only with respect to internal email. I also identified five recruiters for whom email may under-represent communication across media. I believe task differentiation represents the strongest remaining explaining for why email might fail as a proxy in this setting. This possibility, combined with the fact that my regression models do not permit causal inference, suggests statistically significant results should be interpreted as indicators of relationships between email patterns and performance. This suggests the application of results as diagnostics. Significant indicators provide a tool researchers and practitioners can use to focus subsequent investigations into the true causal relationships.

Limitations

This study has important limitations. It is based on a single setting case study. I do not analyze the content of messages and cannot use my OLS regression models to make causal claims or statements about total factor productivity. While these factors are all related to data limitations, I will briefly comment on the limitations they pose and research directions that might provide opportunities for addressing them in the future.

The single setting case study limits the ability to generalize from results. I speculate that the themes I express in the hypotheses and emphasize in the discussion of results would appear in other professional services settings. However, this is an empirical question that would need to be verified through research at other sites. A significant research question for designing multi-site studies involving relationships between communication patterns and white-collar performance is whether performance dimensions can be generalized across settings. The performance dimensions of finding and executing contracts could be interpreted more generally as measures associated with sales of white collar services and white-collar tasks characterized by quasi-routine information processing. In colloquial terms, these performance dimensions could be characterized as “finding” and “grinding.” In settings that involve larger team sizes, I believe additional performance dimensions become important. For example, project management or “minding” and leadership to integrate the performance of others with complementary skills or “binding”. I use this four dimensional representation of white collar performance to sketch an impression of what an eventual classification scheme might look like. The goal of developing such a scheme would be to enable comparisons to be made between studies conducted across different white-collar settings.

My lack of content analysis is a result of the decision to preserve privacy by encoding the words in email messages with a hash function. Since response time and message size measures may vary according to the type of content this significantly limits the interpretation of these results in current work. Lack of knowledge regarding content also means that I must use indirect arguments for email as a proxy for internal communication patterns. Access to message content would make it easier to evaluate the true extent to which communication that occurred over email corresponds to internal communication across media and would make it easier to identify specific biases and limitations associated with the use of email as a network data source. I may still pursue simple comparisons of message similarity in future work. However, I believe efforts towards integrating more general classification of messages on the basis of content with social network results would be best undertaken using a data set that provided richer content cues. In general, I believe the integration of strategies for classification and information retrieval with social network analyses techniques is an extremely rich area for future work. This extends beyond social network research to the development of tools that suggest person-to-person search options when computer-based information retrieval strategies break down.

The OLS models I used for hypothesis testing do not permit inferences regarding the direction of causation. In addition, endogeneity at both the level of ties within network measures and between network measures and performance measures limits my interpretation of results to hypothesis testing as opposed to parameter estimation. The former is often addressed in network analysis using exponential random graph models, such as p* (Wasserman and Robins 2005). However, the latter may be the more serious concern. For example, from the perspective of theory, it is not clear whether a more central position in an email network would enable higher performance or whether higher performers are more likely to occupy more central positions because they are more likely to receive email from colleagues. While I do not know the true direction of this relationship, I suspect it involves a feedback loop, potentially one that also involves search contracts. Forms of instrumental variables estimation or panel models, the typical techniques for addressing endogeneity issues in econometrics, may be difficult to implement with the existing data. The difficulty associated with instrumental variables techniques involves identifying suitable instruments, since most variables that are likely to correlate strongly with either performance measures or centrality metrics are likely to be correlated with both. To set up a panel model, I believe I would need email data collected over a longer time period. Because of variation in the arrival and completion times of search contracts, analyses of the intertemporal reliability of performance measures suggests that these should be computed over time intervals of at least six months with 12 months preferable for billing completions due to seasonal variation.

An inability to compare individual level input and output measures over multiple time periods also limits interpretation of results to factors that influence individual performance as opposed to total factor productivity at the individual level. However, within the context of information related work, I believe the concept of total factor productivity is more meaningful at higher levels of aggregation. If important inputs and outputs to the individual production function pass through relationships with colleagues, as my results suggest, then a conceptual problem with may exist in addition to the measurement issues that motivated this work.

Future Work

There are also opportunities for future work that I could pursue with the existing data. Most of these are associated with the further development of measures and models. The development and selection of centrality metrics now commonly used in social network analysis involved the work of multiple researchers over a period of decades. The email based measures I define and assess in my dissertation should be thought of primarily as a starting point. In addition to measures used in this dissertation, analyses of the data suggested a number of other potentially promising possibilities that I have not yet implemented.

At the level of the population, I found an empirical regularity between the average degree measure and the choice of cutoff point. This raises the question of whether a similar relationship might exist at the individual level. If so, I may be able to estimate an individual specific parameter representing the capacity to engage in relationships over email, an observation made by Co-Chair Marshall Van Alstyne. Whether or not this parameter is related to any of the performance metrics is an interesting question for future research.

The measure I use to assess the performance of others with whom one communicates with over email can be thought of as specific instance of a general class of measures. The general class is defined by measures composed of individual attribute values and weights that express the strength of relationships. This type of measure may be useful for identifying indirect effects in which specific types of behavior may influence the performance of others. A prior limitation in developing and implementing such measures in empirical work is that it is often difficult to derive accurate measures of proportional communication through responses to network surveys. Examples of other attributes that may influence the performance of others include survey measures such as information sharing and mentoring.

Measures that express temporal aspects of email communication, network formation and relationships between email and contract data represent additional opportunities for future research.   Kossinets and Watts (2006) developed an alternative strategy for assessing intertemporal reliability of email measures based on convergence to a stable state using a sliding window. I believe this technique is superior to the one I used and could implement it with respect to all my email measures.

In general, I accept the criticism that my use of Cronbach's alpha to assess intertemporal reliability involves putting the cart before the horse in the sense of having confirmatory analysis precede more detailed evaluation of temporal interrelationships between contract and email measures. Data exploration techniques more commonly associated with statistical process control applications, such as control charts, may be useful for future work exploring aspects of temporal relationships between email communication and contract data. The use of search ID numbers to provide an alternative temporal sequencing to start dates, examination of email activity that precedes contracts with divided booking credit and other details of the data that surfaced during analyses may aid such work. A better understanding of these temporal relationships would be particularly useful for addressing questions of causation.

With respect to the interpretation of email measures, correlation analyses, particularly with respect to survey measures could be pursued further. Relationships between email and performance measures in regression models are often best interpreted as instances in which email patterns serve as indicators. A natural follow up question is what larger set of behaviors might email patterns serve as indicators of? Patterns of correlations with survey measures offer a way of investigating these relationships. I ran many correlation analyses in the course of this research, but have not conducted a systematic exploration of this facet of the data.

While previously mentioned data limitations may preclude some desirable forms of regression models, other improvements are possible. Five years of contract data that both precedes and follows the email data is an important resource. Forecasting models are a logical next step. There are some suggestions of performance trends in the data. Initial examination of longitudinal plots suggests two groups of consultants, one of which had exhibited increasing levels of performance from 1999-2003 and another in which performance levels have fluctuated around a mean or declined. Greater understanding of effects that may have contributed to these differences would strengthen my interpretation of results.

I could extend the model I used to compute the expected numbers of messages exchanged between any two recruiters in a number of useful ways. For example, I could estimate a logit model with the presence or absence of ties as the dependent variable (eg. above 5 or more emails as a cutoff) to examine factors that predict the appearance of ties. By restricting the population to recruiters who were not involved in searches over the study period, I could use this model to investigate factors that help predict email ties in lieu of shared work.

Contributions

Despite the previously mentioned limitations and an abundance of areas left for future work, I believe this research makes a number of significant contributions in the areas of empirical findings, methodology and theory.

I am not aware of existing work contradicting or even testing the null hypothesis of no relationship between email patterns and economic measures of individual performance. I believe evidence that relationships do exist between email patterns and individual performance measures within a white-collar context represents a significant contribution. My results also suggest relationships between email patterns and performance that extend beyond topological features of communication networks to less commonly measured features, such as information flows and response times. I believe the correspondence between my results and theory is strong enough to suggest that the relationships between email patterns and performance were not just a fortuitous accident. Positive results are important because the idea of using email patterns as proxies for attributes of relationships is transferable to economic assessments of individual performance differences in many other contexts.

I believe my development of email based measures of communication and assessment of their validity and reliability is a significant methodological contribution. Email-based measures offer opportunities to address problems associated with informant inaccuracy in network surveys. They also contribute novel ways of assessing characteristics of relationships based on direct measurement at the level of interactions.

In setting expectations, it is important to recognize that the current suite of topological measures used in social network analysis evolved from the work of multiple researchers over a period of decades. But I believe this work represents an important start that introduces new measures and begins an assessment of their properties.

From a theoretical perspective, my work makes the contribution of interpreting classic theories regarding relationships between communication patterns and performance across disciplines. I develop these interpretations as hypotheses that can be tested through the use of email data. By doing this, I am able to show how established theoretical explanations for why some individuals may exhibit higher levels of performance than others may play out in a modern context involving highly distributed work and computer mediated communication. In addition, my focus on properties of interactions that go beyond topology may be useful for analyzing the patterns of decisions people make in the context of socially situated resource allocation problems involving their time. While social network methodologies have traditionally emphasized constraints operating at the level of what might be thought of as the choice set, they have often paid less attention to the tradeoffs people make as the budget constraint of time binds. Burt's (1992) efficiency arguments underlying his theory of structural holes represents an important exception. This work may be thought of as another step in the direction of work that considers both elements.

Conclusion

While I frame my contributions in terms of contributions to knowledge, a more direct question is whether anything more tangible than knowledge is likely to come out of this research. While time will tell, I believe this work exhibits the potential for a number of practical extensions. In recent years, the application of social network methodologies as a way of producing artifacts that capture how things really work within organizations has become increasingly popular (e.g. Cross, Borgatti et al. 2002). My email based measures and methodological strategies have the potential to be incorporated into future social network toolsets. The expected result would be richer and potentially more useful artifacts, particularly with respect to non-topological features associated with the movement of information through communication networks.

One interpretation of the sum of results that emerged from the hypotheses tests is that factors that best predicted individual performance within an organization tended to be structural, while structure was shown to be a broader category than communications network topology. This prompts the question of whether or not this should have been obvious at the beginning. The details of how these relationships would play out in a real organization were not obvious to me. I hope my research gets enough of the details right to say something useful about this particular setting. More generally, the extent to which it is possible to quantitatively estimate the details of how communication patterns and the relationships they support in organizations matter in economic terms will be better understood through subsequent research in other settings. However, evidence that representations based on electronic archival data sources like email may be able to get more of the details right than one would imagine could turn out to be an important step.

Appendix A

Calculating Tie Strength Using Email Data

In social network surveys, researchers typically ask respondents to assess the strength of relationships with others. Researchers use these responses as measures of tie strength. Social network researchers who use email data also need to assess tie strength. In recent studies of search through email networks, researchers have selected cutpoints of 5 or 6 emails to derive a binary classification of links (Adamic and Adar 2005; Zhang and Ackerman 2005). The apparent justification was to set the threshold low enough so that weak ties would be captured, but not so low that occasional announcements would be construed as links. While I have no reason to believe that the thresholds these researchers used were unreasonable, they appear to be arbitrary. It is easy to show that changing the threshold for classifying a quantity of email communication as a tie also changes the resulting social network metrics. In my dissertation research, I did not find any literature that provided methodological guidance around the question of calculating tie strength values from email data.

I begin this appendix by describing a number of methodological problems. Following each problem description, I briefly describe the empirical analyses I conducted. Results of my analyses follow. The resulting list of problems and potential ways of addressing them represents an initial step towards developing standard methodological practices for deriving tie strength values from email data. Because the words in the emails I used were encoded, these strategies do not include techniques involving content analysis.

Problem: Tie strength values can be derived from raw email data in multiple ways. For example, one researcher might use a count of the number of messages. Another might use a count of the number of weeks in which email communication occurred. While either strategy seems reasonable, they will not necessarily produce equivalent results. Is there a best choice of unit for measuring tie strength based on email data?

Analyses: I used the choice between message counts and frequency measured as the number of weeks in which email activity occurred as a starting point. This led to two questions. I addressed the question of whether outliers might have any potential significance by identifying them with a scatterplot (A.1). I addressed the question of correspondence between these two measures through regression analysis (A.2). My regression model suggests an empirical regularity between these two measures.

Problem: Social network theories often implicitly assume person-to-person communication. However, email can also be used as a broadcast medium. Researchers will often want to distinguish between these two uses. I excluded messages sent to email lists on the basis of addresses in the "from:" field. However, individuals could still use email in a broadcast fashion by adding multiple addresses to the "from:" or "cc:" fields. Could the centrality metrics of individuals who use email more extensively in a broadcast fashion exhibit an upward bias?

Analyses: In this setting, I was able to rule out the potential for an upward bias with a simple correlation analyses. I compared my centrality metrics with those calculated from a population that excluded all emails sent to three or more recipients (A.3). However, broadcast communication could play a more significant role in other settings motivating the need for further analyses.

Problem: The cutoff points a researcher uses to represent a pattern of email activity as a link influence the resulting social network measures. How should researchers choose cutoff point(s) to adequately capture an individual's position in the network topology?

<u>Analyses:</u> My initial analyses focused on better understanding how variation in the cutoff points influenced the resulting measures. When the number of messages exchanged between two individuals was at or above the cutoff point I recorded a link, otherwise I did not. To guide the selection of cutoff points, I produced a plot showing the cumulative percentage of dyads with some email activity and the cumulative percentage of messages as a function of the cutoff point (A.4). I also used regression analysis to identify an empirical regularity between the average in and out degrees of recruiters and the cutoff point used to determine a link (A.5).

I selected my specific cutoff points using a process of empirical reasoning based on an analogy to assessments of convergent and discriminant validity. **Convergent validity** is defined as the degree to which concepts that should be related theoretically are interrelated in reality. **Discriminant validity** is defined as the degree to which concepts that should not be related theoretically are, in fact, not interrelated in reality (Campbell and Fiske 1959). In multi-method studies, these concepts are often applied to distinguish between values of measures that accurately reflect the theoretical concepts or traits the researcher intended to study as opposed to those that reflect the method of measurement or other confounds. I used only a single network data source. However, I used the fine level of granularity in email data to create a variety of measures representing gradations in the values of communication parameters. For these gradations to matter, they should both have a theoretical interpretation and lead to the creation of measures that are empirically distinct in the sense of exhibiting discriminant validity.

Relevant theory discusses implications of tie strength in terms of weak and strong ties, but has typically paid far less attention to potential implications of intermediate strength ties (e.g. Granovetter 1973; Granovetter 1983; Krackhardt 1992; Hansen 1999). Prior theory neither provides an explanation for how intermediate strength ties should matter, nor does it rule out the possibility of distinctive effects occurring at intermediate tie strengths. As a result, I chose to investigate whether I could produce distinctive measures of intermediate strength ties through my choice of cutoff points. This can be thought of as asking the question of whether I could generate measures that exhibited discriminant validity.

To do this, I used Cronbach's alpha to compare measures calculated using different tie strength cutoffs. My goal was to identify a set of measures that covered the range over which my data produced distinctive values (A.6). I subsequently used these cutoff points to calculate metrics that act as treatments in subsequent regression models. Since the work is exploratory, I believe it is appropriate to use measures that span the range of potentially relevant values.

Network researchers often use multiple metrics, but at most two gradations of tie strength.[32] Whether this is sufficient is likely to depend on the nature of the research question and the data. From the perspective of the data, situations can exist when variation resulting from differences in cutoff points exceeds variation resulting from differences in metrics. I illustrate this result by using Cronbach's alpha to assess the level of agreement between two sets of measures. In the first set, I varied tie strength cutoffs while keeping the metric constant. In the second, I varied the metrics while keeping tie strength constant (A.7). The result shows that empirically cases can exist in which metrics vary more as a result of differences in tie strength (which is often held constant) than from differences in metrics (for which multiple metrics are often used). This has substantive implications when gradations in tie strength influence results.

[32] My tie strength cutoffs of greater than or equal to 1, 5, 10, 20 and 40 messages could be analogized to survey responses in which communication frequency is assessed as at least occasionally (ge1), monthly (ge5) and weekly (ge40). However, the finer level of granularity I obtained using email data still appears to be useful. The statistical significance of my results changed most frequently between the ge10 and ge20 cutoffs.

Analyses

(A.1) I plotted the fraction of weeks in which email was exchanged (x-axis) against the average number of emails exchanged in those weeks (y-axis). This plot does not identify the number of values sharing the same point.

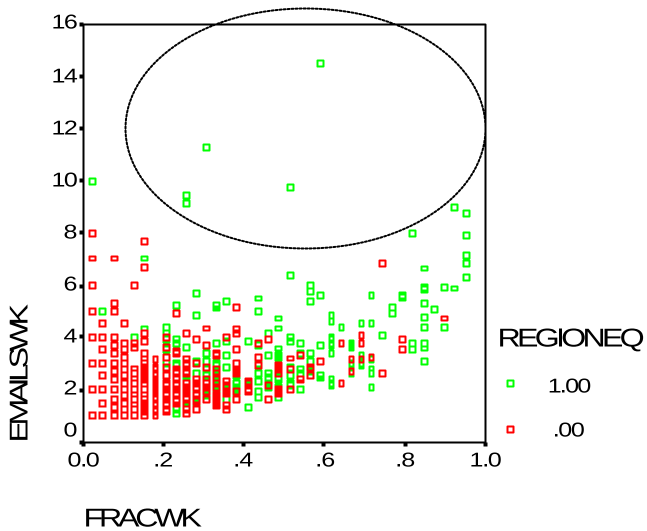

Fig. A.1 Fraction of weeks in which email was exchanged vs. number of messages exchanged in those weeks.

In the figure above, I display email exchanges between recruiters in the same work group in green and exchanges between recruiters in different work groups in red. I used this coding because my preliminary analysis of the data suggested intra-regional communication was more frequent. Recruiters in the same work group exhibit higher email frequencies (F=427, $p < 0.001$) and numbers of messages (F=335, $p < 0.001$). I examined similar effects in more detail through regression models that predict expected number of messages between dyads (Appendix D).

All the points in the circled area involve the same recruiter. If emails sent from this outlier are excluded, the Adj. R^2 of the regression model shown in the next analysis (A.2) increases from 0.836 to 0.877. Based on frequency, ties in this dyad would be intermediate strength; based on number of messages, they would be strong ties. Although this particular recruiter was not included in any of the analyses because she was a late entrant to the firm, this suggests I may need to consider individual specific behavior in specific cases (see Appendix D).

The plot does not identify the number of values sharing the same point. For example, there are more than 200 observations involving recruiters who only exchanged email during a single week; however, because many of these values overlap, only nine points appear in the diagram. At the other extreme, at high frequencies, a single point generally corresponds with a single observation. Taking this into consideration, potential outliers corresponding to dyads in which a relatively high number of messages were exchanged in only a few weeks are not a major concern. These dyads would appear as weak ties based on frequency and at most weak-medium strength ties based on numbers of email exchanged. The plot suggests a quadratic relationship, which was confirmed in the following regression model.

(A.2) The dyadic relationship between the total number of email messages exchanged (during the study) and the number of weeks in which at least one email was exchanged can be expressed in the following equation:

Number of Emails = $B_1 + B_2 * \text{emailwks} + B_3 * \text{emailwks}^2$
where emailwks is number of weeks in which at least one email was sent.

	B	SE	Beta	t
Constant	2.602	0.556		4.678***
Emailwks	14.260	5.264	0.078	2.709***
Emailwks^2	212.209	7.257	0.841	29.242***

*** $p < 0.01$

Adj. $R^2 = 0.836$
N = 1799 (partner or consultant dyads with at least one email exchanged)
Network density = 48.2%

Table A.1. Regression results: numbers of messages vs. weekly frequency.

The regression results above show a strong relationship between the total number of emails exchanged and the number of weeks in which at least one email was exchanged. The latter measure was expressed as the fraction of weeks (out of 39). On the basis of the strength of this relationship, I concluded that using one of the two values was sufficient. I selected the total number of messages exchanged over the course of the study.

One potential explanation for the squared term is that recruiters who communicated in many weeks were more likely to be conducting multiple simultaneous searches, which may lead to more messages per week.

(A.3) I obtained the following Spearman correlations between degree measures calculated on the basis of all emails exchanged between consultants and partners and degree measures calculated on the basis of emails sent to three or fewer recipients:

Corr(Indegree$_{\text{All Email}}$, Indegree$_{<=3 \text{ or recipients}}$)	$\rho > 0.98$	$p < 0.001$
Corr(Outdegree$_{\text{All Email}}$, Outdegree$_{<=3 \text{ or recipients}}$)	$\rho > 0.98$,	$p < 0.001$

Email sent to more than three recipients could potentially be considered broadcast emails. However, the strength of these correlations alleviates concern that misclassification of broadcast emails might influence results in this setting.

(A.4) I plotted the cumulative percentage of email ties at or below a specific cutoff (purple) and the cumulative percentage of emails exchanged in dyads with email activity at or below the cutoff (red).

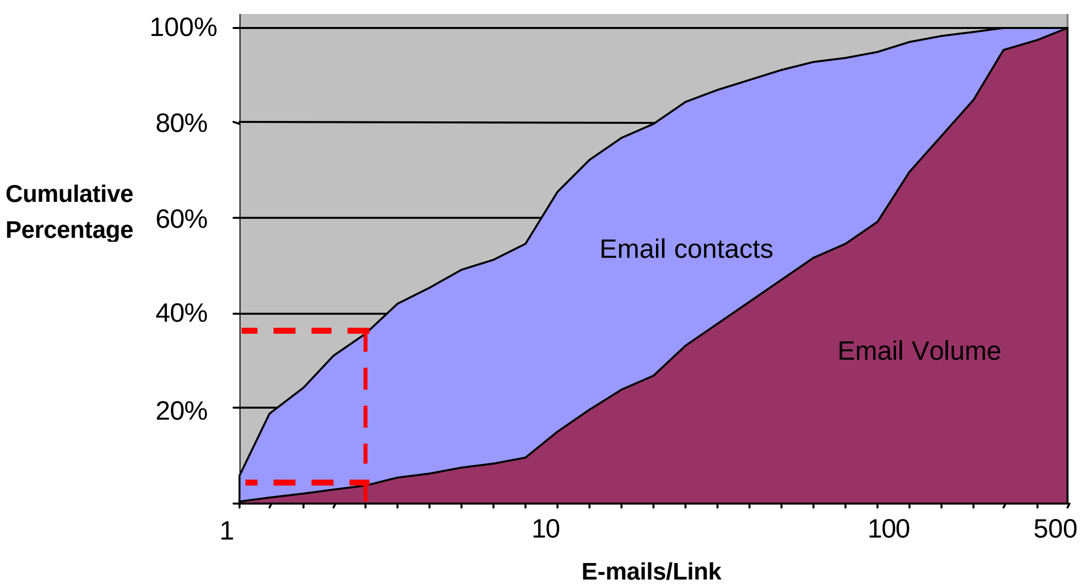

Fig. A.2. Cumulative percentages of email contacts vs. messages as a function of the tie strength cutoff.

The graph above can be used to identify the number of ties that would be affected by changes in the cutoff value above which a given number of messages is interpreted as a link. For example, as shown by the dashed lines, setting a tie strength cutoff at greater than or equal to five emails reduces the density of the network by approximately 37 percent, although it only reduces the number of messages counted by approximately five percent. This provides a way to interpret the implications of setting different cutoffs on the resulting network density. The density of the email network at low cutoff values is relatively high (eg. almost 50 percent for one or more emails). Different centrality metrics are less likely to exhibit discriminant validity when network density is high.

(A.5) The relationship between the average in and out degrees in the partner consultant network at a specific cutoff and the cutoff is well represented by the following equation:

Ave. degree measure at X emails = B_1 (1 / X)
where X is the average point in the cutoff range.

Adj. $R^2_{\text{Outdegree}} = 0.977$; $B_{1\ \text{Outdegree}} = 6.88$
Adj. $R^2_{\text{Indegree}} = 0.964$; $B_{1\ \text{Indegree}} = 6.74$

This result suggests an empirical regularity between the average degree measures and the choice of cutoff point for representing email activity as links. It does not reveal whether the measures generated at different cutoffs have similar or different relationships with performance metrics. As a result, it is still necessary to test the implications of different cutoff points in evaluating models that relate network structure to performance measures.

(A.6) Using betweenness centrality and structural holes as metrics and the following tie strength cutoffs, greater than or equal to one, five, 10, 20, 40 and 80 messages, I used the standardized version of Cronbach's alpha to evaluate two sets of comparisons. First, the same metric was compared at adjacent cutoffs. Then the same metric was compared at cutoffs with one intervening gap.

Tie strength cutoff comparisons			
Adjacent measures			
Structural holes (ge1-ge5)	0.89	Betweenness (ge1-ge5)	0.81
Structural holes (ge5-ge10)	0.94	Betweenness (ge5-ge10)	0.96
Structural holes (ge10-ge20)	0.90	Betweenness (ge10-ge20)	0.85
Structural holes (ge20-ge40)	0.92	Betweenness (ge20-ge40)	0.84
Structural holes (ge 40-ge80)	0.81	Betweenness (ge 40-ge80)	0.70
One gap between measures			
Sholes (ge1-ge10)	0.77	Betweenness (ge1-ge10)	0.77
Sholes (ge5-ge20)	0.83	Betweenness (ge5-ge20)	0.83
Sholes (ge10-ge40)	0.85	Betweenness (ge10-ge40)	0.82
Sholes (ge20-ge80)	0.77	Betweenness (ge20-ge80)	0.56

Table A.2 Cronbach alpha scores for pairs of centrality metrics at different tie strength cutoffs.

With the exception of betweenness centrality compared at cutoffs of greater than 40 and 80 emails, all adjacent measures had scores above 0.80. This suggests the level of granularity is sufficiently fine. At the same time, the majority of scores with one gap between measures are around 0.80. While this suggests I could use a somewhat coarser level of granularity, there does not appear to be any harm in using the proposed division. While the greater than 80 email cutoff point appears to yield divergent measures, it also lacks a clear theoretical interpretation. At the greater than or equal to 80 cutoff, the density of ties is approximately 10 percent of that observed at the greater than or equal to one cutoff. These ties might be thought of as strong ties between recruiters who are heavy emailers. In general, greater variation in metrics calculated at high tie strength cutoffs is expected because as the density of ties in the network decreases, variation in betweenness centrality and structural holes metrics typically increases.

(A.7) I used the standardized version of Cronbach's alpha to compare the level of agreement between the same centrality measure calculated at different tie strengths and different centrality measures calculated at the same tie strength. Tie strengths labeled low, intermediate and high represent divisions of ties into three roughly equal sets. The corresponding tie strength cutoffs are: low, 1-4 messages; intermediate, 5-12 messages; high greater than or equal to 13 messages.

Same Metric, Tie Strength Varies		
	Low-Intermediate-High	*Intermediate-High*
Betweenness	0.45	0.67
Structural holes	0.64	0.77
Indegree	0.30	0.48
Outdegree	0.36	0.70
Metrics Vary, Same Tie Strength		
Low	0.95	
Mid	0.93	
High	0.96	

Table A.3. Reliability comparison varying metrics and tie strength.

The level of agreement among the same centrality metrics calculated at different tie strengths is low ($\alpha < 0.80$), while the level of agreement among different centrality metrics calculated at the same tie strength is high ($\alpha > 0.90$). Correlation matrices showed greater differences between metrics calculated at low tie strengths than between intermediate and high tie strengths. This motivated a separate analysis of correspondence between intermediate and high metrics (right). Again, none of the scores exceed 0.80.

These results suggest that in this context, it is reasonable to interpret all four centrality metrics as expressions of an underlying trait of network centrality, placing less weight on theoretical distinctions that could otherwise be attributed to differences between the metrics. A high level of correspondence among centrality metrics is not unusual in a densely connected network. On the other hand, low levels of agreement among metrics calculated at different tie strengths suggest differences in underlying traits.

However, because tie strengths were defined as mutually exclusive categories in this analysis, the following objection could be raised. In the former case, the network remains the same while the measure varies, while in the latter case, the same measure is being calculated on different networks. To some extent, different choices of tie strength cutoffs will always lead to differences in networks. However, these differences are reduced when tie strengths are defined as partially overlapping thresholds (e.g. greater than 5 messages compared to greater than 10 messages) as they were in the previous analysis (A.6).[33]

[33] A secondary point of interest in the comparison of medium and strong ties is that indegree stands out as the measure with the lowest level of agreement. One possibility is that there is a relatively small subset of recruiters that function as information sinks, receiving a high number of message from an usually high number of others. This appears to be true to some extent, but is difficult to quantify.

Appendix B
Properties of Dyadic Measures

My interest in relationships between information flows and performance led me to create a series of dyadic measures. These include measures of proportions of messages exchanged and email response times and size. I developed these measures using a combination of theory and empirical analyses of the distributional properties of the raw data. The following table gives an overview of the analyses I conducted:

Proportional Information Flows	
Distributional properties of the data	B1-B2
Overview of normality tests and assessments of tendencies towards reciprocity	B3
Response Times	
Messages sent by hour of the day and day of the week	B4
Individual email response profiles	B5
Population level response time distributions and normality tests	B6-B7
Correlations between performance measures and response times	B8
Response time profiles by job level relationship and team status	B9
Email Size	
Distributional properties of email size with and without attachments and normality tests	B10-B11
Correlations between performance measures and email size	B12-B13
Email size profiles by job level relationship and team status	B14-B15

Table B.1 Overview of analyses involving dyadic properties of email

Proportional Information Flow Results

(B.1) I plotted the numbers of internal email messages sent and received by job level for consultants and partners. Sent emails have positive values, received emails have negative values.

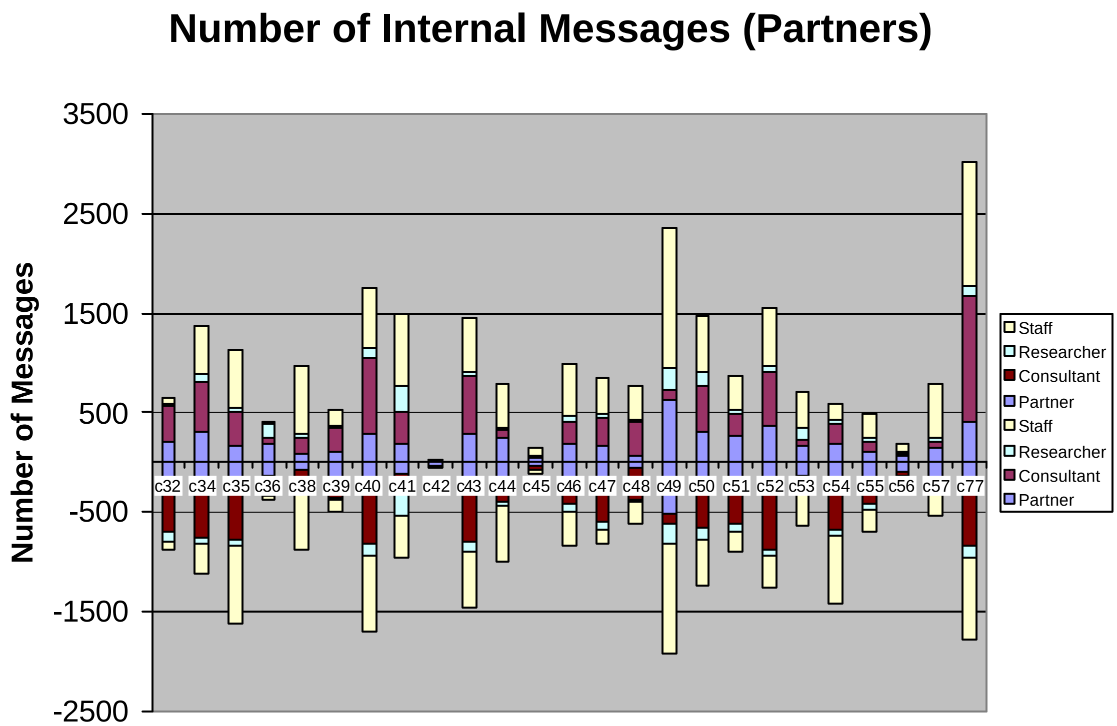

Fig.B.1. Proportions of internal messages partners exchanged by job level.

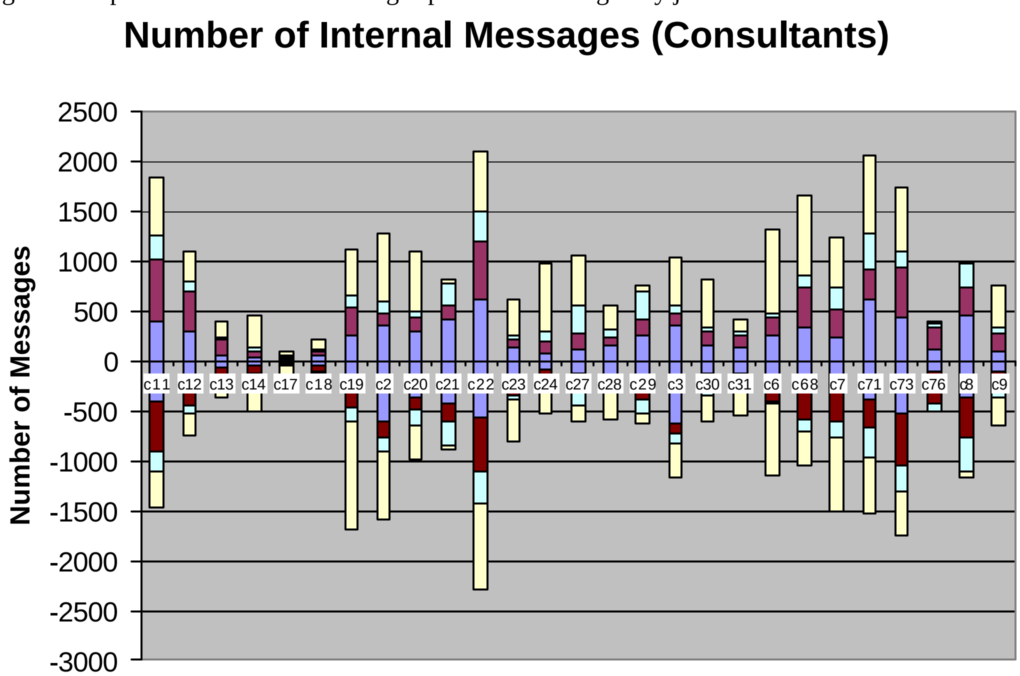

Fig. B.2 Proportion internal messages consultants exchanged by job level.

(B.2) I plotted the numbers of messages sent and received among consultants and partners categorized by the relationship to search activity when the email was sent.

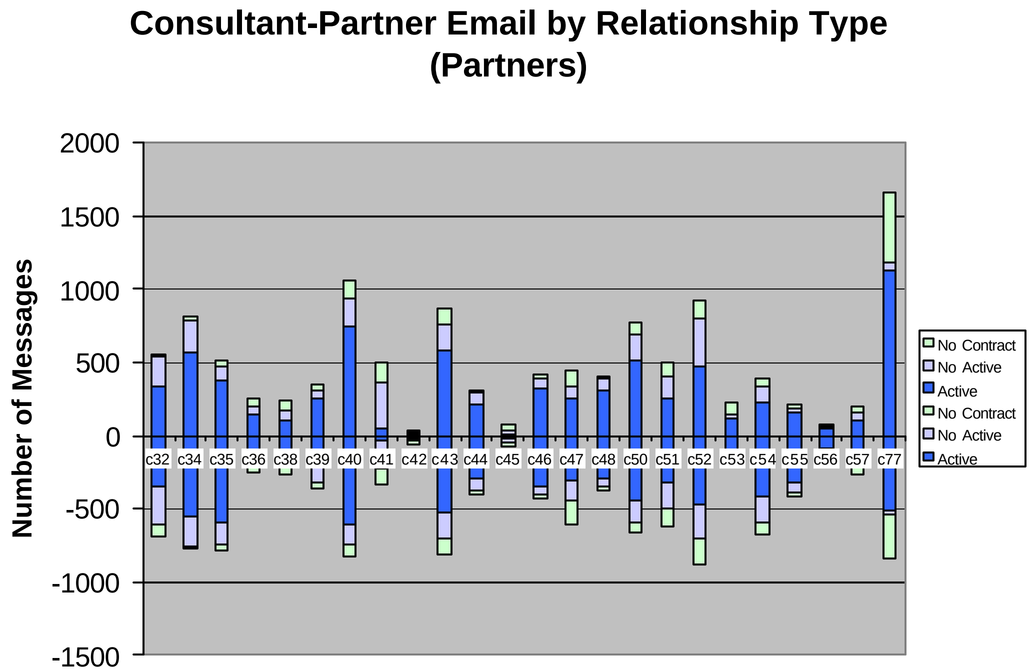

Fig. B.3. Proportion of messages partners exchanged by relationship type.

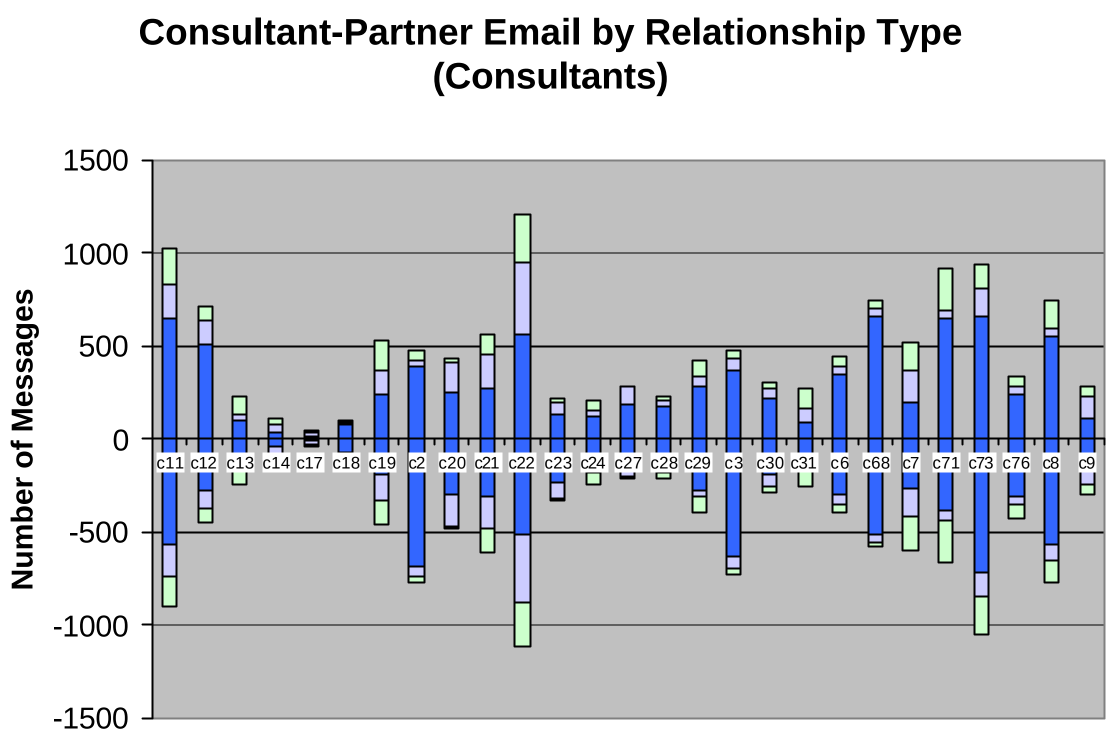

Fig. B.4. Proportion of messages consultants exchanged by relationship type.

I show numbers of messages as opposed to proportions in the graphs above because the former representation gives more information. I also produced proportional plots. The graphs include recruiters who I did not include in subsequent models because they were recent entrants to the firm. The number of messages recent entrants exchanged with staff is likely to be underrepresented.

The graphs above show considerable individual variation in email patterns. This motivates questions about whether differences in proportions of messages, which could be characterized as email information flows, may be related to performance.

(B.3) I plotted histograms of the individual proportions of email exchanged and applied the Shapiro Wilkes test for normality. I also calculated correlations between messages sent vs. received in each category and produced plots.

Shapiro Wilkes test results suggest that some of the distributions are likely to deviate from normality. Test results for proportions exchanged with researchers and the proportion sent to colleagues recruiters had never worked with on searches were significant at $p < 0.01$. About 20 percent of the recruiters send more email to researchers than their colleagues (above 20 percent). The proportion of email recruiters sent to colleagues they had never worked with on searches is skewed. The modal values are 5 and 10 percent. Above 10 percent the distribution declines in a roughly linear fashion to 40 percent with one value at 55 percent. While this is clearly not a normal distribution, it was not clear that it should be transformed.

Correlations between sent and received email provide a rough measure of tendencies towards reciprocity. Proportions of sent and received email are strongly correlated ($\rho > 0.80$) for all three of the relationship types among consultants and partners. Pearson correlations for proportions of email sent and received by internal job level were all above $p < 0.01$. The weakest correlations involved email exchanged with staff ($\rho \sim 0.56$) followed by email exchanges with partners ($\rho \sim 0.67$), with consultants ($\rho \sim 0.71$) and with researchers ($\rho \sim 0.79$).

(B.4) I plotted sent email activity aggregated by hour and day of the week to define the span of the workday

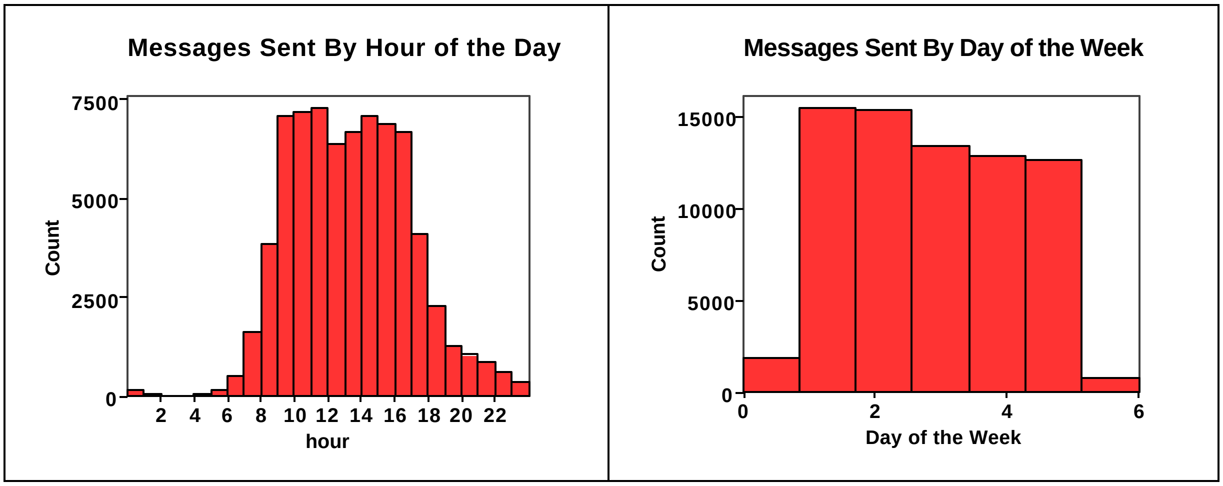

Fig. B.5 Number of messages partners and consultants sent by hour and day of the week.

In the plots above, I used military time and represented the days of the week using numbers ranging from Sunday = 0 to Saturday = 6. While the plot shows a fairly regular start to the workday around 8 am with relatively high levels of email reached by 9 a.m., the decline in email activity at the end of the day is more gradual. Individual plots (not shown) showed that the fat tail at the end of the day is more common among partners than consultants, but is exhibited by some individuals in both categories. It is not generally found among researchers. Weekend activity email was significantly lower as expected. For subsequent analyses, I set the cutoff points for defining the recruiting workday at 8 am to 6 pm.

(B.5) I used plots of individual response times to colleagues segmented into half hour intervals to identify individual median response times. I also plotted colleague response times at the population level.

c22 Response times

All Email

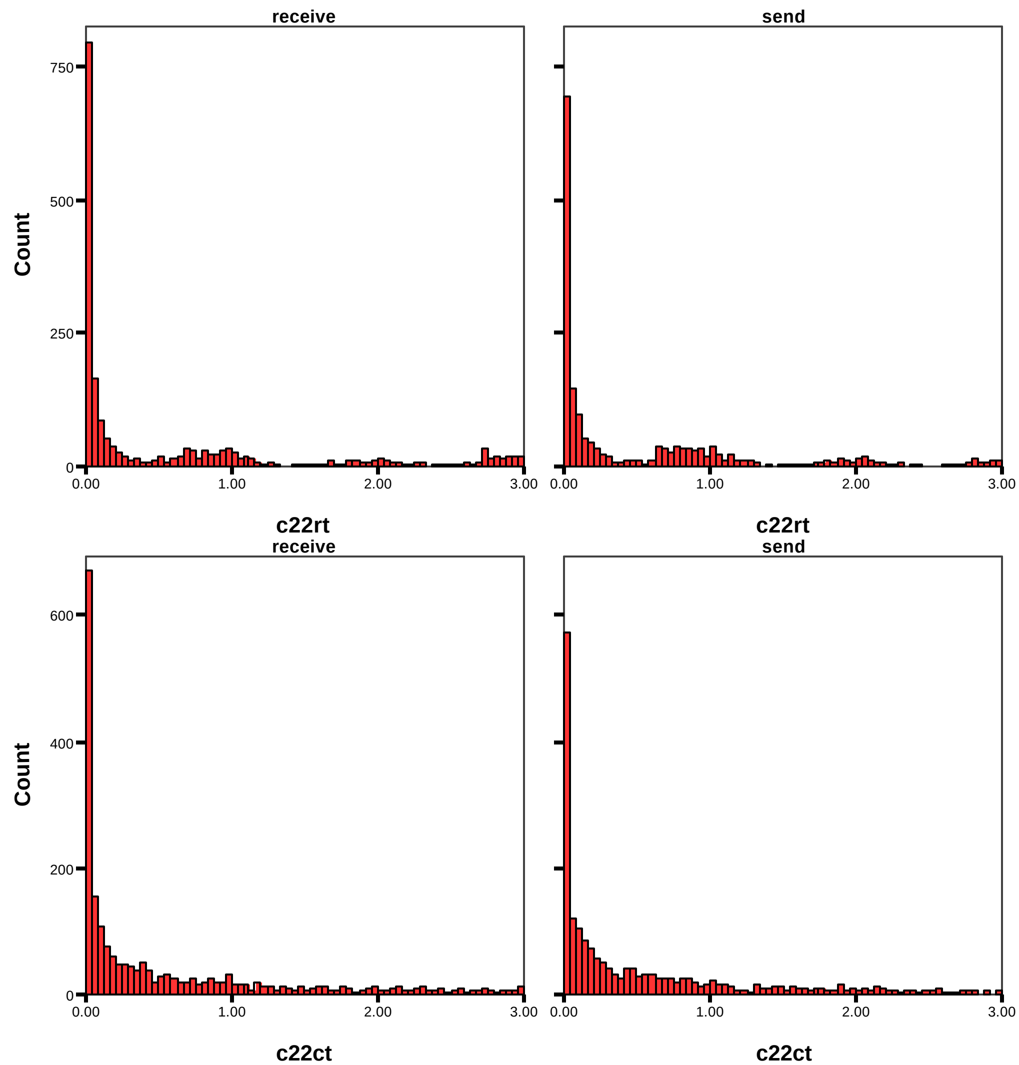

Fig. B.6 Individual response times to colleagues plotted in half-hour intervals.

The response time plots above are segmented into half hour intervals and are truncated at three days. The top plots use raw time stamp data, the bottom plots map time stamps to a 10-hour workday (8 am – 6 pm).

Two features of the plots above are worth noting. The first is the tendency towards rapid responses (within one half hour), shown here for an individual, but characteristic throughout the population. The second is that removing daily periodicity significantly smoothes the response time curve. A reference plot showing the population level distribution of unadjusted response times is given below.

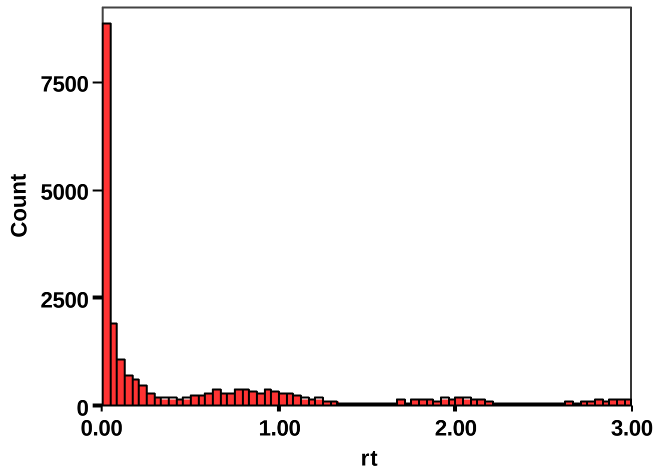

Fig.B.7. Population level distribution of response times to colleagues plotted in half hour intervals.

(B.6) I plotted the population level logged adjusted and non-adjusted response time distributions.

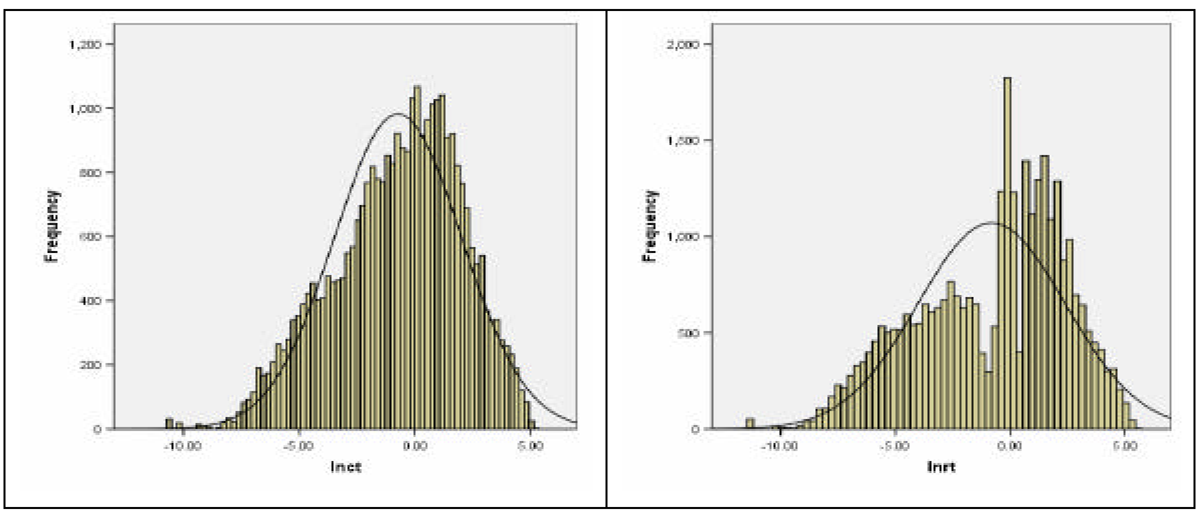

Fig.B.8. Logged response time distributions among partners and consultants.

I applied an additional transformation to the data shown on the left, adjusting response times to reflect the hours of the normal work day. The workday adjusted response time distribution, while skewed to the right, appears easier to parameterize than the unadjusted distribution. The choice also involves an information loss tradeoff, since email exchanges that do not extend into business hours have to be dropped from the logged adjusted response time calculation because the log of zero is undefined. While the rapid modal response time is highlighted by the unlogged plots previously shown, the peaks in the logged plots suggests response times may also cluster around one day.

(B.7) I produced P-P plots of the logged adjusted response time distribution and performed a Kolmogorov-Smirnov test.

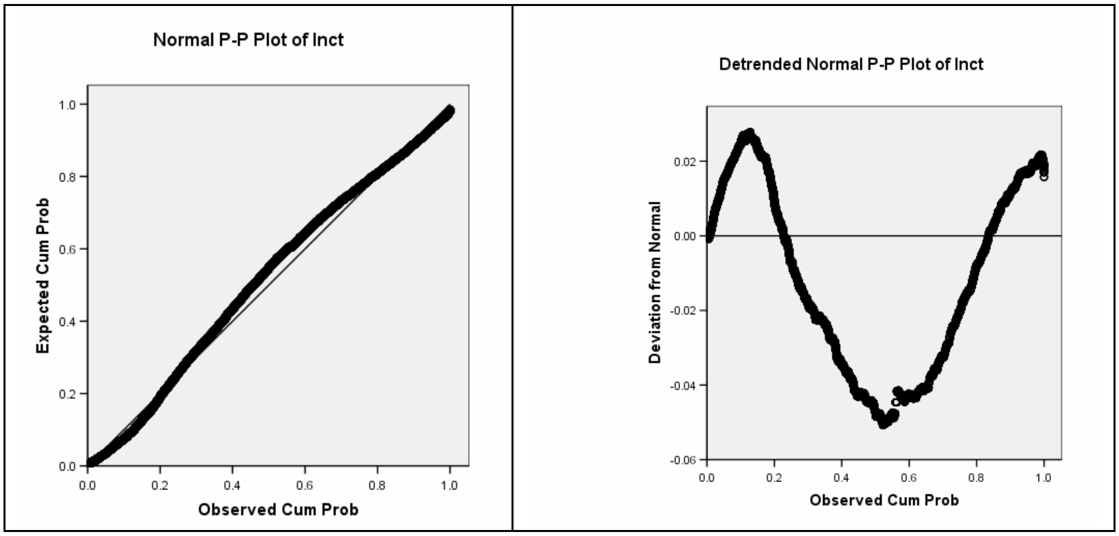

Fig. B.9 Normal P-P plots of the logged adjusted response time distribution.

As shown above, there are more rapid responses than would be implied by a normal distribution (within approximately 10 min), fewer intermediate responses and more responses after a full business day has elapsed. Since the definition of a response is time-based as opposed to content-based, a longer period of time taken in responding to a message is not distinguished from the initiation of a new thread. This is worth keeping in mind for interpreting response times of more than one day.

The Kolmogorov-Smirnov Z-score was 6.435 indicating that there is almost zero probability that the true distribution is normal. In comparison, the Z-score for the unadjusted response time distribution was 12.351. However, with thousands of observations the power of the test is such that an inability to reject the normal distribution would have been surprising. Inspection of the plots suggests that the unadjusted response time distribution is not normal, while the adjusted response time distribution is much closer, but contains a plateau between -5 to -3 (approximately equivalent to 4 to 30 minutes). While distributions that involve more parameters could provide a better fit, it is unclear how additional parameters should be interpreted if used in subsequent regression models.

(B.8) I calculated Spearman correlations between individual billing and booking revenues and email response times. I segmented response times by job level, team vs. non-team communication and sent vs. received messages.

	Percent Email Responses Within (Time) and Revenue								
	Min	**Hr**				**Days**			
	30	1	2	4	8	1	2	3	7
Booking Revenue									
Team									
Sent									
All	-0.13	-0.18	-0.15	-0.13	-0.15	-0.11	-0.09	-0.07	-0.06
Consultants	0.05	0.07	0.15	0.16	0.12	0.23	0.21	0.03	0.15
Partners	-0.10	-0.18	-0.13	-0.06	-0.02	0.11	0.13	0.17	0.22
Received									
All	0.22	0.15	0.13	0.08	0.01	-0.06	-0.07	-0.14	-0.13
Consultants	0.08	0.00	0.07	0.06	0.05	-0.09	-0.09	-0.10	-0.09
Partners	0.15	0.19	0.19	0.14	0.09	0.16	0.32	0.18	0.29
Nonteam									
Sent									
All	-0.47 ***	-0.55 ***	-0.54 ***	-0.53 ***	-0.50 ***	-0.49 ***	-0.43 ***	-0.40 ***	-0.34 **
Consultants	-0.33	-0.34 *	-0.32	-0.32	-0.30	-0.25	-0.22	-0.22	-0.20
Partners	-0.29	-0.33	-0.36 *	-0.32	-0.23	-0.37 *	-0.26	-0.19	-0.11
Received									
All	-0.46 ***	-0.41 ***	-0.44 ***	-0.44 ***	-0.41 ***	-0.37 **	-0.31 **	-0.28 *	-0.32 **
Consultants	-0.34 *	-0.28	-0.27	-0.18	-0.22	-0.24	-0.20	-0.14	-0.27
Partners	-0.57 ***	-0.45 **	-0.52 **	-0.50 **	-0.50 **	-0.52 **	-0.50 **	-0.54 **	-0.47 **
Billing Revenue									
Team									
Sent									
All	0.39 ***	0.37 **	0.37 ***	0.39 ***	0.39 ***	0.44 ***	0.45 ***	0.45 ***	0.41 ***
Consultants	0.39 *	0.38 *	0.43 **	0.44 **	0.42 **	0.51 ***	0.53 ***	0.50 **	0.51 ***
Partners	0.43 **	0.36	0.39 *	0.37 *	0.40 *	0.43 **	0.46 **	0.44 **	0.40 *
Received									
All	0.12	0.04	0.06	0.06	-0.01	-0.02	0.02	-0.03	-0.04
Consultants	0.25	0.12	0.21	0.28	0.24	0.13	0.13	0.12	0.06
Partners	-0.04	-0.07	-0.09	-0.18	-0.27	-0.20	-0.15	-0.21	-0.18
Nonteam									
Sent									
All	0.29 **	0.24 *	0.22	0.17	0.19	0.11	0.13	0.11	0.11
Consultants	0.15	0.08	0.06	-0.06	-0.06	-0.09	-0.05	-0.06	-0.03
Partners	0.42 *	0.44 **	0.40 *	0.35	0.48 **	0.29	0.29	0.24	0.22
Received									
All	0.06	0.10	0.11	0.10	0.11	0.06	0.00	-0.05	-0.06
Consultants	-0.10	-0.07	0.00	0.08	0.10	0.01	0.01	0.09	0.04
Partners	0.18	0.25	0.17	0.11	0.11	0.12	-0.01	-0.18	-0.22

Table. B.2 Correlations between individual email response times and revenues.

As shown above, revenue from completed billings is positively associated with greater responsiveness to teammates among both partners and consultants and across cutoff times. The pattern of correlations suggests long gaps in replying to team members are negatively related to performance in completing search contracts. The correlations are significant at ($p < 0.10$) in all team sent categories except one. A gap of more than seven days would lower the percentages across all categories. Correlations are slightly stronger for the percentage of responses sent within one, two and three days than for percentages of responses within a day. However, more information is needed to distinguish between performance implications, if any, of differences between more rapid responses on the order of minutes and more frequent responses within a week.

Patterns of statistically significant negative correlations with respect to booking revenue and non team communication suggest responsiveness is not critical in all contexts. Since these patterns of correlations are generally significant across all categories, they can interpreted as a positive association with sending or receiving email from colleagues who have not been recent correspondents (within the past week). This suggests booking revenue is likely to be associated with weak ties, but not strong ones, which is consistent with results in the first set of regression models. The evidence above comes from the perspective of longer time intervals; the evidence from hypothesis 1 regression models involves message counts over the study period.

Sent email response times to non teammates are more strongly correlated within the population than either of the split samples, suggesting this is primarily a job level difference. This appears clearly in scatter plots (not shown). Booking revenues are generally higher for partners than consultants. Email activity is more sporadic within the partner peer-to-peer network than it is within the consultant peer-to-peer network, which is shown in subsequent plots.

However, received email response times are also consistently significant for partners in a split sample. An interpretation is that partners with higher booking revenue are more likely to receive email from colleagues who they have not corresponded with in the past week. A result that is insignificant in the direction of recruiter initiated email, but significant in the direction of colleague initiated email suggests that the direction of causality is more likely to run from colleagues. In this case it involves weak ties and runs to partners with higher booking revenue.

Finally, some relationships between being more responsive within a day to non-teammates and partner billing revenues are statistically significant. The interpretation is less clear. Scatter plots reveal that two senior partners who have low billing revenue and specific administrative roles contribute to the statistical significance of these correlations. Without these two partners, only the association with the percentage of emails responses within 8 hours is significant at ($p < 0.10$). A stronger correlation specifically at the eight hour level suggests more after hours emailing to non-teammates among partners with high billings, but further investigation would be needed to confirm this conjecture.

(B.9) I plotted email response times (10^{th} – 90^{th} percentile cutoff points) by job type (consultant and partner) and task (team and non team).

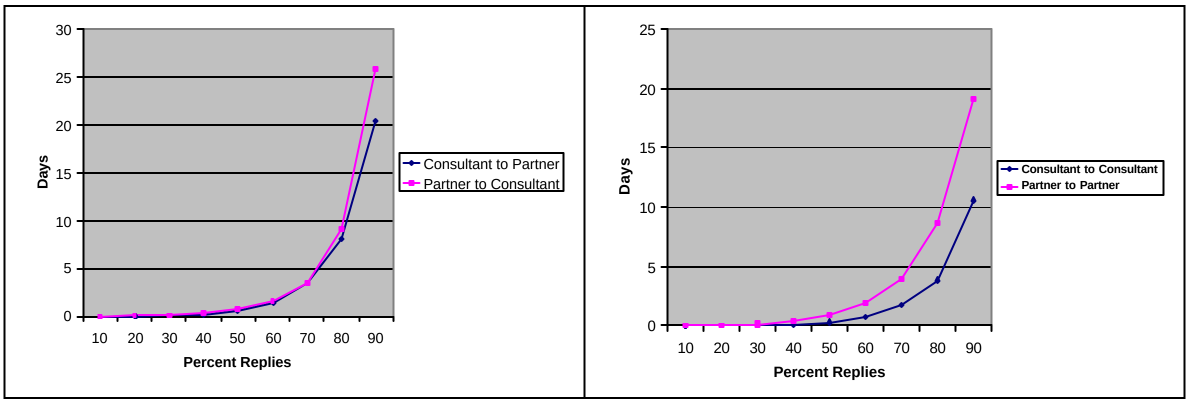

Fig. B.10 Response times by job level.

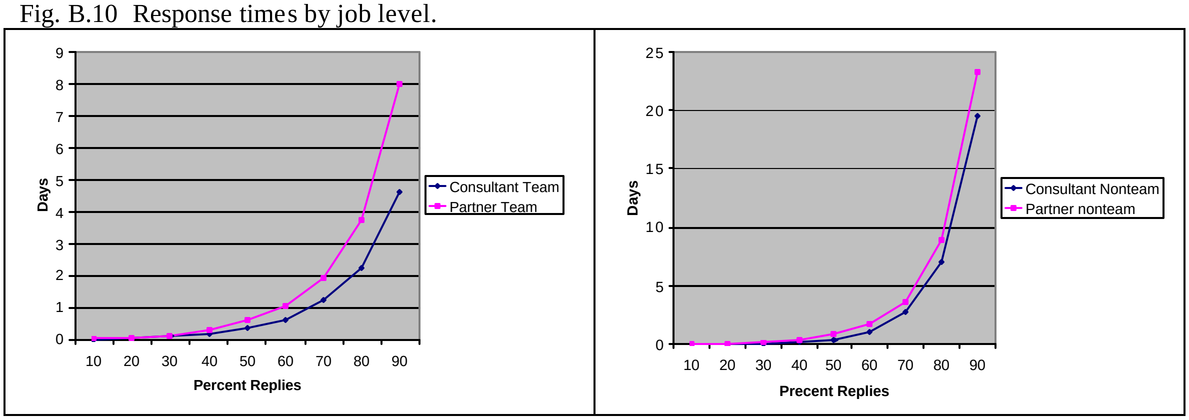

Fig. B.11 Response times within and outside search teams.

In figures B.10 and B.11, partner initiated emails are shown in pink and consultant initiated emails appear in navy. The most striking feature in the top graphs is the significantly longer time partners take to reply to peers than consultants. This may reflect job level differences in the type of networking that recruiters conduct with peers. Consultants focus more on executing contracts, an activity that is associated with more frequent email communication, while partners focus more landing contracts, which is associated with more sporadic email communication. A higher proportion of internal email sent to peers is associated with higher levels of performance in landing contracts among consultants, but not partners (see hypothesis 2 results).

While partners respond more slowly than consultants to team members (lower left), differences between the time partners take to respond to consultants and visa versa are smaller (upper left). One interpretation is that the teammates that partners respond to more slowly are more likely to be other partners. This would be consistent with other information on the research setting, which suggests that in search teams with multiple partners, one of the partners is likely to play a more peripheral role in search execution. In Appendix D, I show that partner-partner pairings on search teams are associated with a disproportionately high number of dyads that fall in the lowest percentiles of email activity among active search team members.

(B.10) I produced population level plots of the natural log of the size of text email (no attachments), email with attachments and a combined sample of text email and email with attachments.

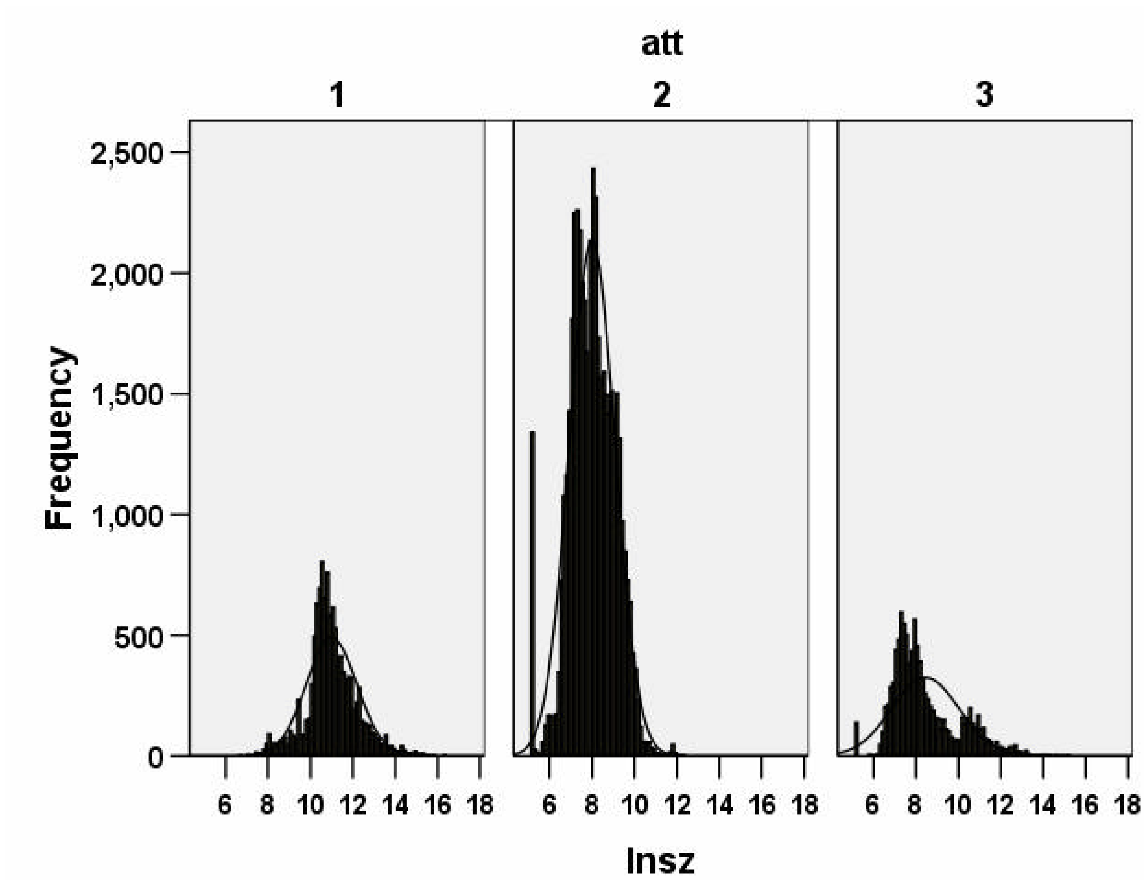

Fig. B.12 The natural log of email sizes by attachment status.

The plots in fig. B.12 compare the natural log of email sizes among messages with attachments (left), messages without attachments (middle) and a combined sample (right). A visual comparison reveals that the presence or absence of attachments contributes to bimodality in logged email size distributions.

For emails without attachments, a large spike appears at the left tail of the distribution that is consistent with very short messages (< 250 bytes). For one consultant, one partner and two researchers, more than 15 percent of sent emails are very short. Among all other individuals, the average percentage of very short emails is slightly less than one percent. While this pattern could be consistent with the use of a handheld BlackBerry like device it is not possible to rule out other explanations. For example, it could reflect a habit of sending email in which the subject line conveys the message. I flagged the two revenue generating recruiters with this pattern as potential outliers with respect to email size.

(B.11) I produced P-P plots of the logged text email size distributions and performed Kolmogorov-Smirnov tests.

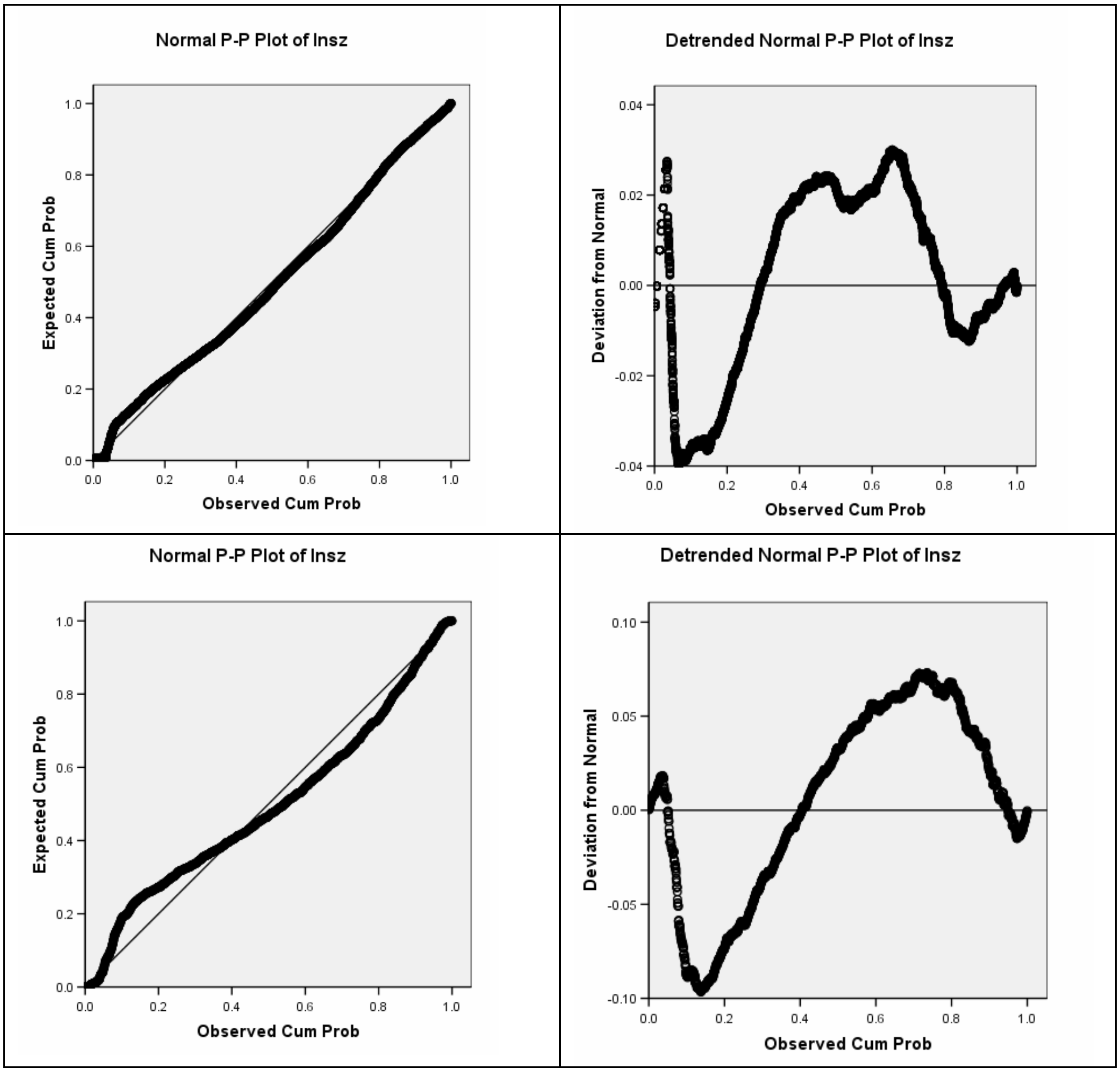

Fig.B.13. P-P plots of logged email size distributions.

Text only emails are shown in the top P-P plots, emails with attachments are shown in the bottom plots. The logged size of email messages without attachments distribution (top) deviates from a normal distribution primarily in the left tail. This is consistent with a larger number of very short messages (at most a few words) and fewer messages that are slightly longer. In other words, email messages are likely to consist of either a few words or a paragraph or more with few sizes in between. The Kolmogorov-Smirnov Z-test statistic was 4.60, which indicates a very low probability that the true distribution is normal. However, the very short messages are not the sole source of the deviation and removing them increases the deviation from normality. Given the high power of the test with thousands of observations, deviation from normality is expected.

In comparison to a normal distribution, the logged message sizes of emails with attachments has a higher peak in the middle and fans out more on both tails, displaying a tendency of values to cluster around the mean, which corresponds to a size of 53.5 kB. As a Microsoft Word file, this is slightly longer than the introductory chapter in this dissertation, which would lie close to the median of the distribution. The Kolmororov-Smirnov Z-test statistic was 4.75.

(B.12) I calculated Spearman correlations between billing and booking revenues, mean logged email sizes and the proportion of messages sent with attachments. I segmented message types by the distinguishing between messages with and without attachments and including a category that excludes forwarded messages. I segmented message populations by job level, team vs. non-team communications and sent vs. received messages.

Average Logged Email Sizes and Revenues

	No Attachments	NoFwd	Attachments	Both	NoFwd	% Attach
Booking Revenue						
Team						
Sent						
All	0.09	0.07	0.11	-0.16	-0.25 *	-0.27 *
Consultants	-0.14	-0.09	0.11	-0.23	-0.28	-0.25
Partners	0.26	0.21	0.32	0.15	0.06	0.30
Received						
All	0.08	0.08	0.02	-0.10	0.07	-0.09
Consultants	0.03	0.04	0.01	-0.23	-0.11	-0.16
Partners	0.26	0.25	0.18	0.25	0.42 **	0.25
Nonteam						
Sent						
All	0.17	0.18	0.03	0.15	0.22	0.02
Consultants	0.13	0.11	0.19	0.09	0.18	0.10
Partners	-0.18	-0.15	0.00	-0.18	-0.17	-0.24
Received						
All	0.18	0.17	0.10	0.38 ***	0.27 *	0.30 **
Consultants	0.26	0.28	0.01	0.36 *	0.35 *	0.11
Partners	0.05	0.06	0.16	0.17	0.24	0.31
Billing Revenue						
Team						
Sent						
All	0.01	0.02	0.08	-0.19	-0.22	-0.20
Consultants	-0.06	-0.05	-0.01	-0.36 *	-0.34 *	-0.40 **
Partners	0.09	0.08	0.32	0.03	-0.11	0.06
Received						
All	0.18	0.15	0.23	-0.02	-0.05	-0.08
Consultants	0.08	0.05	0.27	-0.38 *	-0.49 **	-0.70 ***
Partners	0.26	0.25	0.25	0.30	0.37 *	0.49 **
Nonteam						
Sent						
All	-0.18	-0.20	0.13	-0.26 *	-0.27 *	-0.23
Consultants	0.00	0.01	0.33	-0.05	-0.04	-0.12
Partners	-0.26	-0.33	-0.07	-0.41 *	-0.45 **	-0.36
Received						
All	0.03	0.06	-0.06	-0.05	-0.04	-0.08
Consultants	0.00	0.06	0.03	-0.04	-0.04	-0.07
Partners	0.11	0.14	-0.06	-0.02	-0.04	0.04

Table B.3. Correlations between revenues and email sizes.

In the table above, messages types (from left): (1) exclude messages with attachments, (2) exclude messages with attachments and forwarded messages, (3) include only messages with attachments, (4) include all messages and (5) exclude forwarded messages. The right column is the percentage of messages with attachments. I calculated the figures based on messages sent among revenue generating consultants and partners.

When message populations are segmented by the presence or absence of attachments (1st three columns from left), the average message size is not correlated with revenues at statistically significant levels, although a few are close to being significant. However, if no distinction is made regarding attachments (4th and 5th columns), there are a number of statistically significant correlations between message sizes and revenues. In most of these cases, the percentage of messages sent with attachments is also correlated with revenues at statistically significant levels.

The results bear some relation to the hypothesis relating smaller emails exchanged between team members to billing revenue from completed contracts, although they suggest that the overall relationship is significantly more complicated. Among consultants, correlations between the size of all emails exchanged among team members and billing revenue are all negative and significant. Correlations between the percentage of attachments and billing revenue are also negative and stronger. Using the human analogy to the queuing theory problem regarding the optimal chunk size, consultant processors may be delayed when team members exchange emails with attachments.

However, longer emails are not always negatively correlated with revenue. Partners who receive longer non-forwarded emails from teammates had higher billing and booking revenue. Consultants who receive longer emails from non teammates also had higher booking revenue. Without information regarding content, it may be difficult to differentiate between different potential interpretations of these results.

(B.13) I calculated Spearman correlations between billing and booking revenues and natural log of text email size ($10^{th} – 90^{th}$ percentile). In making these calculations I segmented messages by job level, team vs. non-team communications and sent vs. received messages.

	Size Percentile (No Attachments)								
	10	20	30	40	50	60	70	80	90
Booking Revenue									
Team									
Sent									
All	-0.05	-0.01	0.02	0.01	0.01	-0.01	-0.03	-0.05	0.00
Consultants	-0.13	-0.10	-0.19	-0.23	-0.16	-0.19	-0.14	-0.25	-0.26
Partners	-0.02	0.05	0.14	0.16	0.09	0.09	0.05	0.13	0.22
Received									
All	0.02	0.08	0.05	0.06	0.13	0.07	0.06	0.05	0.09
Consultants	-0.03	0.19	-0.01	0.02	0.04	0.03	-0.06	-0.13	-0.22
Partners	0.09	0.09	0.16	0.27	0.39 *	0.28	0.28	0.33	0.20
Nonteam									
Sent									
All	0.23	0.29 **	0.23	0.19	0.14	0.08	0.01	-0.02	-0.01
Consultants	0.30	0.18	0.05	-0.07	-0.04	-0.07	-0.13	-0.16	0.02
Partners	-0.16	-0.11	-0.04	0.04	0.03	-0.08	-0.20	-0.17	-0.17
Received									
All	0.26 *	0.25 *	0.22	0.21	0.23	0.31 **	0.14	0.17	0.02
Consultants	0.25	0.49 **	0.33	0.19	0.21	0.31	0.13	0.12	0.22
Partners	0.03	0.12	0.14	0.12	0.07	0.11	0.05	0.26	-0.16
Billing Revenue									
Team									
Sent									
All	-0.10	-0.14	-0.20	-0.17	-0.12	-0.12	-0.07	-0.10	-0.10
Consultants	-0.05	-0.18	-0.23	-0.22	-0.23	-0.24	-0.12	-0.20	-0.26
Partners	-0.12	-0.02	-0.14	-0.13	-0.02	0.03	0.05	0.03	0.10
Received									
All	0.23	0.13	0.10	0.08	0.08	0.10	0.07	0.05	-0.03
Consultants	0.03	0.03	-0.08	-0.05	-0.02	0.03	-0.07	-0.18	-0.28
Partners	0.44 **	0.19	0.24	0.19	0.15	0.18	0.22	0.26	0.16
Nonteam									
Sent									
All	0.04	-0.15	-0.22	-0.26 *	-0.29 **	-0.29 **	-0.31 **	-0.30 **	-0.22
Consultants	0.51 ***	0.18	-0.11	-0.11	-0.23	-0.27	-0.28	-0.30	-0.23
Partners	-0.37 *	-0.38 *	-0.28	-0.36	-0.29	-0.25	-0.31	-0.24	-0.23
Received									
All	0.00	0.14	0.14	0.04	0.09	0.05	-0.12	-0.10	-0.05
Consultants	-0.04	0.16	0.13	-0.05	0.04	0.14	-0.02	-0.12	-0.08
Partners	0.01	0.16	0.16	0.14	0.09	-0.05	-0.18	-0.03	-0.06

Table B.4 Correlations between revenues and text email size (10^{th}-90^{th} percentiles).

Results above show little evidence of the hypothesized relationship between smaller message sizes and higher billings revenue with respect to text email size. While sending smaller emails to teammates is correlated with higher billing revenues, the effects are not statistically significant, although they are stronger for consultants than partners. The only team related effect that is significant at $p < 0.05$ is a positive correlation between the size of email received in the lowest percentile and partner billing revenues. An interpretation is that partners who were more successful at completing contracts received fewer very short (ie. a few words) responses from teammates.

Although the effects are weak, the percentile based division appears modestly helpful for interpreting relationships between non team email sent and billing revenue. The results suggest that recruiters who were most successful at executing contracts tended not to send long text emails to colleagues outside their search team ($p < 0.05$ for the 50^{th} – 80^{th} size percentiles). Effects associated with sending very short messages to non-teammates varied by job level. Partners who sent very short messages had higher billing revenue (-0.37, $p < 0.10$), but the opposite relationship appeared among consultants (0.51, $p < 0.01$).

(B.14) I plotted sent email size (10^{th} – 90^{th} percentiles) for: (1) team vs. non-team email, (2) team email – consultant vs. partner and (3) non-team email – consultant vs. partner. I produced plots for text only emails, only emails that include attachments and the joint population.

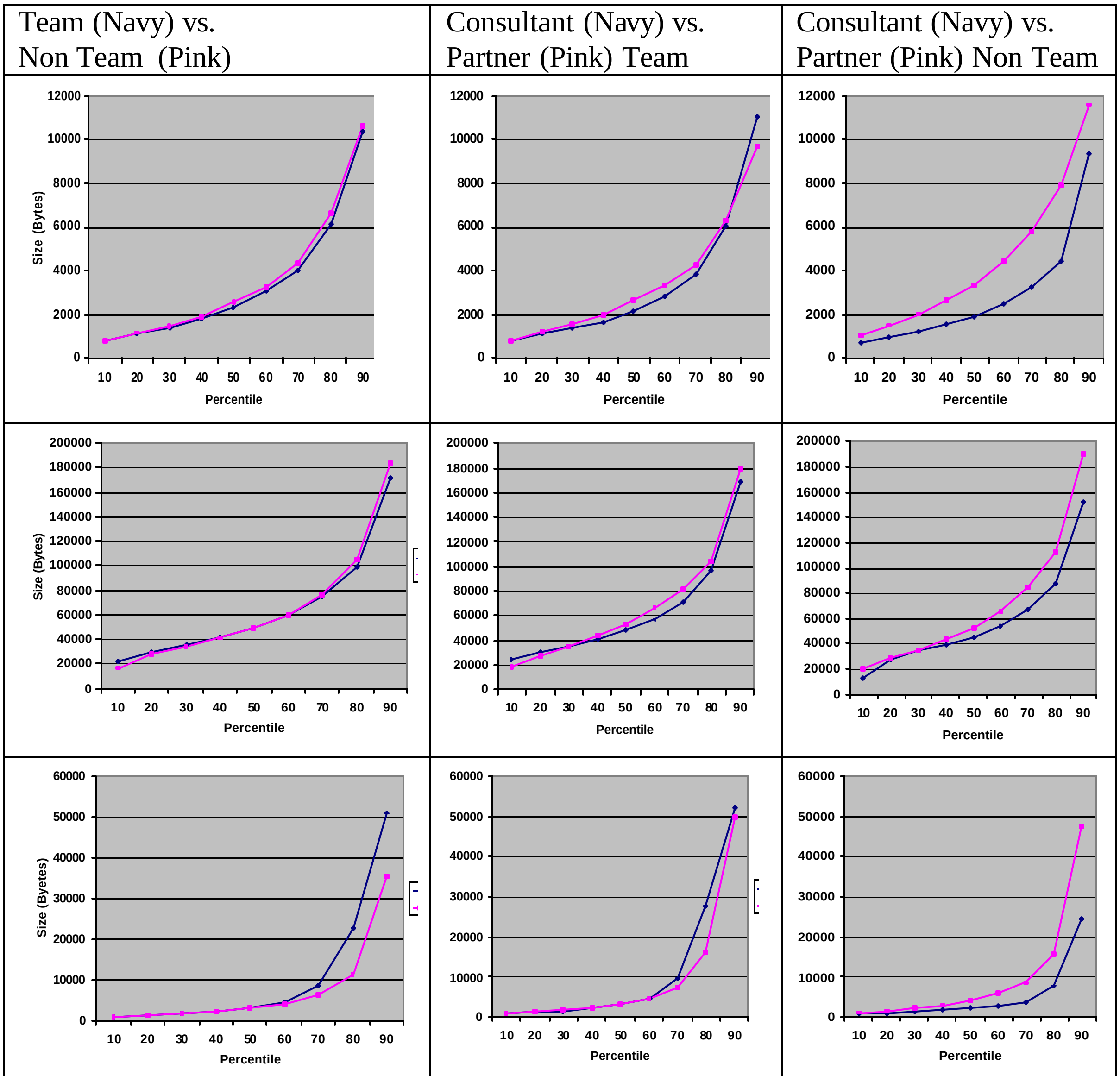

Fig. B.14 Sent email size (10^{th}-90^{th} percentiles) (3 x 3).

From top, the plots above show emails with: no attachments, attachments only and both. From left, the plots show: team vs. non team, consultant vs. partner team, and consultant vs. partner non team. All plots show email exchanged among revenue generating partners and consultants.

The most significant difference that appears in this series of plots is a tendency for partners to send longer emails to non team members. The relative difference is greatest with respect to text emails (top right), but also applies to attachments (middle right) and both types of email (bottom right), a category in which the ratio of email with attachments influences size. Within teams, partners also tend to send longer text only messages (middle top) and messages with attachments (middle middle), although partners send smaller messages overall, reflecting a lower ratio of emails with attachments. Within the population, team and non team email sizes are similar with respect to messages segmented by the presence or absence of attachments. When both are considered together, team emails in the higher percentiles are larger, reflecting a greater proportion of attachments. This panel of plots suggests variation in the percentage of emails with attachments across groups influences email size.

(B.15) I plotted sent email size (10th -90th percentiles) for: (1) peer-to-peer email and (2) vertical exchanges.

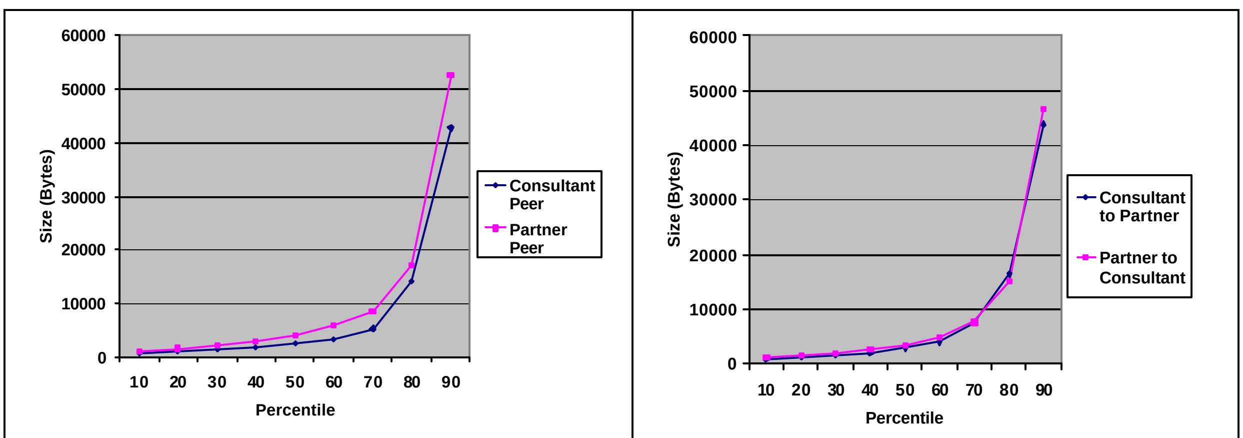

Fig. B.15 Sent email size (10th – 90th percentiles) for peer-to-peer and vertical exchanges.

The left plot shows that partners send larger messages to their peers than consultants. The right plot shows that email sizes in vertical exchanges tend to be similar, although in the lower percentiles, partners tend to send somewhat longer text only emails to consultants than consultants send to partners.

With respect to email size, the data do not appear to support the prediction of the status based theory, which suggests that consultant to partner emails should be longer than partner to consultant emails.

Appendix C

Intertemporal Reliability of Email and Performance Measures

Although I used cross sectional regression models, my individual email and performance measures are aggregations of observations that occur at distinct points in time. In developing measures, I had to consider the implications of aggregating observations over different time intervals.

Prior research provided little intuition regarding the extent to which specific email measures might correspond with individual traits. Alternatively, some email measures could be state-like. In that case, values would be determined primarily in response to contextual features of the environment that varied during the study. For email measures, my objective was to make a heuristic assessment of temporal stability. I did this by dividing the data into three roughly three month intervals and comparing the level of agreement between individual measures in each period. High levels of agreement across time periods would suggest trait-like qualities. Lower levels of agreement would suggest state-like variation. I used the standardized version of Cronbach's alpha to evaluate the level of agreement[34]

I found that centrality metrics, proportions of messages exchanged with colleagues at different job levels and the size of text emails generally exhibited high levels of agreement. This suggests that had I calculated these measures using data from a slightly different time frame, I probably would have obtained similar results. If gaps between sampling frames extended over a long period of time, such as several years, differences associated with individual trends could potentially affect my measures. But I

[34] Period 1 data spans 8/23/2002 – 11/20/2002; period 2 spans 11/21/2002 – 2/18/2003; and period 3 spans 11/17/03 – 2/11/04. The first two periods cover the study period. Because not all recruiters continued to be employed in the third period, the third period sample size is smaller (n = 43 vs. n=47). Searches are also more likely to overlap in the first two periods than in the third period because of the nine month gap between periods two and three.

did not collect data over a long enough period to investigate the possibility of individual trends in email behavior.

On the other hand, several email measures exhibited low levels of agreement across periods. These include the percentages of messages sent as attachments, the average size of attachments and to a lesser extent response time measures and the proportion of messages sent to former teammates. State-like variation coupled with an understanding of the causal factors would be a useful result. In this context, state-like variation in email measures could be related to contract activity. I include some initial exploratory analyses that consider population and subpopulation level relationships between measures of contract activity and a selection of email measures that exhibited low levels of intertemporal reliability at the end of this appendix. However, this is primarily a subject for future research.[35]

Two validity issues motivated my temporal analyses of performance measures. I needed to assess seasonal variation in contract activity and temporal volatility in the arrival rate of contracts to select a reasonable time interval for measuring individual performance. I also used these analyses to assess whether I needed to control for economic shocks or other unusual activity in my regression models. The following table gives an overview of these analyses.

Email Measures	
Intertemporal reliability (3 month intervals)	C1-C2
Contract Activity and Performance Measures	
Seasonal and year-to-year variation in contract activity	C3-C5
Numbers of consultants and partners (1999 vs. 2003)	C6
Intertemporal reliability of performance measures	C7
Temporal Relationships Between Email and Contract Activity	
Weekly plots of contract and email activity	C8
Correlations between email measures and contract activity (weekly)	C9
Individual level plots of active contracts, outdegree and sent emails (weekly)	C10

Table C.1 Overview of temporal analyses

[35] Ideally, I would have analyzed temporal variation in email among teammates at the level of individual searches. Among recruiters who did not work together on searches during the study, I would ideally have analyzed temporal variation at the dyadic level. However, because recruiters often worked on multiple simultaneous searches, search level analysis requires a strategy for disambiguating email by search. While it might be possible to partially differentiate messages by using clustering techniques on the encoded data this remains a subject for future work. To analyze temporal variation in email activity among recruiters who did not work on searches during the study, it would be useful to begin with an understanding of factors that predict email activity. This could be done by using the predictive model I describe in Appendix D (D.1), but also remains a subject for future work.

Temporal Variation in Email Measures

(C.1) I used Cronbach's alpha to assess correlations among the following centrality metrics across three time periods: betweenness centrality, structural holes, indegree and outdegree. I used a cutoff of 5 or more messages to represent a tie.

Email social network metrics – Intertemporal reliability	
Structural holes (ge5)	0.89
Betweenness (ge5)	0.82
Indegree (ge5)	0.88
Outdegree (ge5)	0.88

Table C.2. Intertemporal reliability of centrality measures.

The table above shows Cronbach's alpha scores for centrality metrics computed over three approximately three month intervals. While betweenness centrality exhibits the lowest level of intertemporal reliability, all four metrics measured at approximately three month intervals have Cronbach's $\alpha > 0.80$. This suggests measures of centrality in the email network are fairly stable.

(C.2) I used Cronbach's alpha to assess correlations among the following types of individual email measures across multiple time periods: proportional flows, email sizes and response times.

	2 period			3 period		
	Consultants and Partners	Consultants	Partners	Consultants and Partners	Consultants	Partners
Sent to						
Partner	0.84	0.81	0.89	0.83	0.86	0.80
Consultant	0.85	0.69	0.95	0.86	0.74	0.90
Researcher	0.85	0.75	0.98	0.83	0.78	0.91
Staff	0.95	0.93	0.98	0.90	0.93	0.87
Received from						
Partner	0.89	0.87	0.96	0.79	0.83	0.76
Consultant	0.87	0.83	0.92	0.85	0.80	0.88
Researcher	0.87	0.88	0.81	0.80	0.81	0.67
Staff	0.94	0.93	0.96	0.89	0.90	0.88

Table C.3 Intertemporal reliability of proportions of internal email sent and received.

As shown in the Table C.3, among both partners and consultants, Cronbach alpha scores for the proportions of email sent and received over the three approximately three month periods exceeded 0.80 with the exception of email received from partners. Correlations with period 3 values were often weaker than those between period 1 and 2 values (the study period).

Among consultants only, the proportions sent to consultants and researchers fall below 0.80. In both cases, plots reveal that a single outlier weakens the correlation. For emails sent to consultants, the outlier appears to represent a relationship with another consultant who was promoted to partner during or soon after the study. It is unclear why another consultant would have significantly different proportions of email sent to researchers, although it could be related to the nature of a specific search. Among partners only, larger third period variation in the proportion of email sent to other partners is related to two outliers. One received significantly more email after the study period. The other sent less email. The reasons for these differences are unclear. Despite these differences, internal proportions of email sent to colleagues at different job levels appear to be fairly stable over three month intervals.

	2 period			3 period		
	Consultants and Partners	Consultants	Partners	Consultants and Partners	Consultants	Partners
Sent to						
Active	0.83	0.84	0.82	0.78	0.68	0.86
Previous	0.71	0.68	0.74	0.57	0.51	0.63
Never	0.85	0.81	0.90	0.86	0.90	0.85
Received from						
Active	0.89	0.89	0.90	0.81	0.74	0.86
Previous	0.82	0.79	0.87	0.66	0.64	0.67
Never	0.80	0.77	0.82	0.80	0.89	0.71

Table C.4 Intertemporal reliability of proportional email measures by relationship type.

As shown in Table C.4, among partners and consultants, most of the Cronbach alpha scores for the proportion of email sent and received classified by relationship type were around 0.80. The lowest levels of agreement occurred among proportions of email exchanged between recruiters who were previously teammates. There are at least three possible explanations. When recruiters finish searches they may email former teammates to identify new team assignments. In that case, weekly measures of proportions of messages sent to previous search team members may be positively correlated with revenue associated with contract completions. Alternatively, email between recruiters who have previously served as teammates could represent attempts to land searches. In that case, email between recruiters who were previously teammates might be more likely to precede shared bookings.[36] A third possibility is that recruiters may turn to former teammates for advice. Advice seeking could correspond with a number of different temporal sequences. It might be correlated with contract starts, relative down time, or difficult periods in during a search. The latter is hard to measure without access to email content. In analysis C.9, I investigate some of these possibilities by measuring temporal correlations between the proportion of messages sent to former teammates, contract starts and completions, and measures of overall email activity.

	Consultants and Partners	Consultants	Partners	Consultants and Partners	Consultants	Partners
Team	2 period			3 period		
Sent						
All	0.64	0.76	0.43	0.48	0.66	0.30
No Attachments	0.91	0.89	0.92	0.78	0.82	0.77
Attachments Only	0.44	-0.41	0.71	0.36	-0.50	0.54
% Attachments	0.44	0.30	0.57	0.51	0.61	0.42
Received						
All	0.58	0.33	0.86	0.63	0.45	0.80
No Attachments	0.71	0.72	0.77	0.71	0.77	0.71
Attachments Only	-0.02	0.00	-0.05	0.11	0.11	0.20
% Attachments	0.72	0.59	0.86	0.66	0.55	0.75
Nonteam						
Sent						
All	0.81	0.86	0.72	0.73	0.75	0.65
No Attachments	0.81	0.81	0.80	0.69	0.77	0.53
Attachments Only	0.18	0.64	-0.30	0.42	0.72	0.20
% Attachments	0.33	0.64	0.00	0.46	0.44	0.36
Received						
All	0.82	0.90	0.67	0.56	0.70	0.16
No Attachments	0.82	0.88	0.69	0.48	0.61	0.18
Attachments Only	-0.39	-0.95	0.09	-0.67	-2.97	-0.11
% Attachments	0.59	0.55	0.63	0.55	0.38	0.51

Table C.5. Intertemporal reliability of email size measures.

As shown in table C.5, the level of agreement for the size of text only email sent (without attachments) is generally near $\alpha = 0.80$ or above, while the level of agreement for the size of email sent with attachments is consistently low. The percentage of emails sent with attachments also exhibits a relatively low level of intertemporal reliability. This

[36] I do not currently have a temporal measure of shared bookings, but I could calculate this in future work.

suggests that the length of the text portion of email may be influenced by individual traits. However, the length of emails attachments and the proportion of messages sent as attachments may be more dependent on the context of the interaction.

The size of attachments or the percentage of emails exchanged with attachments could be related to contract activity. Emails with attachments may reflect specific deliverables in the search process, such as contracts, position descriptions or candidate lists. They could also include candidate resumes. If so, these might be correlated with either the start or completion of contracts. I investigate this possibility in analysis C.9.[37]

	2 period			3 period		
	Consultants and Partners	Consultants	Partners	Consultants and Partners	Consultants	Partners
Team						
Sent						
Ave. Response Time	0.12	0.08	0.19	0.64	0.71	0.50
Ave. Ln (Response Time)	0.67	0.69	0.56	0.81	0.82	0.75
% Responses wi/30 min	0.65	0.82	0.40	0.75	0.79	0.69
"" 1 day	0.68	0.66	0.62	0.78	0.67	0.78
"" 1 week	0.70	0.48	0.86	0.81	0.65	0.81
Received						
Ave. Response Time	0.66	0.54	0.70	0.69	0.80	0.67
Ave. Ln (Response Time)	0.70	0.61	0.76	0.74	0.72	0.78
% Responses wi/30 min	0.37	0.20	0.53	0.50	0.51	0.63
"" 1 day	0.73	0.66	0.75	0.73	0.75	0.67
"" 1 week	0.68	0.63	0.67	0.63	0.74	0.53
NonTeam						
Sent						
Ave. Response Time	0.75	0.60	0.89	0.61	0.60	0.58
Ave. Ln (Response Time)	0.79	0.80	0.64	0.87	0.88	0.79
% Responses wi/30 min	0.75	0.79	0.59	0.87	0.86	0.84
"" 1 day	0.70	0.73	0.51	0.80	0.81	0.71
"" 1 week	0.74	0.59	0.83	0.67	0.65	0.69
Received						
Ave. Response Time	0.15	0.58	-0.48	0.07	0.64	-1.36
Ave. Ln (Response Time)	0.62	0.70	0.41	0.59	0.68	0.36
% Responses wi/30 min	0.64	0.61	0.65	0.73	0.77	0.63
"" 1 day	0.69	0.76	0.54	0.58	0.59	0.48
"" 1 week	0.38	0.64	0.04	0.41	0.66	-0.03

Table C.6 Intertemporal reliability of email response time measures.

[37] I used the same size measures I used in regression models, which reflect only email exchanged among consultants and partners. Relationships between email with attachments and search activity could also involve external email or email exchanged with researchers or staff. Investigation of these possibilities is a subject for future work.

As shown in Table C.6, response times generally exhibited lower levels of reliability than degree measures, proportional measures or text email sizes. One unexpected pattern involves differences between consultants and partners in the percentage of responses to teammates within specific time intervals. Among consultants, the level of agreement falls as the time interval increases from 30 minutes to a week. Among partners, the level of agreement rises as the time interval increases. This suggests a tendency towards rapid responses may be more of a trait among consultants and more context dependent among partners. Among partners, a tendency to send email to teammates at least once a week may be more of a trait. The level of agreement among average response times was often higher for values that were logged before they were averaged than for raw values.[38]

Response times might be related to contract activity in a number of ways. Client interactions at the beginning and end of searches may involve a different mix of tasks. This could lead to longer internal response times because recruiters are busy with clients or shorter response times because they place a higher priority on communications that could supply information they need for client interactions. Alternatively, response times could be more strongly related to levels of email activity than contract activity. By definition, exchanging more messages with the same group of individuals in an equivalent period of time will lead to lower response times. In analysis C.8, I assess temporal relationships between levels of email activity and contract activity. In analysis C.9, I compare correlations between response times, numbers of messages and contract starts and completions.

[38] For response times of less than one day, taking the log of the values before they are averaged increases the influence of the shortest response times. For response times of more than one day, taking the log of the values before they are averaged decreases the influence of the longest response times. Periods two and three span Thanksgiving, Christmas, Hanukah and New Years. Longer response intervals may be more common during holiday periods.

Temporal Variation in Performance Measures

(C.3) I plotted the historical relationship between revenues associated with the start and stop dates of contracts at monthly intervals.

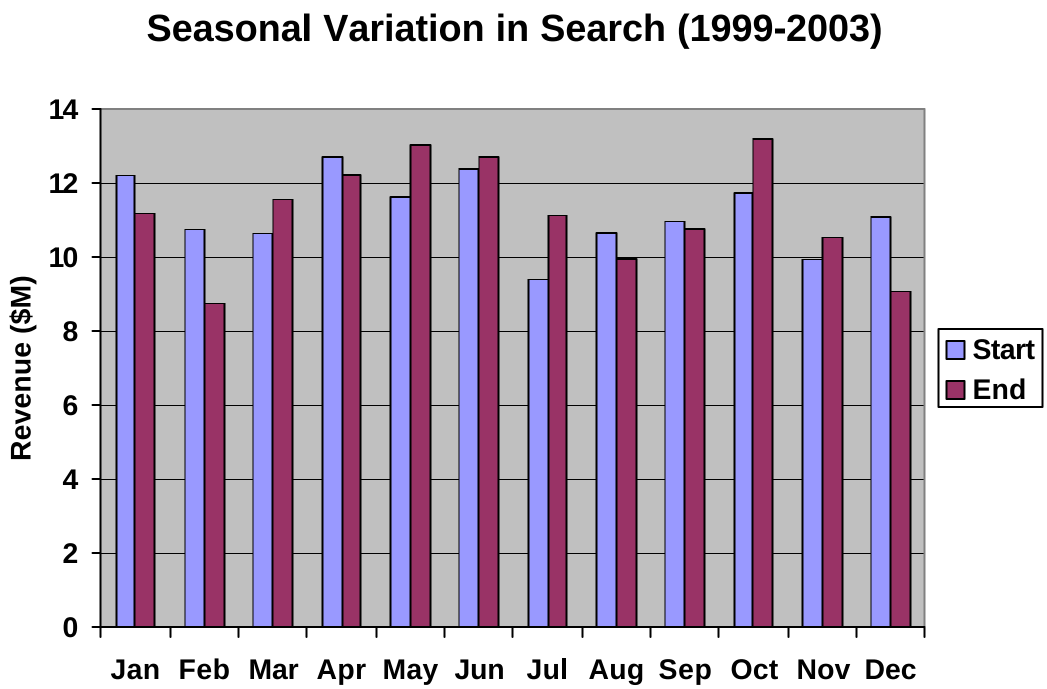

Fig. C.1. Monthly contract revenues (start and stop dates).

The plot shows average monthly revenues associated with the initiation and completion of search contracts at the firm level. It suggests contract activity in the firm is likely to be seasonal. This is not unexpected. For example, labor statistics are typically seasonally adjusted. However, the study period (Aug – Feb), covers an above average number of slow months. If hiring cycles in the different markets in which the firm operates are not in synch, it is possible that revenue measures taken over one seasonal period would identify a different group of recruiters as high performers than measures taken over another seasonal period. This motivated my evaluations of contract activity with respect to seasonal averages.

(C.4) I plotted monthly firm revenues with reference to the historical monthly averages. I produced one view that covering the full duration of the contract data and another focused specifically on the study period.

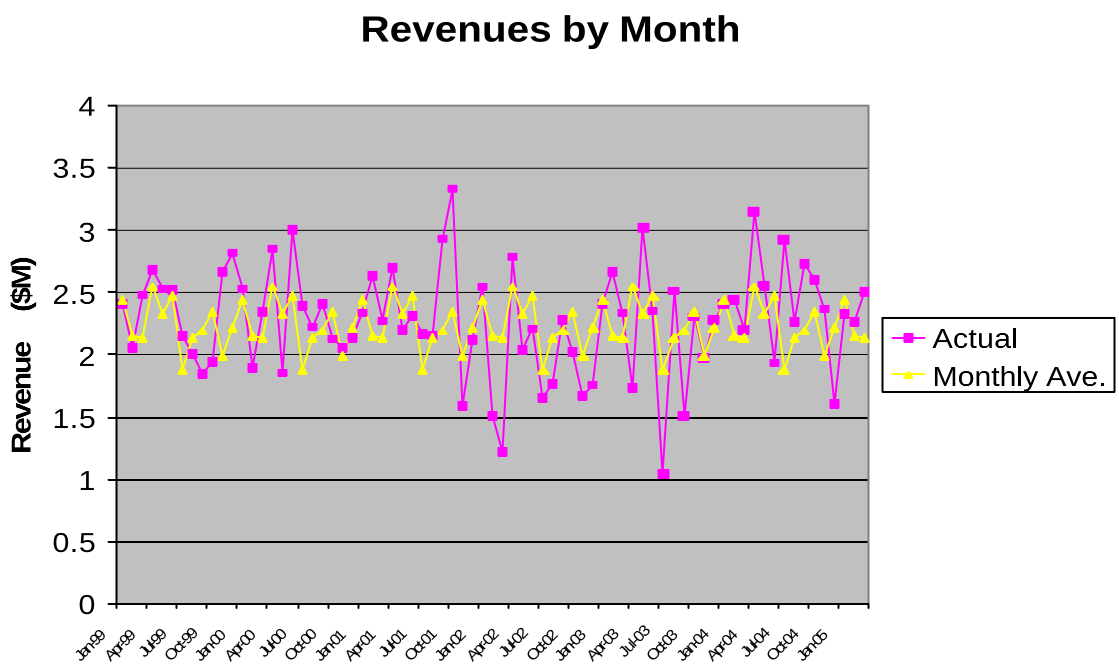

Fig C.2. Contract starts: monthly revenues and historical averages.

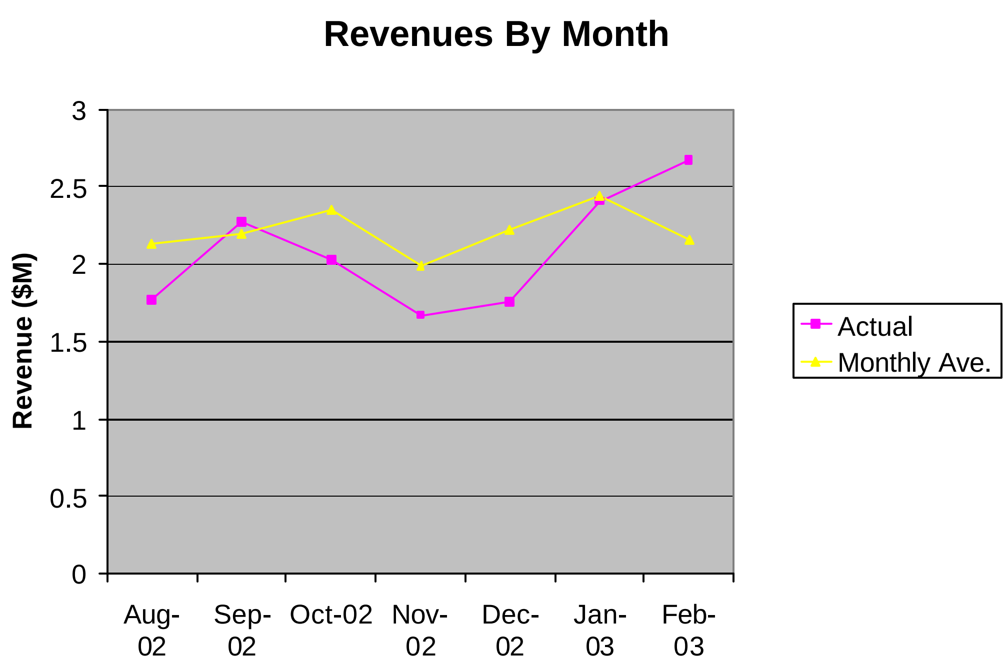

Fig C.3. Contract starts: monthly revenues and historical averages (study period only)

(C.5) I plotted historical and post-study revenues covering the same calendar period as the study by search type and new and existing clients.[39]

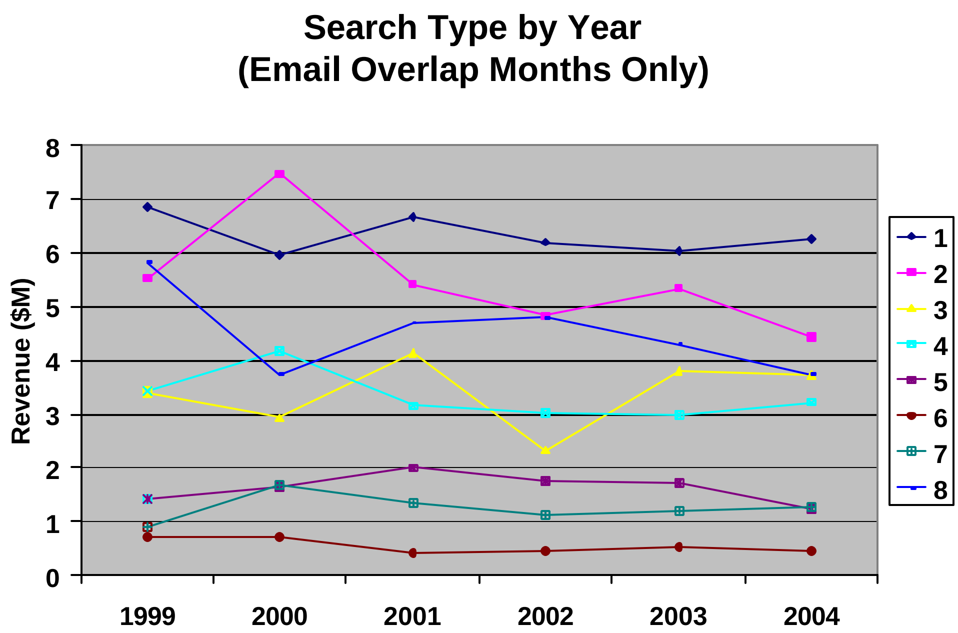

Fig. C.4. Search revenues by year segmented by type of contract.

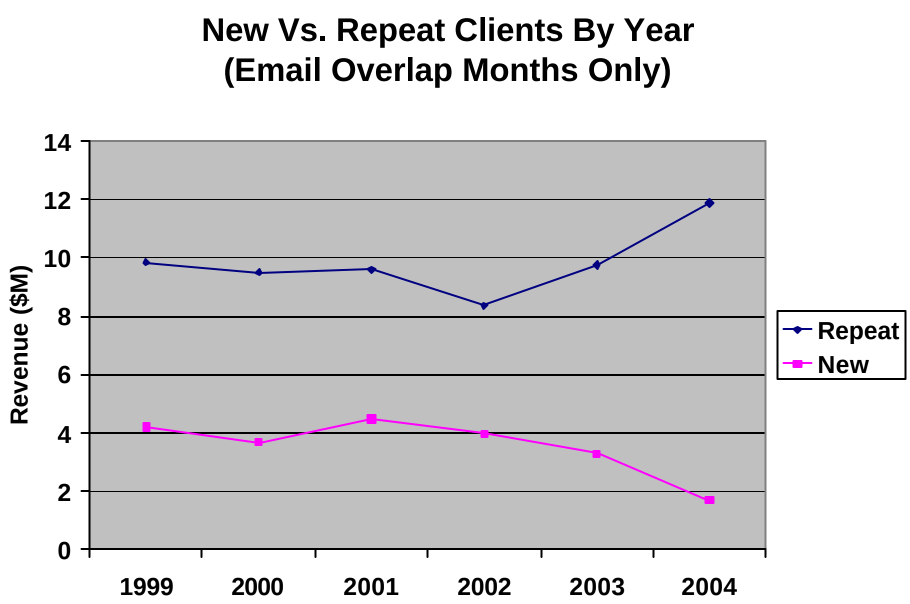

Fig. C.5 Search revenues by year segmented by repeat vs. new clients.

[39] To remove seasonal effects, I made year-to-year comparisons between contracts started in the period from 8/23 – 2/18 (e.g. 2001 revenues cover 8/23/2001-2/8/2002; 2002 revenues reflect the study period).

Figures C.2-C.5 offer perspective on seasonal variation and the extent to which the study period might have been an unusual time in the history of the firm. As shown in figure C.2, seasonal variation appears to explain a significant portion of the monthly fluctuations preceding Sept. 2001; however, after Sept. 2001 monthly firm revenues enter a period of above average volatility. Figure C.3 focuses on the study period. Firm revenues were below historical averages during this time. Interview data suggested it was a particularly bad period for the firm and the search industry in general.

Figure C.4 shows variation in contract revenues classified by the type of search. I used six month increments running from Aug. to Feb. to enable year-to-year comparisons over the same seasonal period as the study. The number of the year is the earlier year. For example, 2002 covers Aug. 2002-Feb. 2003.[40] Revenues in sector 3 (medical executives) hit a low during the study period.[41] The only sector in which revenues were higher in the 2002 period than 2001 is sector 8 (other). Figure C.5 suggests a trend that would have followed the study period in which the proportion of revenues from existing as opposed to new clients increases. The explanation for this change is unclear.

(C.6) I compared the number of partners and consultants in the firm for which some contract activity was recorded in 1999 and in 2003.

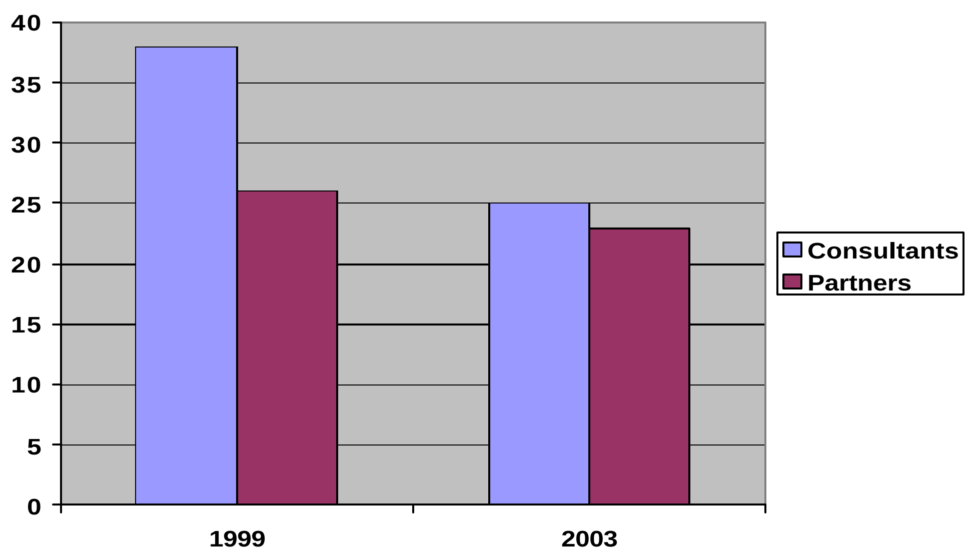

Fig. C.6 Number of consultants and partners in 1999 and 2003.

[40] The reason the 2004 period can be included in this graph and is not included in others is that while revenues associated with searches through Mar. 2005 are known, individual breakdowns of booking revenues are only known through Nov. 2003. This is covered in the section on missing data.
[41] In my regression models, this effect is partially controlled for through the sector B dummy variable.

Fig. C.6 shows a sizable decline in the ratio of consultants to partners over the period 1999-2003. I classified recruiters not specifically identified by job type by the firm on the basis of a comparison of billing and booking revenues. One explanation is that the firm may have added consultants around 1999 anticipating future demand and eliminated these positions when economic conditions deteriorated. Another possibility is that productivity gains at the consultant level, partially related to technology, may have led to the elimination of jobs.

(C.7) I used Cronbach's alpha to calculate correlations among individual revenue measures calculated over successively longer periods of time. I used billing and booking starts and completions as performance measures. I used three sets of time intervals: the study period divided into halves, the study period compared with periods from prior years covering the same dates and full year comparisons.

Intertemporal Reliability of Performance Measures			
	Period1-2	***6-months***	***Full year***
All			
Billing Starts	0.02	0.72	0.81
Billing Completions	-0.01	0.52	0.77
Booking Starts	0.75	0.91	0.96
Booking Completions	0.60	0.92	0.96
Consultants			
Billing Starts	0.04	0.64	0.79
Billing Completions	-0.11	0.31	0.75
Booking Starts	0.69	0.91	0.96
Booking Completions	0.56	0.77	0.92
Partners			
Billing Starts	-0.04	0.80	0.85
Billing Completions	0.25	0.63	0.79
Booking Starts	0.14	0.61	0.83
Booking Completions	0.43	0.79	0.83

Table C.7 Intertemporal reliability of individual revenue measures.

Table C.7 shows standardized Cronbach alpha scores for comparisons of individual contract revenue measures calculated over successively longer time periods.

Six-month values reflect overlap with previous year's revenues calculated over the same calendar dates as the study period. Six-month and full year comparisons involved four time periods, starting with 1999 data. Increasing the length of the time period over which performance is measured smoothes volatility in the arrival rate of contracts. This appears as higher level of agreement as performance measures are calculated over successively longer time periods.

Based on the level of agreement between measures, splitting the study period into two halves (left column) does not appear to be a viable option for evaluating performance. All of the scores in this column fall below 0.80 and some are negative, indicating an invalid score caused by negative correlation between measures in successive periods. From a theoretical perspective, the most desirable measures are booking starts as a measure of landing contracts and billing completions as measure of contract execution. Using a study period measure of booking starts appears reasonable based on the population level score ($\alpha = 0.91$), although the level of agreement among partner values is lower ($\alpha = 0.63$). For billing completions, a full year measure should be given more weight in interpretation, as the level of agreement when measures are calculated over study period length increments is low ($\alpha = 0.52$). Because the average length of time for completing a search is approximately six months, a full year of billing completions would provide a time window consistent with the completion of the majority of searches initiated during the study period as well as those completed within the study period but initiated before it began.

Temporal Relationships Between Email and Performance Measures

(C.8) I plotted four potential sources or indicators of state-like variation in email measures at weekly intervals: contract starts (revenue), contract completions (revenue), the number of internal messages sent (consultants and partners) and the number of external messages sent (consultants and partners).

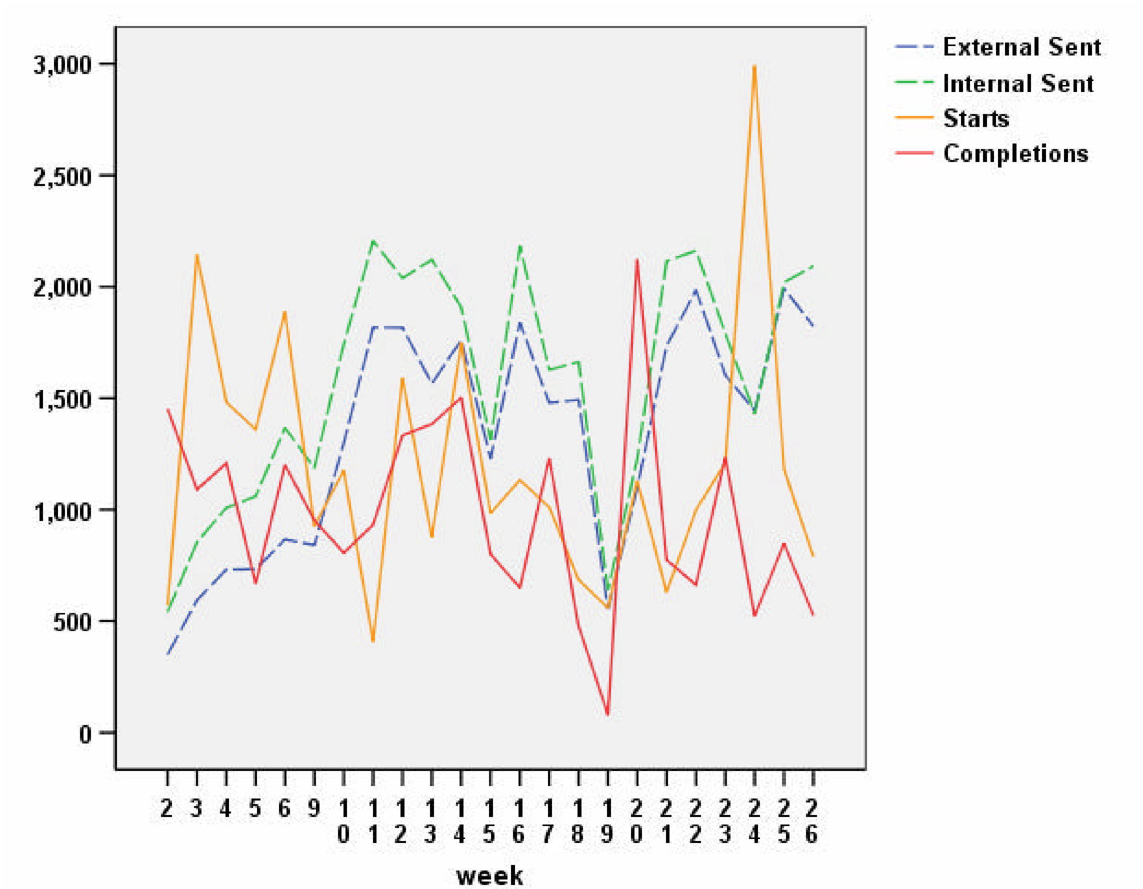

Fig. C.7 Contract starts and completions and email levels (weekly plot)

Figure C.7 shows weekly variation in contract starts, contract completions, and the numbers of internal and external email messages sent by consultants and partners over the study period. Weeks one and 27 are not included because email activity was only recorded for part of those weeks. I also dropped weeks seven and eight because problems with the email capture software resulted in missing emails. I scaled revenues associated with contract starts and completions to fit the graph.

While the internal and external email measures are strongly correlated across weeks ($p < 0.01$), the other relationships are more complex. If two peak weeks are dropped, contract starts and completions are correlated ($p < 0.10$). The peak week for contract completions coincides with the end of the calendar year (week beginning Dec. 30, 2002). The peak week for contract starts is the week beginning Jan. 27, 2003. Contract completions are correlated with the email measures in approximately half the weeks, but diverge in others.

In interviews, recruiters suggested that levels of email activity were likely to be highest during the start and completion of contracts and at points during the search that involved interactions with clients. While true to some extent, this is unlikely to provide a complete explanation for differences in email levels unless client interactions have a strong tendency to cluster during specific time periods. In some cases, levels of email activity appear to be related to seasonal factors. For example, the drop off in all measures during week 19 (week beginning Dec. 23) is presumably associated with the holiday period. A less severe drop in email activity in week 15 is likely to be associated with the Thanksgiving holiday. However, after accounting for contract activity and likely seasonal effects, there still appears to be considerable unexplained variation in overall levels of email activity.[42]

(C.9) I calculated correlations between email measures I previously identified as temporally unstable over the study period and potential sources of state-like variation. I calculated measures at the population level in weekly intervals. Email measures included the proportion of messages sent to previous teammates, the percentage of emails sent as attachments, the average size of attachments and the percentage of responses within 30 minutes, 1 day and one week. Measures of potential sources of state-like variation included revenues associated with the start and completion of contracts and the total number of internal and external messages sent by consultants and partners.

[42] Some suggestions of periodicity appear in the email and contract data which I could investigate with time series analysis in future work. In addition, it is worth considering what other factors might influence levels of email activity in this setting.

	Starts		Completions		Starts and completions		Internal sent		External sent	
Consultants										
Team										
Sent										
Attachments (%)	0.34		-0.02		0.25		0.06		0.24	
Size (ln) Attachments Only	0.38		0.02		0.33		-0.19		-0.04	
% Responses wi/30 min	-0.41	*	-0.09		-0.33		0.39	*	0.37	*
% Responses wi/1 day	-0.14		-0.12		-0.19		0.64	***	0.68	***
% Responses wi/1 week	0.08		0.24		0.15		0.66	***	0.74	***
Received										
Attachments (%)	0.26		-0.21		0.02		0.37		0.58	**
Size (ln) Attachments Only	0.30		0.13		0.27		-0.16		-0.02	
% Responses wi/30 min	-0.22		0.11		-0.12		0.42	**	0.40	*
% Responses wi/1 day	-0.13		-0.02		-0.14		0.65	***	0.63	***
% Responses wi/1 week	0.04		0.03		0.00		0.67	***	0.70	***
Nonteam										
Sent										
Previous Teammate (%)	0.21		-0.08		0.23		-0.42	**	-0.34	
Attachments (%)	0.09		0.09		0.00		0.10		0.23	
Size (ln) Attachments Only	-0.11		0.22		-0.02		-0.02		-0.08	
% Responses wi/30 min	-0.42	**	-0.44	**	-0.42	**	0.43	**	0.36	*
% Responses wi/1 day	-0.31		-0.41	*	-0.34		0.58	***	0.58	***
% Responses wi/1 week	-0.10		-0.26		-0.11		0.70	***	0.76	***
Received										
Previous Teammate (%)	0.01		0.00		0.11		-0.16		-0.13	
Attachments (%)	-0.21		-0.51	**	-0.41		-0.23		-0.07	
Size (ln) Attachments Only	0.16		0.38		0.20		-0.25		-0.17	
% Responses wi/30 min	-0.38	*	-0.37	*	-0.39	*	0.57	***	0.49	**
% Responses wi/1 day	-0.11		-0.22		-0.12		0.67	***	0.66	***
% Responses wi/1 week	-0.02		-0.23		-0.07		0.73	***	0.76	***

Table.C.8 Correlations between selected email measures and contract activity measured at weekly intervals (consultants).

	Starts		Completions	Starts and completions	Internal sent		External sent	
Partners								
Team								
Sent								
Attachments (%)	0.09		-0.33	-0.13	0.21		0.40	
Size (ln) Attachments Only	0.18		0.21	0.19	-0.03		-0.09	
% Responses wi/30 min	-0.25		0.08	-0.11	0.33		0.40	*
% Responses wi/1 day	-0.29		0.02	-0.19	0.67	***	0.62	***
% Responses wi/1 week	-0.24		-0.14	-0.24	0.59	***	0.68	***
Received								
Attachments (%)	0.19		0.10	0.22	-0.10		-0.03	
Size (ln) Attachments Only	0.07		-0.05	0.05	0.16		0.12	
% Responses wi/30 min	-0.46	**	-0.11	-0.33	0.38	*	0.37	*
% Responses wi/1 day	-0.18		0.00	-0.15	0.74	***	0.78	***
% Responses wi/1 week	-0.11		0.08	0.00	0.68	***	0.75	***
Nonteam								
Sent								
Previous Teammate (%)	-0.38	*	-0.02	-0.18	-0.17		-0.28	
Attachments (%)	0.19		0.00	0.19	0.09		0.06	
Size (ln) Attachments Only	0.50	**	-0.18	0.24	-0.31		-0.21	
% Responses wi/30 min	-0.44	**	-0.19	-0.30	0.44	**	0.37	
% Responses wi/1 day	-0.31		0.05	-0.13	0.60	***	0.54	***
% Responses wi/1 week	-0.28		0.13	-0.11	0.58	***	0.63	***
Received								
Previous Teammate (%)	-0.08		-0.16	-0.01	-0.02		0.00	
Attachments (%)	0.01		0.38	0.16	0.16		0.06	
Size (ln) Attachments Only	0.44	*	-0.30	0.09	-0.35		-0.13	
% Responses wi/30 min	-0.49	**	-0.26	-0.33	0.36	*	0.27	
% Responses wi/1 day	-0.32		0.03	-0.19	0.58	***	0.55	***
% Responses wi/1 week	-0.16		0.08	-0.03	0.58	***	0.63	***

Table C.9 Correlations between selected email measures and contract activity measured at weekly intervals (partners).

I selected the email measures shown on the left hand side of tables C.8 and C.9 based on evidence of temporal instability at the individual level (analyses C.1 and C.2). The columns represent potential sources or indicators of temporal variation in email patterns across the population. The values are Spearman correlations. I am interested in whether these measures are correlated at the aggregate level of the population and subpopulations as a prelude to exploring potential individual level relationships in future work.

Higher levels of email activity in a particular week could be associated with more frequent exchanges, exchanges with a greater number of people or both. The results suggest they are clearly associated with the former. Among both consultants and partners, the percentages of responses that occur within a day and within a week are strongly correlated with overall levels of internal and external email activity ($p < 0.01$). Email exchanges with colleagues also have a tendency to occur more rapidly during peak email periods. Among consultants, the percentages of responses within 30 minutes are positively correlated with overall levels of internal and external email activity at $p < 0.10$ or greater. Among partners, the signs are all positive, although some of the results are only marginally significant.

Rapid email exchanges among colleagues occur less frequently during weeks with high numbers of contract starts. Correlations are stronger for messages sent to non teammates. Again, the distinction between message frequency and the number of unique respondents is worth considering. If contract starts were positively correlated with the number of unique respondents, response times could be longer because recruiters are tapping more weak ties. A negative correlation would suggest activities related to contract starts may be associated with email delays.

Email attachments are likely to serve multiple purposes. In future work, the names of email attachments could be used to develop a classification scheme that might better explain relationships with measures involving attachments. Among partners, contract starts were positively correlated with the size of attachments exchanged with non team members. This suggests partners may send a specific type of message to colleagues after they land a search. Within search teams, the percentage of messages sent as attachments is related to levels of email communication with people outside the firm. Consultants receive a higher proportion of messages with attachments ($p < 0.05$). Partners send a higher proportion of messages with attachments ($p < 0.15$).

(C.10) I produced individual plots combining measures of outdegree, number of emails sent and active contracts measured at weekly intervals.

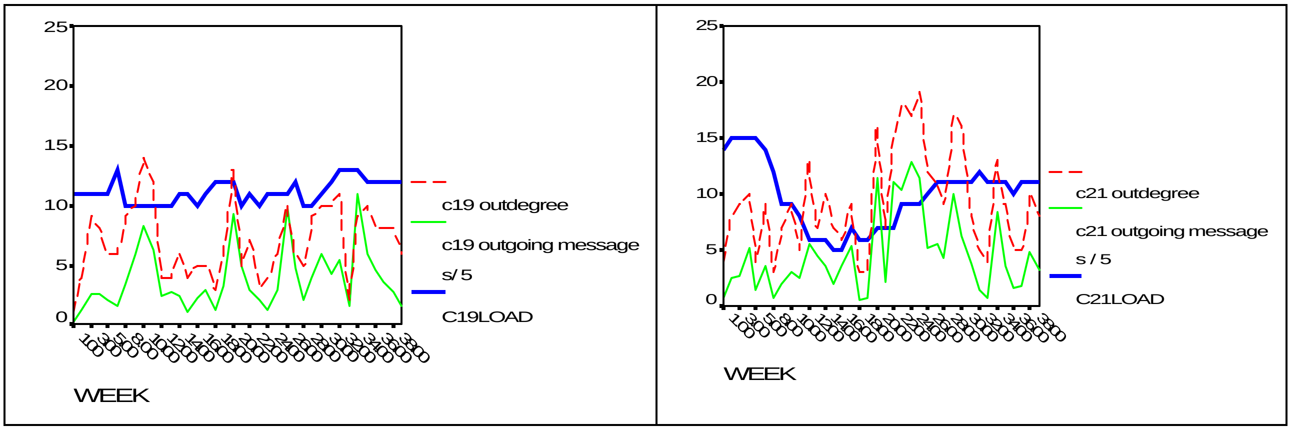

Fig.C.8 Email activity (outdegree and messages sent /5) and contract load (weekly). Contract load is defined as a count of the number of active contracts in a particular week. Individual plots for two consultants are shown.

While the plots above show only two individuals, they are representative of similar plots produced for all revenue generating recruiters. Relationships between search and email activity do appear to be present, but these relationships also appear to be fairly irregular. One possibility is that while the initiation and conclusion of searches may tend to be associated with higher levels of email activity, as suggested by anecdotal evidence from recruiter interviews, it is difficult to tease out these periods out given multiple searches.

Appendix D

Email as a Proxy for General Communication Patterns

A general question for interpreting results is whether they reflect the role of email as a technology or the role of general communication patterns for which email measures serve as proxies. In this particular setting, I believe email measures can generally be interpreted as proxies for more general communication patterns. I describe the combination of results that led to this interpretation in the final chapter of my dissertation. In this appendix, I give the results of the analyses I used to develop that interpretation.

I considered two reasons why email might fail to serve as a good proxy for general communication patterns. One problem is that some individuals may use email infrequently; for these individuals, email based measures could provide too weak a signal to assess general communication patterns. A second problem is that factors such as collocation or media preferences may mediate relationships between email patterns and performance.

To assess potential problems with low email users, I identified and classified dyads in which email frequency was lower than expected. I first used regression analysis to identify predictors of email communication in this setting. Communications theories and prior empirical research in other settings suggested that many of the best predictors were likely to involve homophily, the selection of others who are similar (Monge and Contractor 2003). A broad interpretation suggested similarities including gender, email preference, job level, physical location, as well as the potential for shared membership in search teams, work groups and practice areas. I assessed each of these factors and found that search team membership was by far the strongest predictor of email frequency. Using that result, I identified and classified the dyads with the lowest email frequencies among those involving recruiters who had worked together on a search contract for more than half the study period. This led me to identify five partners who may be low email users.

The second general problem I considered was the role of media preferences and collocation as factors that could mediate relationships between email communication patterns and performance. With respect to media preference, I believe it is useful to differentiate between two potentially problematic situations. The first involves media substitution with respect to a particular task. For example, if some recruiters use email and others use phone for a specific task, such as screening candidates, then email based measures will overstate the communication frequency of some recruiters and understate the communication frequency of others with respect to that task. This is a potential measurement error problem that is likely to be difficult to correct with the existing data. A second potential problem is that media preferences may reflect task differentiation. For example, self-reported measures of time spent and value received from face-to-face communication are positively correlated with booking revenue, reflecting a preference for face-to-face interactions with clients. This does not necessarily create a measurement error problem because relationships between email patterns and performance could be independent of relationships between face-to-face communication and performance measures. But it would suggest an omitted variable in my regression models. And it could lead to an attribution error in interpreting results if face-to-face communication was correlated with specific email measures. Unfortunately, my survey measures of media preference do not distinguish between tasks. As a result, I often found it difficult to conclusively differentiate between media substitution effects and task differentiation as factors that might influence the results of my analyses. However, in many cases it is possible to make informed judgments.

I used survey data on media preferences to identify situations in which recruiters may substitute other media for email. A negative correlation between email use and the use of another medium suggests potential substitution effects. However, because my survey measures of media use are not task specific, I also consider evidence that this result might be caused by task differentiation.

The second potential mediating factor I considered was collocation. From the literature, it is not clear whether collocation is likely to lead to more or less email communication. However, in discussing my research with others, collocation was frequently raised as a potential treat to the validity of email measures.

One way to assess collocation effects is through natural experiments in which two groups perform similar activities, one of which is collocated and the other is not. Although I did not have any pure natural experiments, I identified two situations that were roughly analogous. A significant majority of searches are conducted by recruiters in the same workgroup, while approximately half of these searches are conducted by recruiters who were physically collocated. I used a comparison of network density at different tie strengths to assess whether physical collocation was related to differences in email frequency among recruiters in the same work group. I did not find evidence of differences.

A second natural experiment involves differences between recruiters in the central office and satellite offices. Recruiters in the central office have at least four times as many collocated colleagues as recruiters in the satellite offices. Although an ANOVA revealed some differences between these groups, they could be caused by other factors. I constructed a second measure of collocation by using the percentage of searches recruiters conducted with collocated colleagues, based on shares of billing credits. A correlation analysis revealed a number of statistically significant relationships with email patterns and information behaviors from the survey. However, only one measure was statistically significant in both the ANOVA of differences between recruiters in the central and satellite offices and the correlation analysis involving the percentage of collocated searches. This suggests that collocation alone is unlikely to have a significant influence on the measures used in my subsequent regression analyses.

I conclude this appendix with results of analyses involving measures of specialization. Specialization and task differentiation could lead to statistically significant relationships between email patterns and individual performance. In such instances, results could reflect unmeasured features of the setting as opposed to features described in the development of hypotheses.

Hierarchical specialization, which reflects the balance of billing and booking activity recruiters perform, plays a particularly important role in interpreting results. I constructed a measure of hierarchical specialization by calculating the proportion of revenues recruiters derived from bookings (ie. bookings / (bookings + billings)). A correlation analysis suggests relationships between email communication patterns, information behaviors and performance measures exist on a continuum running from junior consultants who focus primarily on billings through partners with the most valuable client bases who focus more on bookings. An awareness of this pattern is helpful for interpreting results from hypotheses two and three.

I control for horizontal specialization in my base model through dummy variables for industry sector, which correspond to the practice areas of the firm. An ANOVA between practice areas suggests that some differences in email patterns do exist. This reinforces the importance of these controls and suggests considering interaction terms in future work.

I considered developing a control for technological specialization because it could influence email patterns. However, I found it difficult to develop a reasonable measure from the survey and email data. My last two analyses suggest that technology use in this context is likely to be a highly multidimensional concept. The following table gives an overview of the analyses in this appendix:

Identification and Classification of Low Email Users	
Predictive model of email frequency (dyad level)	D.1
Regression results and residual plots: search team activity as a predictor of email activity	D.2
Classification of dyads with lower than expected email message counts	D.3-D.4
Potential Mediating Variables	
Correlations between email activity and the self-reported number of people communicated with per day across all media	D.5
Correlations between email activity and self-reported media use measures (by medium)	D.6
Density of ties between practice group members (collocated vs. non collocated)	D.7
Correlation analysis and ANOVA related to collocation	D.8-D.10
Specialization	
Correlation analysis for percentage of revenue associated with booking	D.11
ANOVA of differences related to practice area	D.12
Agreement among technology related survey measures	D.13
Correlations between performance measures and technology related survey measures	D.14

Table D.1 Overview of additional validity analyses

(D.1) I constructed models using at most two independent variables and assessed their ability to explain variation in email communication within dyads. My dependent variables included the number of messages, natural log of number of messages, number of weeks in which email activity occurred.

Model		Emails	Ln(emails)	Email weeks
	Collocation			
1	Physical collocation (dummy)	0.028	0.026	0.033
2	Central office collocation (dummy)	0.002	0.002	0.002
	Time on email			
3	Proportion of time on email/sender	0.003	0.002	0.001
4	Proportion of time on email/receiver	0.001	0.000	0.000
5	Proportion of time on email/both	0.005	0.002	0.003
	Job level relationships			
6	Partner sender (dummy)	0.001	0.003	0.002
7	Partner receiver (dummy)	0.001	0.007	0.005
8	Consultant to consultant (dummy)	0.002	0.001	0.003
9	Consultant to partner (dummy)	0.000	0.000	0.000
10	Partner to consultant (dummy)	0.000	0.003	0.000
11	Partner to partner (dummy)	0.000	0.019	0.007
	Practice area			
12	Sender practice area (dummy)	0.005	0.000	0.001
13	Receiver practice area (dummy)	0.005	0.000	0.001
14	Both in minority practice area (dummy)	0.137	0.098	0.118
	Gender			
15	Sender gender (dummy)	0.000	0.000	0.000
16	Receiver gender (dummy)	0.000	0.000	0.000
	Similarity			
17	Same workgroup	0.162	0.179	0.201
18	Same practice area	0.026	0.069	0.046
19	Same gender	0.000	0.000	0.000
	Other organizational structure relationships			
20	Same work group, not collocated	0.077	0.108	0.104
21	Same practice area, different workgroup	0.020	0.004	0.016
22	Collocated in workgroup	0.071	0.058	0.080
	Search activity			
23	Weeks with active searches	0.372	0.321	0.436
24	Active search weeks	0.375	0.236	0.364
25	Number of previous searches	0.205	0.131	0.216
26	Previous searches (dummy)	0.079	0.114	0.121

Table D.2. Predictive model of email frequency results

The values in the table above are the Adj. R^2 of models composed of the independent variable(s) listed after the model number and the dependent variable listed in the respective column. I highlighted Adj. R^2's > 0.05.

This series of models shows that search activity is the best single predictor of the number and frequency of messages exchanged within dyads. Models with Adj. $R^2 > 0.05$ that do not directly measure search activity are all measures that make it more likely that recruiters are, in fact, working together on searches during the study period. These include variants on being in the same work group (eg. collocated in same work group, both in minority practice area) or search activity that preceded the study. The variable labeled "active search weeks" (24) sums the number of searches each week that a dyad was actively pursuing. "Weeks with active searches" (23) counts the number of weeks in which at least one search was pursued. The overall pattern relating the level of email activity to the level of search activity is consistent across multiple measures of the extent of email communication within dyads.

Results shown above were based on the full population of dyadic relationships (N = 3,422 dyads or N= 1,892 depending on whether the independent variable(s) in the model were derived from survey measures). I also ran these models on a subsample restricted to dyads for which at least one email was exchanged during the study period. The Adj R^2's were slightly lower, but the results were otherwise similar.

(D.2) I regressed the number of messages exchanged within a dyad on the number of weeks of search activity and the sum of the number of searches in each week. I produced a histogram of the regression standardized residuals plotted against a normal curve and a normal P-P plot of the regression standardized residuals.

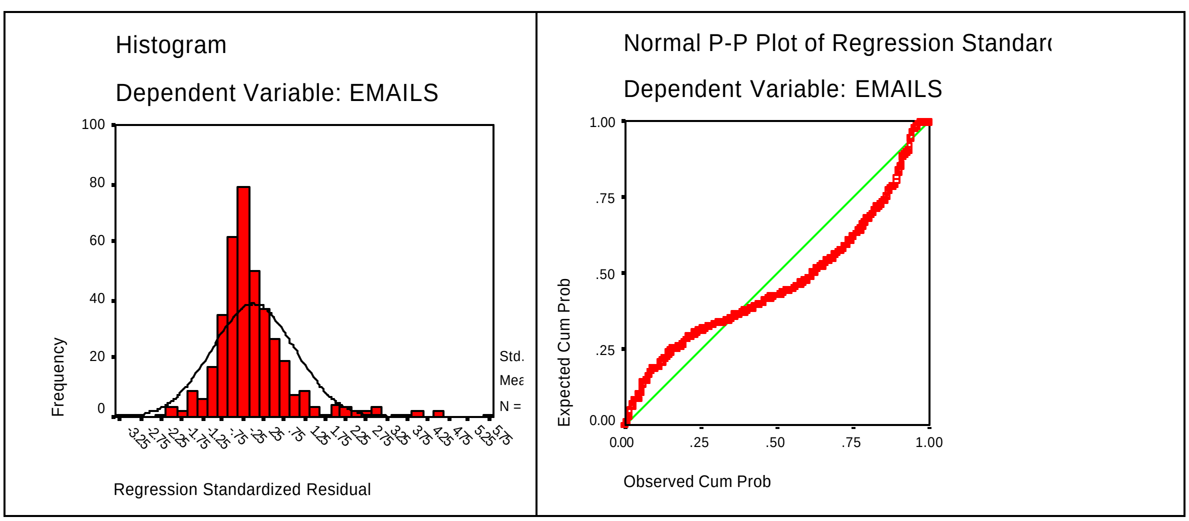

Fig. D.1. Residual plots from email frequency regression

As shown above, the regression standardized residuals are clearly not normally distributed. Given the direction of skewness, selection of outliers based on the 95% confidence interval of parameter estimates would substantially over estimate the number of cases that should be investigated. In actually, the skewness was so severe that approximately two-thirds of the cases fall below the 95% confidence interval. Since this clearly violates the assumption of normally distributed residuals, I decided to use a non-parametric strategy.

(D.3) I identified and classified dyads in which search activity was present for at least half the duration of the study period within which less than 10 emails were exchanged (bottom 19.4% of the population).

Circumstance	**Dyads**
Left company	9
Both opt out	2
Partner to Partner	8
c57	6
c42 (opt out)	4
c56	4
c48	4
c46	3
Total	40

Table D.3. Case-by-case classification of dyads (bottom 20 percent in email frequency)

The table above summarizes characteristics of each of the 40 dyads in which the expected email activity based on the number of weeks search contracts were being pursued falls in the bottom 20 percent. I was able to explain 11 of these cases in terms of specific data limitations (both opting out or a recruiter who left the company during the study). Eight cases involve partner-to-partner communication. The remaining 21 cases involve communication between consultants and one of five partners. Only in the latter category do I suspect that levels of email activity might understate overall levels of communication activity within a dyad. Taken together, these cases involved five partners who may use email less frequently than their peers for the coordination of searches. The basis for this interpretation follows.

In the 11 cases involving specific limitations of the data, the analysis highlights other problems with the data that provide highly probable explanations for observation of low levels of email activity. In nine cases, one of the recruiters in the dyad left the company during the study period. I do not know the specific exit date, but analysis of the email data suggests the recruiter left the company before the completion of the search so that the number of weeks that recruiter was involved in the search is overstated. Two of the dyads involve email activity between recruiters who both opted out of email collection. Therefore, the only way email between these recruiters would have been recorded is if they had sent email to each other and a third recruiter who opted in. Only one such email is recorded.

This leaves 29 cases to interpret. Eight of the remaining cases involve partner-to-partner communication. The majority of searches with multiple partners involve more than two recruiters. In three or more person search teams, it is quite possible that low levels of email communication are consistent with low levels of overall communication within specific dyads. This situation can arise when one of the partners is identified with the search because he or she had a role in landing the business, but does not take an active role in the execution of the search. While I have no way of independently verifying this explanation with the existing data, there is also no additional evidence that the low number of messages are inconsistent with low levels of overall communication within the specific dyads. The remaining 21 cases all involve communication between a consultant and one of five partners. This suggests five partners for whom email may not be the preferred medium for communicating with teammates on a search.

(D.4) I identified and classified dyads in which search activity was present for at least half the duration of the study period within which less than one email per week of search activity was exchanged during the study period (bottom 40.8% of the population).

Circumstance	Dyads
Left company	20
Both opt out	2
Partner to Partner	19
c57	8
c42 (opt out)	5
c56	5
c48	4
c46	5
Other	16
Total	84

Table D.4 Case-by-case classification of dyads involved in active searches over more than half of the study period in which the numbers of messages exchanged fell in the bottom 20 percent of the population.

The 68 cases not labeled "other" can be interpreted in the same way as cases in (D.3) were interpreted. Therefore, setting a higher cutoff led to the identification of cases exhibiting similar patterns in 28 additional cases. I focused my attention on the 16 cases labeled "other" that do not correspond to phenomena I observed with the more restrictive cutoff.

The most important thing to note is that 16 cases in which email activity lies above the lowest 20 percent but below the rate of one email per week is not necessarily cause for concern. These 16 cases represent 7.8 percent of a relevant subpopulation of 206 dyads for which search activity was present over at least half the study period. These numbers are not out of line with an interpretation in which email activity is lower in some dyads than others as the result of factors that are idiosyncratic to a particular dyad and can therefore legitimately be attributed to the error term in a regression. Closer examination of these 16 cases may also reveal additional explanations for specific cases. For example, at least two of the dyads involve recruiters whose only shared search activity was as part of an unusually large five person search team. Within the context of such a relatively large team, it is not unreasonable to expect that some dyads would exhibit low levels of overall communication.

(D.5) I calculated Spearman correlations between numbers of email messages and the self-reported number of people communicated with per day across all media.

Correlations - Actual Email and Self-Reports Across All Media						
	All		*Consultants Only*		*Partners Only*	
Sent						
Internal	0.43	***	0.36		0.64	***
External	0.29	*	0.16		0.51	**
All	0.46	***	0.31		0.61	***
Received						
Internal	0.45	***	0.45	**	0.55	**
External	0.51	***	0.50	**	0.45	*
All	0.58	***	0.57	***	0.62	***
Total	0.50	***	0.40	*	0.68	***

N = 40, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table D.5 Correlations between actual email and self-reported communication across media (numbers of people per day)

As shown in the table above, among all revenue generating consultants and partners, the self-reported number of people recruiters communicate with per day in all media was correlated with actual numbers of email messages at ($p < 0.01$) across all categories except for external email sent ($p < 0.10$). This suggests a strong relationship between communication volumes in other media and actual email communication volumes.

When I split the sample along consultant partner lines, relationships with consultant sent email were not statistically significant. When I excluded two outliers, consultant correlations were within ($p < 0.02$), with the exception of external email sent ($p < 0.15$). The outliers involve consultants who had the highest self-reported numbers of people communicated with per day using face-to-face and phone respectively. Even with these outliers, correlations with received email among consultants are all within ($p < 0.05$). This suggests that a difference in communication strategy for screening candidates may play a larger role than potentially inflated self-reports. These two consultants may use face-to-face and phone for outgoing communication with a large number of candidates, but often receive external communications by email.

The population for the correlations reported above is composed of all revenue generating recruiters who completed the survey question on the number of people they communicated with per day across media. Since there were four recruiters who completed this survey question, but opted out of email collection, missing external email data is a potential explanation for why correlations with external email messages sent could be weaker. However, this appears to have had little effect. The correlations are actually stronger when these recruiters are included. My analysis of the two outliers suggests media substitution effects with respect to external communication may play a role.

Spam and other forms of automated email such as news feeds do not appear to have influenced these results, although they can also be a concern with respect to received external email. The correlations above are based on external email after I filtered out messages that I could identified as either spam or news. If automated emails were a problem, correlations with external emails sent would be likely to be stronger than with external emails received, but this generally does not appear to be the case.

(D.6) I calculated Spearman correlations between the numbers of email messages and self-reported values for the (a) number of people communicated with per day by medium, (b) the proportion of time spent by medium, (c) the proportion of value spent by medium, and (d) the relative proportion of value over time spent by medium. Numbers of messages include the number of internal, external and total messages sent and the total number of emails sent and received. The first table shows (a), while subsequent tables show (b-d) grouped by consultants and partners, consultants only and partners only.

Partners and Consultants

	email_day	ftf_day	phone_day	hardcopy_day	total_day	sent_internal	sent_external	sent_all
email_day	__							
ftf_day	-0.34 **	__						
phone_day	-0.65 ***	-0.07	__					
hardcopy_day	-0.43 ***	0.13	0.05	__				
total_day	0.14	-0.24	-0.14	-0.18				
sent_internal	0.53 ***	-0.40 **	-0.30 *	-0.31 *	0.46 ***	__		
sent_external	0.46 ***	-0.25	-0.19	-0.17	0.29 *	0.68 ***	__	
sent_all	0.47 ***	-0.37 **	-0.21	-0.22	0.43 ***	0.89 ***	0.92 ***	__
all_email	0.49 ***	-0.37 **	-0.22	-0.23	0.50 ***	0.86 ***	0.88 ***	0.95 ***

Consultants Only

	email_day	ftf_day	phone_day	hardcopy_day	total_day	sent_internal	sent_external	sent_all
email_day	__							
ftf_day	-0.13	__						
phone_day	-0.58 ***	-0.21	__					
hardcopy_day	-0.60 ***	0.10	0.22	__				
total_day	0.03	-0.10	-0.01	-0.23	__			
sent_internal	0.71 ***	-0.30	-0.40 *	-0.39 *	0.35	__		
sent_external	0.71 ***	0.05	-0.35	-0.24	0.15	0.61 ***	__	
sent_all	0.71 ***	-0.18	-0.32	-0.30	0.30	0.89 ***	0.88 ***	__
all_email	0.60 ***	-0.16	-0.26	-0.26	0.39 *	0.84 ***	0.81 ***	0.94 ***

Partners Only

	email_day	ftf_day	phone_day	hardcopy_day	total_day	sent_internal	sent_external	sent_all
email_day	__							
ftf_day	-0.57 **	__						
phone_day	-0.70 ***	0.12	__					
hardcopy_day	-0.24	0.16	-0.25	__				
total_day	0.25	-0.43 *	-0.30	-0.17				
sent_internal	0.41 *	-0.49 **	-0.24	-0.28	0.64 ***	__		
sent_external	0.19	-0.22	-0.14	-0.17	0.51 **	0.70 ***	__	
sent_all	0.32	-0.35	-0.23	-0.22	0.61 ***	0.91 ***	0.91 ***	__
all_email	0.44 *	-0.43 *	-0.33	-0.23	0.68 ***	0.91 ***	0.86 ***	0.95 ***

Table. D.6. Correlations between measured email and self-reported number of people communicated with per day (by medium).

As shown in the table above, for the whole population, the self-reported number of people recruiters communicate with each day over email was correlated with the actual numbers of messages across all categories at ($p < 0.01$). Correlations among consultants were stronger than those among partners, but with the exception of actual numbers messages partners send to external sources, actual and self-reported email counts appear to be strongly in agreement.

The self-reported data suggest that email and phone may be substitutes for both partners and consultants (-0.65, $p < 0.01$). Email and face-to-face may be substitutes for partners (-0.57, $p < 0.05$) and email and hardcopy may be substitutes for consultants (-0.60, $p < 0.01$). While correlations with the actual numbers of email messages all have the same signs, these correlations are weaker than those with the self-reported values.

Only categories that include the numbers of internal email messages sent are statistically significant.

Partners and Consultants

Time Spent

	email_time	ftf_time	phone_time	computer_time	emcomp_time	hardcopy_time
email_time	__					
ftf_time	-0.17	__				
phone_time	-0.30 *	-0.43 ***	__			
computer_time	-0.13	-0.34 **	-0.23	__		
emcomp_time	0.99 ***	-0.21	-0.32 **	-0.04	__	
hardcopy_time	-0.08	-0.11	0.06	-0.13	-0.08	
sent_internal	0.40 **	-0.28 *	-0.05	0.12	0.41 ***	-0.22
sent_external	0.44 ***	-0.24	0.03	0.09	0.45 ***	-0.09
sent_all	0.43 ***	-0.27 *	0.01	0.11	0.44 ***	-0.18
all_email	0.45 ***	-0.25	0.07	0.00	0.45 ***	-0.12

Perceived Value

	email_value	ftf_value	phone_value	computer_value	emcomp_value	hardcopy_value
email_value	__					
ftf_value	-0.52 ***	__				
phone_value	-0.13	-0.52 ***	__			
computer_value	0.08	-0.17	-0.26	__		
emcomp_value	0.99 ***	-0.53 ***	-0.15	0.16	__	
hardcopy_value	0.03	-0.30 *	0.03	-0.01	0.03	
sent_internal	0.38 **	-0.12	-0.11	0.09	0.37 **	-0.19
sent_external	0.30 *	-0.14	-0.06	0.16	0.30 *	-0.01
sent_all	0.35 **	-0.13	-0.08	0.13	0.35 **	-0.09
all_email	0.27 *	-0.10	-0.04	0.06	0.26	-0.05

Perceived Value Relative to Time Spent

	email_relval	ftf_relval	phone_relval	computer_relval	emcomp_relval	hardcopy_relval
email_relval	__					
ftf_relval	0.11	__				
phone_relval	0.01	-0.68 ***	__			
computer_relval	-0.43	0.06	-0.22	__		
emcomp_relval	0.75 ***	-0.07	-0.04	0.40	__	
hardcopy_relval	-0.19	-0.54 ***	0.37 *	0.05	-0.28	__
sent_internal	-0.04	0.24	0.05	-0.19	-0.06	-0.09
sent_external	-0.21	0.21	-0.02	0.17	-0.08	-0.09
sent_all	-0.11	0.26	0.01	0.07	-0.07	-0.09
all_email	-0.24	0.25	0.00	0.13	-0.14	-0.10

Table D.7 Correlations between email activity and survey measures of media preference (partners and consultants).

The tables above show correlations between different sets of survey measures assessing media preference and measured email. Survey measures of media use include: time spent (top), proportion of value received (middle) and the ratio of the value over time (bottom). These correlations are based on all partners and consultants.

The perceived proportion of time and perceived value received from email was correlated with actual numbers of messages in all categories at $p < 0.10$ or greater.

Although the types of measures are slightly different, this suggests a reasonable level of agreement between self-reported and measured values.

A comparison of results relating email and phone use from the tables above and the preceding set of tables suggests a potential discrepancy between email message counts and self-reported values. While self-reported values for the number of people communicated with per day via email and phone were strongly negatively correlated (-0.65, $p < 0.01$), actual numbers of email messages are only very weakly negatively correlated with the perceived time spent and value of phone communication. These differences may be related to differences in the measures. However, it is also possible that the actual substitution effect is weaker than the perceived one. Split sample results for consultants and partners given in the next two sets of tables, suggests that substitution effects between email and phone may be more likely to occur externally among consultants and internally among partners.

Internal email sent and all sent email are also negatively correlated with the perceived time spent communicating with others face-to-face ($p < 0.10$). Again, split sample results aid interpretation. These correlations are much stronger among consultants than partners. This suggests a media effect related to the division of labor. Correlations with the percentage of revenues from bookings (D.16) support the interpretation that more experienced consultants get more face-to-face time.

Although correlations between actual numbers of messages and the ratio of value received over time spent across different media (bottom table) are not statistically significant, the signs are consistent across email categories. The results suggest recruiters who send the most email messages perceive that the time spent using email is greater than the value (negative correlation). At the same time, they perceive that the value of face-to-face is greater than the time spent (positive correlation). A possible interpretation is that there may be diminishing returns to more email communication, while at the same time, more email communication can potentially increase the value of time spent face-to-face. Alternatively, recruiters who have the most face-to-face time may value it less in relative terms and send a relatively high number of messages.

Consultants Only

Time Spent

	email_time	ftf_time	phone_time	computer_time	emcomp_time	hardcopy_time
email_time	__					
ftf_time	-0.16	__				
phone_time	-0.52 **	-0.27	__			
computer_time	-0.14	-0.37 *	-0.30	__		
emcomp_time	0.99 ***	-0.21	-0.54 ***	-0.05	__	
hardcopy_time	0.12	0.08	-0.26	-0.25	0.11	
sent_internal	0.50 **	-0.47 **	0.05	0.05	0.52 **	-0.15
sent_external	0.43 **	-0.33	0.00	-0.02	0.45 **	-0.02
sent_all	0.48 **	-0.40 *	0.05	-0.01	0.50 **	-0.14
all_email	0.49 **	-0.31	0.08	-0.15	0.49 **	-0.05

Perceived Value

	email_value	ftf_value	phone_value	computer_value	emcomp_value	hardcopy_value
email_value	__					
ftf_value	-0.44 **	__				
phone_value	-0.39 *	-0.38 *	__			
computer_value	0.18	-0.12	-0.44 **	__		
emcomp_value	0.99 ***	-0.45 **	-0.42 *	0.26	__	
hardcopy_value	-0.13	-0.25	0.02	0.01	-0.12	
sent_internal	0.55 ***	-0.25	-0.07	0.06	0.53 **	-0.16
sent_external	0.43 **	-0.06	-0.24	0.23	0.44	-0.17
sent_all	0.51 **	-0.15	-0.15	0.16	0.50 **	-0.16
all_email	0.39 *	-0.15	-0.08	0.04	0.37 *	0.01

Perceived Value Relative to Time Spent

	email_relval	ftf_relval	phone_relval	computer_relval	emcomp_relval	hardcopy_relval
email_relval	__					
ftf_relval	0.30	__				
phone_relval	-0.30	-0.82 ***	__			
computer_relval	-0.58 *	-0.12	-0.12	__		
emcomp_relval	0.72 ***	0.11	-0.28	0.35	__	
hardcopy_relval	-0.13	-0.57 **	0.43 *	0.01	-0.11	__
sent_internal	0.08	0.35	-0.10	-0.28	0.10	-0.20
sent_external	-0.03	0.36	-0.21	0.40	0.27	-0.40
sent_all	0.04	0.38 *	-0.19	0.18	0.23	-0.28
all_email	-0.16	0.31	-0.12	0.20	0.06	-0.21

Table. D.8 Correlations between email activity and survey measures of media preference (consultants only)

Partners Only

Time Spent

	email_time	ftf_time	phone_time	computer_time	emcomp_time	hardcopy_time
email_time	__					
ftf_time	-0.25	__				
phone_time	0.05	-0.49 **	__			
computer_time	-0.12	-0.23	-0.40 *	__		
emcomp_time	1.00 ***	-0.27	0.02	-0.05	__	
hardcopy_time	-0.29	-0.24	0.40 *	0.00	-0.30	
sent_internal	0.23	-0.02	-0.36	0.11	0.25	-0.28
sent_external	0.41 *	-0.10	-0.19	0.15	0.43 *	-0.16
sent_all	0.31	0.02	-0.34	0.18	0.33	-0.23
all_email	0.35	-0.06	-0.20	0.14	0.36	-0.20

Perceived Value

	email_value	ftf_value	phone_value	computer_value	emcomp_value	hardcopy_value
value_email	__					
value_ftf	-0.76 ***	__				
value_phone	0.32	-0.66 ***	__			
value_computer	-0.07	-0.16	-0.20	__		
value_emcomp	0.99 ***	-0.78 ***	0.30	0.06	__	
value_hardcopy	0.29	-0.42 *	0.02	-0.02	0.26	
sent_internal	0.19	0.10	-0.26	0.01	0.21	-0.16
sent_external	0.20	-0.11	-0.02	-0.03	0.22	0.09
sent_all	0.16	0.06	-0.23	-0.03	0.17	0.00
all_email	0.14	0.10	-0.19	0.00	0.15	-0.11

Perceived Value Relative to Time Spent

	email_relval	ftf_relval	phone_relval	computer_relval	emcomp_relval	hardcopy_relval
email_relval	__					
ftf_relval	-0.02	__				
phone_relval	0.25	-0.57 **	__			
computer_relval	-0.22	0.29	-0.18	__		
emcomp_relval	0.83 ***	-0.26	0.17	0.06	__	
hardcopy_relval	-0.49	-0.51	0.30	__	-0.45	__
sent_internal	-0.08	0.09	0.11	-0.11	-0.21	-0.06
sent_external	-0.23	0.06	0.14	-0.34	-0.35	0.14
sent_all	-0.18	0.08	0.10	-0.34	-0.34	0.14
all_email	-0.21	0.16	0.04	-0.34	-0.32	-0.07

Table D.9 Correlations between email activity and survey measures of media preference (partners only)

The two preceding tables suggest a number of differences between consultants and partners with respect to relationships between actual email communication and perceptions of email use. Among consultants, more messages are correlated with more time spent and more perceived value from email at statistically significant levels. Among partners, the signs remain the same, but the correlations are generally not significant. In addition, for partners, the relative value vs. time spent for email is negatively correlated with numbers of messages, although again these are not significant. Taken together, these results suggest consultants have a more favorable opinion of higher email message volumes.

It is also possible to interpret a number of results relating numbers of email messages to perceptions of other kinds of media use that differ among consultants and partners. These results are generally not statistically significant, although the signs are consistent. Among consultants more email messages, particularly external messages sent, are correlated with a higher perceived value of time spent in front of the computer display. This would be consistent with a weak complementarity between external email use of the internal database or other search technologies. In addition, more email is positively correlated with a higher value of face-to-face relative to the perceived amount of time spent. Since the amount of time spent face-to-face is negatively correlated with the number of email messages, this effect might be interpreted as a desire for more face time on the part of consultants who are heavy email users.

<u>Collocation</u>

(D.7) I plotted the density of ties (actual/possible) at or above a given strength among dyads for four classifications of dyads based on differences in geographic, workgroup and practice area proximity.

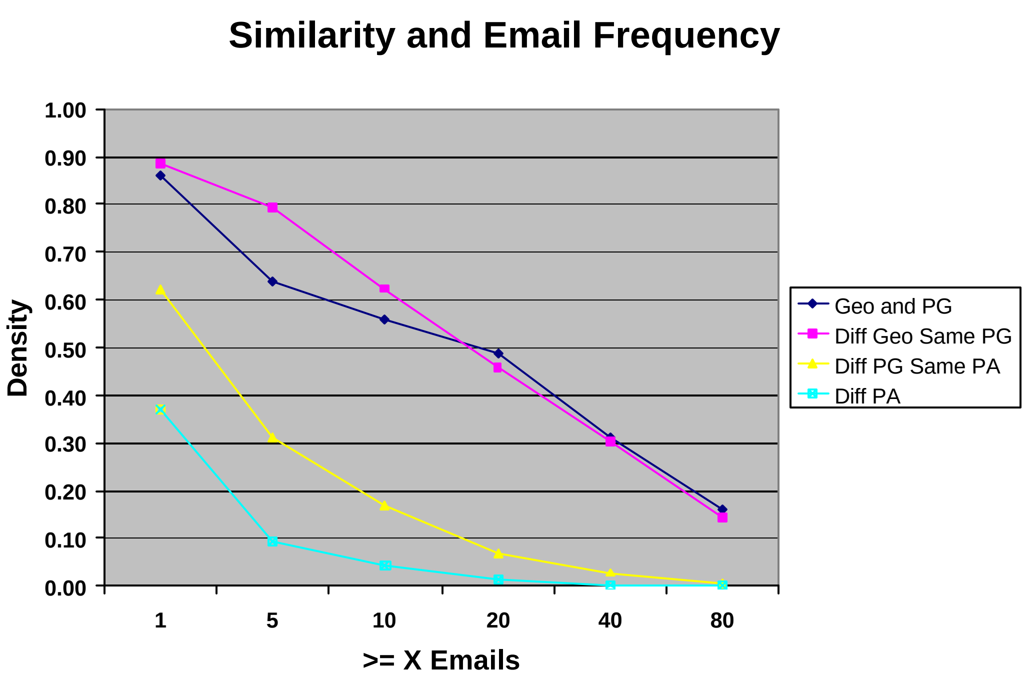

Fig.D.2. Relationships between tie density and collocation, practice group and practice area affiliations.

Fig. D.2. shows the density of email ties (actual/possible) at a given strength (>=x emails) for four groups of recruiters. Tie density is highest among recruiters in the same practice group. For recruiters in the same practice group, tie densities among collocated recruiters (navy) are similar to those among recruiters in different geographic locations (pink). Most email ties among recruiters in different practice groups are weak ties. This effect is stronger among recruiters who are also in different practice areas (light blue).

Fig. D.2 suggests email frequency is related to work group and practice area affiliations, but is not necessarily related to physical collocation. More generally, email frequency appears to be related to similarity on the basis of common interests as opposed to a common physical location. Recruiters in different practice groups are less likely to work together on search contracts. A tendency to maintain these relationships as weak ties over email is consistent with themes from the literature on the role of weak ties at a distance. On average, recruiters in different practice areas are likely to have the weakest common interests. This suggests that similarity in interests is related to the probability of email ties and the strength of those ties.

(D.8) I calculated Spearman correlations between the percentage of collocated searches based on billing credits and all survey measures as well as all email and performance measures used in subsequent regression models.

Survey Measures	
Email - time spent (%) (q27c scaled)	0.28 *
Information overload (q31)	0.27 *
Colleagues are willing to share their private information with me (q2)	-0.27 *
Computer - time spent (%) (q27e scaled)	-0.32 **
Perception of firm's external info gathering (q40)	-0.30 *
Years of education	-0.39 **
Hypothesis 1 - Centrality Measures	
Outdegree (ge20)	0.26 *
Outdegree (ge40)	0.25 *
Hypothesis 2 - Internal Proportions of Email	
Sent to consultants (%)	0.28 *
Sent to researchers (%)	-0.27 *
Received from researchers (%)	-0.37 **
Sent to former team members(%)	-0.33 **
Received from former team members (%)	-0.27 *
Hypothesis 4 - Email Response Times and Size	
Responses within 1 week (%) - Received from team	0.28 *
Ave. response time - Received from team	-0.27 *
Size (ln) - Received from team (all)	-0.26 *
Attachments (%) - Received from team	-0.33 **

N=47 recruiters, *** p < 0.01, ** p < 0.05, * p < 0.10

Table D.10. Correlations involving the percentage of collocated billings (consultants and partners).

Consultants		Partners	
Survey Measures			
Type of info shared - declarative vs. procedural (q23)	0.37 *	Information overload (q31)	0.54 **
People per day - face-to-face (q24a)	0.40 *	Technology allows me to handle more projects (q46)	0.48 *
Trade press - value of info (%) (q26g)	0.41 *	Mentoring to others (q47)	0.58 **
Email - time spent (%) (q27c)	0.47 **		
Email and comupter - time spent (%) (q27c + q27e)	0.44 **		
External databases - time spent (%) (q27f)	0.38 *		
People outside the company - value of info (%) (q26c)	-0.38 *	Computer - Time spent (q27e)	-0.48 **
Confidence on the phone (q34)	-0.42 *	Hardcopy - value (%) (q28f)	-0.47 **
Years of education (q44)	-0.47 **	Perception of firm's external info gathering (q40)	-0.42 *
Hypothesis 1 - Centrality Measures			
Structural holes (ge10)	0.35 *		
Structural holes (ge20)	0.40 *		
Betweenness (ge1)	0.42 **		
Outdegree (ge1)	0.35 *		
Outdegree (ge20)	0.52 ***		
Outdegree (ge40)	0.35 *		
		Contract network - structural holes	-0.42 **
		Contract network - betweenness	-0.41 *
Hypothesis 2 - Internal Proportions of Email			
Sent to partners (%)	0.34 *		
		Sent to researchers (%)	-0.56 ***
		Sent to former team members (%)	-0.51 **
		Received from researchers (%)	-0.61 ***
Hypothesis 3 - Colleague Performance			
Email in * Bookings	0.38 *		
Contracts * Bookings	0.41 **		
		Contracts * Bookings	-0.51 **
Hypothesis 4 - Email Response Times and Size			
Responses within 30 min (%) - Sent team	0.43 **		
Responses within 1 week (%) - Sent team	0.41 **		
Ave. response time - Sent to team	-0.46 **	Size (ln) - Received from team (all)	-0.38 *
Ave. ln(response time) - Sent to team	-0.45 **	Size (ln) - Received from team (no attachments)	-0.37 *
Ave. response time - received from team	-0.38 *	Attachments (%) - Received from team	-0.38 *

N=47 recruiters, *** p < 0.01, ** p < 0.05, * p < 0.10

Table D.11 Correlations involving the percentage of collocated billings (split sample).

Tables D.10 and D.11 show statistically significant correlations between the percentage of collocated searches and survey, email and performance measures. The percentage of collocated searches appears to be correlated with a team selection effect. Collocated search teams are more likely to have partners with higher past bookings paired with consultants with lower past bookings. With respect to the interpretation of hypothesis 3, this suggests the tendency for availability to be a more important criterion than experience in team assignment may diminish with physical distance. However, the causal direction is unclear. The firm could intentionally staff its offices so that more experienced partners are more likely to work alongside less experienced consultants.

The results suggest that the percentage of collocated searches may be related to some differences in email patterns. Among consultants, the percentage of collocated searches is positively correlated with time spent on email, faster email responses to teammates, the percentage of internal messages sent to partners and strong outgoing email ties. Among partners it is positively correlated with smaller messages received from teammates, both overall and for text messages, and a lower percentage of messages with attachments. It is also negatively correlated with the percentage of messages exchanged with researchers. This pattern of results suggests that email ties from consultants to partners on the same search team tend to be stronger when they are collocated. In addition, partners perceive they give more mentoring and consultants perceive they exchange more procedural information with colleagues. However, these results could also be related to team assignments in which more experienced partners work with less experienced consultants.

The percentage of collocated searches was not correlated with any of the performance measures. Among partners, it was positively correlated with the perception that information technology allows them to handle more simultaneous searches, as well as perceptions of information overload. This suggests ambiguity around the question of whether differences in email patterns associated with the percentage of collocated searches might help or hinder performance. Partners who conduct a higher percentage of collocated searches occupied less central positions in the contract network and sent a lower percentage of email to former team members.

(D.9) I conducted an ANOVA to assess differences between recruiters located in the central and satellite offices with respect to all survey measures and all email and performance measures used in subsequent regression models.

	Central	Non-Central	F	Sig.
Survey				
Reason info not in db - too valuable personally (%) (q5b)	12.86	4.07	4.96	0.03
Peer input into compensation (%) (q12c)	6.93	2.19	3.44	0.07
Face-to-face - number of people per day (q24 scaled)	0.14	0.08	3.22	0.08
Colleagues not on my project team - time spent (%) (q25b)	13.00	5.85	2.94	0.09
Public access Web pages - time spent (%) (q25d)	8.54	3.93	3.01	0.09
Years of experience (q45)	21.00	13.96	5.22	0.03
Phone - Number of people per day (q24b)	21.15	31.48	3.97	0.05
All media - Number of people per day (q24t)	58.92	78.67	3.13	0.08
News or trade press - % of value (q27g)	1.92	5.89	3.13	0.08
Effectiveness on the phone (q34)	359.38	398.31	3.30	0.08
Hypothesis 4 - Email Response Times and Size				
Response time - receive nonteam	10.46	7.63	6.97	0.01
Ave. (ln) size - receive team (no attachments)	8.15	7.88	4.31	0.04
Ave. (ln) size - send nonteam (all)	8.54	8.19	5.41	0.02
Ave. (ln) size - send nonteam (no attachments)	8.14	7.87	3.53	0.07
Attachments (%) - nonteam sent	14.15	10.14	3.06	0.09
Ave. (ln) size - receive nonteam (no attachments)	8.12	7.92	3.48	0.07
Attachments (%) - team receive	16.45	24.55	6.42	0.01

N=47 recruiters

Table D.12 Central vs. satellite office ANOVA results (consultants and partners).

Consultants	Central	Satellite	F	Sig.	Partners	Central	Satellite	F	Sig.
Survey									
Reason information doesn't make it into the db - too valuable to me personally (%) (q5)	19.29	5.31	4.94	0.04	Compensation based on whole company performance (%) (q10c)	23.57	11.82	3.05	0.10
Interdependent tasks (q6)	335.43	255.63	3.02	0.10	Supervisor input into compensation (%) (q12a)	61.14	28.55	3.26	0.09
Information systems for coordination (q7)	343.00	258.25	4.10	0.06	Type of information exchanged declarative vs. procedural (q23)	302.57	207.27	3.73	0.07
Proportion of email I read (q22)	95.57	86.13	4.37	0.05	People per day - face to face (q24a)	9.71	5.64	3.65	0.07
Use the Web to find information it is usually… work-related vs. personal (q36)	328.50	272.50	3.45	0.08	People per day - phone (q24b)	19.86	4.82	3.22	0.09
					Phone - value (%) (q28b)	0.41	0.26	11.06	0.00
					Years of experience (q45)	26.83	19.50	3.77	0.07
Supervisor input into compensation (q12a)	61.29	81.75	2.99	0.10	Client input into compensation (%) (q12e)	23.57	56.73	3.22	0.09
People per day - phone (q24b)	17.50	33.75	4.74	0.04	Effectiveness on the phone (q34)	344.00	409.10	3.37	0.09
People per day - total (q24t)	49.33	82.94	4.45	0.05	Born in 19xx (q43)	46.83	53.10	6.61	0.02
					Years of education (q44)	18.00	18.70	3.18	0.10
Hypothesis 4 - Email Response Times and Size									
Ave. response time - received nonteam	9.61	7.06	4.10	0.05	Response time - sent nonteam	14.63	8.56	7.66	0.01
Size (ln) - sent team (all)	8.25	7.84	5.20	0.03	Response time - receive nonteam	11.42	8.27	3.11	0.09
Size (ln) - receive team (no attachments)	8.37	7.86	9.83	0.00	Ave. (ln) size - sent nonteam (all)	8.67	8.34	3.21	0.09
Size (ln) - sent nonteam (no attachments)	8.16	7.75	3.39	0.08	Ave. (ln) size - receive nonteam (with attachments)	11.07	10.78	3.47	0.08
Size (ln) - receive nonteam (no attachments)	8.20	7.86	3.91	0.06					
					Responses within 1 week (%) - sent nonteam	51.50	66.71	4.47	0.05
					Responses within 30 min (%) - receive nonteam	16.40	23.94	3.31	0.08
					Attachments (%) - team sent	9.96	18.90	5.17	0.03
					Ave. (ln) size - receive team (with attachments)	10.74	10.95	3.71	0.07
					Attachments (%) - team receive	12.97	22.12	4.83	0.04
Performance Measures									
					Billing Share	5.99	8.64	3.87	0.06

N=47 recruiters

Table D.13 Central vs. satellite office ANOVA results (split sample).

Tables D.12 and D.13 show statistically significant ANOVA results from comparisons between recruiters in the central and satellite offices across all survey, email and performance measures. Differences associated with the central vs. satellite office distinction are primarily related to survey measures and email response time and size measures.

In addition to collocation, there are at least two alternative explanations for many of the differences. Partners in the central office tend to be older and more experienced. More phone communication, longer gaps in response times to non teammates and a tendency to exchange fewer email attachments with teammates could reflect either age or physical proximity. Consultants in the central office may feel more pressure to conform to the company culture. Self reported tendencies to read a higher percentage of email and use the Web for business as opposed to pleasure could reflect either cultural differences between offices or physical proximity.

With the exception of billing shares, which are higher among partners in satellite offices, there are no statistically significant performance differences.

(D.10) I identified measures that were related to both measures of collocation at statistically significant levels.

There is little evidence of a collocation effect that is related both to how work is conducted (percentage of collocated searches) and physical location (central vs. satellite office ANOVA). Only one measure, the percentage of emails received from team members with attachments, is related to both measures of collocation at statistically significant levels.

To the extent that the presence or absence of collocation may mediate relationships between email patterns and performance measures, it seems unlikely that collocation alone has this effect. Interactions between collocation effects and other variables may have some mediating influence. However, these effects do not appear clearly as factors that should be controlled for in this setting. Instead, they appear to be general effects that can be attributed to the error term in regression models.

(D.11) I calculated Spearman correlations between the proportion of revenue associated with booking searches and all survey measures and all email and performance measures used in subsequent regression models.

Survey		
Compensation is objective (q11)	0.29	*
Peer input into compensation (q12c)	0.27	*
Routine information gathering is automated (q15)	0.38	**
Multiple information sources (q16)	0.32	**
Type of info shared - declarative vs. procedural (q23)	0.37	**
Face-to-face - number of people per day (q24a)	0.40	**
Face-to-face - % of time spent (q27a)	0.43	***
Face-to-face - % of value from time spent (q28a)	0.42	***
Search team - % of time spent (q25a)	0.35	**
Search team - % of value from time spent (q26a)	0.29	*
Firm gathers a lot of internal information (q39)	0.38	*
Firm does data mining (q41)	0.32	*
Years of education	0.41	**
Years of experience	0.58	***
I have provided mentoring to others (q47)	0.30	*
Contacts in rolodex (q50)	0.31	*
Supervisor input into compensation (q12a)	-0.40	**
Info supplied vs. requested (q21)	-0.37	*
Internal database - % of time spent (q25e)	-0.30	*
Phone - % of value (q28b scaled)	-0.29	**
Effectiveness with database (q35)	-0.34	**
I was born in 19xx	-0.38	**
Performance		
Booking revenue	0.76	***
New booking revenue	0.62	***
Repeat booking revenue	0.70	***
Booking share	0.72	***
New booking share	0.55	***
Repeat booking share	0.67	***
Billing share	-0.30	**
Other		
Client ownership	0.90	***

N=47 recruiters, *** p < 0.01, ** p < 0.05, * p < 0.10

Table D.14. Correlations with percentage of revenues from bookings: survey and performance measures (consultants and partners)

Hypothesis 1 - Centrality Measures		
Structural holes (ge1)	0.36	**
Indegree (ge1)	0.30	**
Contract network - structural holes	0.33	**
Contract network - betweenness	0.35	**
Contract network - degree	0.31	**
Hypothesis 2 - Internal Proportions of Email		
Sent to consultants (%)	0.47	**
Received from consultants (%)	0.48	***
Sent to researchers (%)	-0.50	***
Sent to staff (%)	-0.25	*
Received from researchers (%)	-0.34	**
Herf - Sent Partner	-0.60	***
Herf - Rec Partner	-0.64	***
Hypothesis 3 - Colleagues Performance		
Bookings * Email in	-0.37	**
Bookings * Email out	-0.41	***
Contract * Billings	-0.41	***
Contract * Bookings	-0.78	***
Hypothesis 4 - Email Response Times and Size		
Ave. response time - send team	0.38	***
Ave ln(response time) - send team	0.33	**
Ave. response time - receive from team	0.34	**
Ave. response time - send nonteam	0.25	*
Ave ln(response time) - send nonteam	0.56	***
Ave. response time - receive nonteam	0.41	***
Ave ln(response time) - receive nonteam	0.40	***
Size - send nonteam (all)	0.26	*
Size - send nonteam (no attachments)	0.26	*
Size - receive nonteam (all)	0.34	**
% Attachments - nonteam receive	0.28	*
Responses wi/30 minutes - team send	-0.26	*
Responses wi/1 day - team send	-0.32	**
Responses wi/1 week - team send	-0.24	*
Responses wi/1 week - team receive	-0.30	**
Responses wi/30 min. - nonteam send	-0.56	***
Responses wi/1 day - nonteam send	-0.47	***
Responses wi/1 week - nonteam send	-0.33	**
Responses wi/30 min. - nonteam receive	-0.39	***
Responses wi/1 day - nonteam receive	-0.34	**
Responses wi/1 week - nonteam receive	-0.25	*
% Attachments - team send	-0.28	*

N=47 recruiters, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table D.15. Correlations with percentage of revenues from bookings: email measures (consultants and partners)

Consultants			Partners		
Survey Measures					
Peer input into compensation (%) (q12c)	0.55	***	Interdependent tasks (q6)	0.54	**
Subordinate input into compensation (%) (q12d)	0.47	**	Project team performance influence on compensation (%) (q10b)	0.44	*
Routine information gathering is automated (q15)	0.44	**	Highly routine data requirements (q14)	0.46	*
Overlapping social structure (q20)	0.38	*	Relative value of colleagues not on my project (q26b)	0.51	**
People per day - face-to-face (q24a)	0.44	**	I have provided mentoring to others (q47)	0.64	***
People outside the company (%) - time spent (q25c)	0.39	*			
Value of face-to-face	0.46	**			
Years of experience (q45)	0.39	*			
Contacts in rolodex (q50)	0.48	**			
Internal database - time spent (%) (q25e)	-0.37	*	People per day - email (q24c)	-0.55	**
Email and computer - value (%) (q28c + q28e)	-0.37	*	People per day - all media (q24t)	-0.43	*
Routine stayed the same after 9-11 (q33)	-0.39	*	Time spent with computer (%) - (q27e)	-0.46	*
			Time spent with email and computer (%) - (q27c + q27e)	-0.40	*
			I am happy in my current job (q51)	-0.49	*
Performance Measures					
Booking revenue	0.73	***	New booking revenue	0.41	*
New booking revenue	0.38	*			
Repeat booking revenue	0.64	***			
Booking shares	0.73	***			
Repeat booking shares	0.69	***			
			Billing shares	-0.43	**
Other					
Client ownership	0.73	***	Client ownership	0.64	***

N=47 recruiters, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table D.16. Correlations with percentage of revenues from bookings: survey and performance measures (split sample)

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Consultants		Partners	
Hypothesis 1 - Centrality Measures			
Indegree (ge40)	-0.39 *		
Hypothesis 2 - Internal Proportions of Email			
Received from consultants (%)	0.39 *	Sent to consultants (%)	0.61 ***
Received from researchers (%)	0.34 *	Received from consultants (%)	0.42 *
Received from former team members (%)	0.49 **		
Received from team members(%)	-0.37 *	Sent to researchers (%)	-0.60 ***
Herfindahl - sent to partners	-0.35 *	Sent to staff (%)	-0.53 **
Herfindahl - received from partners	-0.44 **	Received from researchers (%)	-0.44 **
Hypothesis 3 - Colleagues Performance			
Email In * Bookings	-0.54 ***		
Email Out * Bookings	-0.59 ***		
Contracts * Billings	-0.48 **		
Contracts * Bookings	-0.53 ***		
Hypothesis 4 - Email Response Times and Size			
Ave. response Time - Received from team	0.34 *	Ave. response time - Received from nonteam	0.41 *
Ave. response Time - Received from nonteam	0.44 **	Ave ln(response time) - Received from nonteam	0.39 *
Ave ln(response time) - Received from nonteam	0.45 **		
Size (ln) - Received from nonteam (all)	0.41 **		
Size (ln) - Received from nonteam (no attachments)	0.41 **		
Responses within 30 min (%) - Sent nonteam	-0.44 **	Responses within 30 min (%) - Sent team	-0.39 *
Responses within 30 min (%) - Received nonteam	-0.38 *	Responses within 30 min (%) - Sent nonteam	-0.44 **
		Responses within 1 day (%) - Sent nonteam	-0.42 *
		Responses within 30 min (%) - Received nonteam	-0.42 *
		Responses within 1 day (%) - Received nonteam	-0.49 **
		Responses within 1 week (%) - Received nonteam	-0.40 *
		Size (ln) - Sent to team	-0.36 *

N=47 recruiters, *** p < 0.01, ** p < 0.05, * p < 0.10

Table D.17. Correlations with percentage of revenues from bookings: email measures (split sample)

Statistically significant correlations between the percentage of revenues from bookings (booking revenue / booking + billing revenue) and survey, email and performance measures are shown in tables D.14-D.17. I use the percentage of revenues from bookings as a measure of hierarchical specialization. Positive correlations indicate measures associated with recruiters who receive a higher proportion of revenue from landing searches; negative correlations indicate measures associated with recruiters who receive a higher proportion of revenue from executing searches.

Among both consultants and partners, the strongest correlation involves a proxy for client ownership (ρ=0.90 population; ρ=0.73 consultants; ρ=0.64 partners).[43] The temporal sequencing suggests a causal relationship in which the division of labor between booking and billing is determined largely by the value of a recruiter's client base. As shown by the number and strength of statistically significant correlations, this division of labor may be the single most important factor influencing patterns of information use and email communication within the firm.

Within the full population, most statistically significant correlations with the percentage of revenue from bookings are also significant in an ANOVA of differences between consultants and partners. In split samples, the results suggest that the distinction between consultants and partners could be interpreted as a continuum running from junior consultants who focus primarily on billings to senior partners with the most valuable client bases.

At the junior level, consultants spend the most time with the database and perceive they get the most value from email and computers. They receive a high proportion of email from partners on their search teams. They also have more rapid email exchanges with colleagues outside the search team. As consultants begin to develop clients, their information behaviors and email communication patterns become more similar to those of junior partners. They report communicating with more people face-to-face and spend more time with people outside the company. They also

[43] The client ownership proxy is the sum of booking revenues for all searches for which recruiters received more than 0.5 booking shares conducted from Jan. 1, 1999 to the day before start of the study period. Recruiters receive 0.5 booking shares for client "ownership." The client ownership proxy records past booking revenues associated with all searches in which a recruiter clearly had "ownership" of the client.

communicate more widely with partners on email and receive higher proportions of email from peers, researchers and former team members.

Partners who generate more value from bookings appear to adopt a more focused strategy towards relationships with others. They report communicating with fewer people per day both overall and on email. They perceive their tasks as more interdependent, attribute more value to time spent with colleagues outside their project team and believe they provide more mentoring to others. They send smaller emails to team members and are less likely to respond quickly on email. Longer gaps consistently appear in their email communication outside the project team.

Among both consultants and partners, correlations between the proportion of revenue from bookings and the herfindahls of message share received and sent to partners are strongly negative (-0.60 and -0.64 in the population, $p < 0.01$). Partner response times are generally longer than consultant response times. This suggests that longer non-team response times do not necessarily indicate problems with the non-responsiveness of colleagues. Part of the effect is likely to be related to more with communication with a larger number of partners, who tend to respond slower on average to their internal email.

For both consultants and partners, the percentage of revenue from bookings is also positively correlated with receiving a greater proportion of internal email from colleagues directly below them in the organizational hierarchy. For partners, the proportion of revenue from bookings is correlated with the proportion of email exchanged with consultants (0.61, $p < 0.01$ sent; 0.42, $p < 0.10$ received); for consultants, it is associated with the proportion of email received from researchers (0.34, $p < 0.10$).

Patterns of correlations with the percentage of revenue from bookings are similar to relationships between information flows and bookings in hypothesis two, as well as the hypothesis three finding that bookings are negatively related to the lagged bookings of colleagues. These patterns suggest that the division of labor may be determined as much if not more by a recruiter's success in landing clients than by job titles.

(D.12) I performed an ANOVA to assess differences between recruiters based on their practice area identification with respect to all survey measures and all email and performance measures used in subsequent regression models.

	Sec. A	Not A	F	Sig.
Survey Measures				
A lot of my personal knowledge doesn't make it into the database (q4)	283.88	189.19	7.20	0.01
Mentor input into compensation (%) (q12b)	7.86	2.36	4.16	0.05
Subordinate input into compensation (q12d)	11.00	2.97	5.54	0.02
Email - Number of people per day (q24c)	0.53	0.41	3.54	0.07
Public access Web pages - % of time spent (q25d)	12.57	3.97	7.47	0.01
Pulbic access Web pages - % of value (q26d)	12.14	3.69	4.92	0.03
Use the Web to find information it is usually… work-related vs. personal (q36)	328.71	277.81	3.83	0.06
The firm gathers a lot of external information (q40)	283.57	206.90	3.20	0.08
I need as much information as possible before making a decision about a candidate (q8)	272.86	370.03	6.07	0.02
Phone - Number of people per day	15.71	30.31	5.41	0.03
All media - Number of people per day (q24t)	52.00	76.53	3.08	0.09
Years of experience (q45)	10.14	18.03	4.61	0.04
Hypothesis 1 - Centrality Measures				
Structural holes (ge1)	20.02	28.48	10.70	0.00
Structural holes (ge5)	9.18	13.31	3.27	0.08
Indegree (ge1)	20.63	29.11	11.01	0.00
Outdegree (ge1)	20.75	28.97	8.01	0.01
Hypothesis 2 - Internal Proportions of Email				
Received from partners (%)	0.30	0.21	6.33	0.02
Herfindahl - Received from partners	0.28	0.19	5.69	0.02
Received from staff (%)	0.26	0.40	7.82	0.01
Sent to colleagues who have never been team members (%)	0.10	0.20	4.98	0.03
Hypothesis 3 - Colleagues Performance				
Billings * Email In	978,696	1,461,569	53.47	0.00
Billings * Email Out	1,093,026	1,487,341	42.29	0.00
Bookings * Email In	1,171,596	1,472,791	5.72	0.02
Bookings * Email Out	1,301,250	1,581,016	4.73	0.04
Contracts * Billings	1,124,641	1,425,226	7.40	0.01
Hypothesis 4 - Email Response Times and Size				
Responses wi/1 week - team send	87.65	77.29	2.83	0.10
Size - sent team (all)	8.77	8.44	3.12	0.08
Size - received team (all)	8.80	8.50	3.08	0.09
Size - received nonteam (all)	8.65	8.28	7.63	0.01
Size - received nonteam (no attachments)	8.24	7.94	5.64	0.02
Size - received nonteam (attachments only)	11.10	10.81	4.43	0.04
Responses wi/30 min. - nonteam send	16.52	24.29	2.91	0.10
Responses wi/30 min. - nonteam receive	15.83	25.81	6.94	0.01
Ave. response time - nonteam receive	6.29	9.00	3.83	0.06

Table D.18 Practice area ANOVA: (consultants and partners)

Consultants	Sec. A	Not A	F	Sig.	**Partners**	Sec. A	Not A	F	Sig.
Survey Measures									
Web pages - time spent (%) (q25d)	14.60	3.81	4.81	0.04	My knowledge not in database (q4)	305.33	183.43	5.31	0.04
Computer display - value (%) (q28 scaled)	0.12	0.04	3.16	0.09	Subordinate input into compensation (%) (q12d)	23.50	4.25	6.80	0.02
Amount I have learned from others about doing my job (q48)	402.20	302.69	3.86	0.06	People per day - hardcopy	11.00	4.25	3.06	0.10
					Contacts in rolodex (q50)	1250.00	372.14	7.35	0.02
I need as much info about a candidate as possible (q8)	299.80	387.13	3.48	0.08	I need as much info about a candidate as possible (q8)	205.50	352.94	4.12	0.06
People per day - phone (q24b)	16.00	32.50	4.17	0.06	Routine information gathering is automated (q15)	175.50	353.06	6.68	0.02
People per day - overall (q24t)	47.40	81.81	3.80	0.07	People I trade info with have a background similar to my own (q19)	157.00	282.50	3.05	0.10
					People per day (%) - phone (q24b scaled)	0.21	0.41	5.19	0.04
					I have control over my information (q37)	154.50	278.80	4.26	0.06
					Years of experience (q45)	12.50	23.64	4.15	0.06
Performance Measures									
New booking share	1.32	0.58	3.04	0.10					

Table D.19 Practice area ANOVA: survey and performance measures (split sample)

Consultants	Sec. A	Not A	F	Sig.	Partners	Sec. A	Not A	F	Sig.
Hypothesis 1 - Centrality Measures									
					Indegree (ge20)	7.33	3.79	4.79	0.04
					Indegree(ge40)	4.00	1.68	4.78	0.04
					Outdegree(ge20)	7.00	3.42	3.38	0.08
Structural holes (ge1)	17.87	26.62	5.32	0.03	Structural holes (ge1)	23.62	30.34	4.72	0.04
Indegree (ge1)	18.40	27.58	6.41	0.02	Indegree (ge1)	24.33	30.63	3.42	0.08
Outdegree (ge1)	19.00	28.05	4.36	0.05					
Hypothesis 2 - Internal Proportions of Email									
Sent to team members (%)	0.70	0.52	4.23	0.05	Received from partners (%)	0.36	0.21	7.81	0.01
Received from team members (%)	0.67	0.52	3.02	0.10	Herfindahl - received from partner	0.19	0.13	4.64	0.04
Herfinhahl - received from partners	0.34	0.25	3.19	0.09					
Sent to colleagues who have never been team members (%)	0.08	0.22	9.65	0.01	Received from staff (%)	0.18	0.40	10.68	0.00
Received from colleagues who have never been team members (%)	0.09	0.24	11.39	0.00					
Hypothesis 3 - Colleagues Performance									
Email In * Billings (100,000s)	9.52	14.99	33.12	0.00	Email In * Billings (100,000s)	10.23	14.24	19.97	0.00
Email Out * Billings (100,000s)	10.50	15.23	29.23	0.00	Email Out * Billings (100,000s)	11.64	14.51	12.98	0.00
Contract * Billings (100,000s)	11.13	15.36	8.61	0.01	Email In * Bookings (100,000s)	10.03	13.96	4.20	0.05
Contract * Bookings (100,000s)	16.52	24.05	4.12	0.05	Email Out * Bookings (100,000s)	11.18	15.14	3.12	0.09
Hypothesis 4 - Email Response Times and Size									
Size (ln) - sent nonteam (all)	8.55	8.10	3.02	0.10	Responses within 1 wk - received from team	89.99	76.42	3.51	0.08
Size (ln) - sent nonteam (attachments only)	11.39	10.88	3.43	0.08	Responses within 1 wk - received from nonteam	79.64	64.74	4.45	0.05
Size (ln) - received nonteam (all)	8.59	8.18	3.80	0.06	Size (ln) - received nonteam (all)	8.73	8.37	7.31	0.01
Size (ln) - received nonteam (attachments only)	11.16	10.78	4.80	0.04	Size (ln) - received noteam (no attachments)	8.28	7.96	4.87	0.04
Responses within 30 min - sent nonteam	18.51	29.71	3.86	0.06					
Responses within 1 day - sent nonteam	46.79	58.19	3.01	0.10					
Responses within 30 min - received nonteam	15.26	29.32	9.19	0.01					

Table D.20 Practice area ANOVA: email measures (split sample)

Sample size is an important caveat in evaluating results from tables D.18-D.20. There were only five consultants and three partners in practice area A, one of whom was a survey non-respondent.[44] This means that partner results are based on an extremely small sample and results for all partners and consultants need to be interpreted with caution because the ratio of partners to consultants is higher in practice area B. This appears to have been a temporary imbalance as one of the practice area A consultants was promoted near the end or shortly after the conclusion of the study period.

However, the results do suggest some differences in media use across practice areas. Recruiters in practice area A reported that they communicated with a lower number of people by phone and over all media, while a higher proportion of their communications occurred over email. Consultants in practice area A reported spending more time with Web pages, receiving more value from time spent in front of the computer and exchanging a greater proportion of email with team members. Partners in practice area A may communicate more extensively among themselves over email. This suggests that horizontal as well as vertical differences in job types are important to consider in evaluating relationships between communication patterns and performance.

Given the small sample size, it is also possible that some differences are related more to particular aspects of the individuals in the smaller practice group than characteristics of the work. In particular, recruiters in practice area A tend to have less experience (average 10.1 vs. 18.0 years overall, $F=4.61$, $p < 0.05$; 12.5 vs. 23.6 years among partners, $F=4.15$, $p < 0.10$). Less experienced recruiters are likely to have generated less revenue from 1999 through the beginning of the study period, so this could influence results in models that use lagged revenues to assess co-specialization effects. While a practice area dummy variable is included in subsequent regression models, the addition of practice area interaction terms is suggested as an area for future work.

[44] One recruiter's contracts were split between the two practice areas. This recruiter was dropped from the ANOVA.

(D.13) I used Cronbach's alpha to assess agreement among technology related survey measures. Comparisons included time spent vs. value (phone, email, databases), time spent vs. proficiency (phone, databases), value vs. proficiency (phone, databases) and proficiency vs. proficiency (phone vs. databases).

	All	Consultants	Partners
Time vs. Value			
Phone	0.78	0.81	0.66
Email	0.83	0.90	0.64
Internal Database	0.76	0.55	0.95
All Databases	0.74	0.56	0.95
Time vs. Proficiency			
Phone	-0.15	0.27	-0.94
Database	0.55	0.48	0.59
All Databases	0.54	0.45	0.61
Value vs. Proficiency			
Phone	-0.52	0.24	-4.14
Database	0.61	0.55	0.65
All Databases	0.62	0.56	0.69
Relative Value vs. Proficiency			
Phone	-0.23	-0.12	-0.30
Database	-0.07	-0.20	0.22
All Databases	-0.02	-0.19	0.40
Proficiency vs. Proficiency			
Phone and DB	0.31	0.28	0.36

Table D.21 Standardized Cronbach's alpha scores for the reliability of technology related survey measures.

As shown in the table above, the only area in which there is significant agreement between technology related survey measures involves perceptions of time spent vs. value received. However, even among these measures, there are distinct job level differences. Consultant reports of time spent and value received can be interpreted as similar for email ($\alpha = 0.90$) and marginally similar for phone use ($\alpha > 0.80$); partner reports of time spent and value received can be interpreted as similar for database use ($\alpha = 0.95$). However, the results suggest that partners perceive differences between time spent and value received with respect to both phone and email, while consultants perceive differences with respect to databases.

Self-reported proficiency in a medium or technology is generally not strongly related to self-reported time spent, value received or relative value. This makes it considerably harder to find measures that are candidates for proxies to represent relationships between technological specialization and performance. A number of these tests show negative measures, an indication of negative correlation in which case Cronbach's alpha is undefined. Levels of agreement in the proficiency vs. proficiency comparison of phone and database use are also low. This suggests that these differences cannot be explained away solely in terms of individual differences in perceptions of self-efficacy. A particularly striking result is observed with respect to perceived partner efficacy on the phone and perceived value of phone interactions, which are negatively correlated at a statistically significant level (-0.46, $p < 0.10$).

I derived the measures in the following way. Proportional measures of time spent were derived from the multipart survey questions q27 for phone and email (media comparisons) and q25 for database use (information source comparisons). Due to the low number of respondents indicating "other" for q25 and q27 and "instant messenger" for q27, values were rescaled so that each individual total summed to 100 percent when these categories were excluded. The internal database value refers specifically to q25e, the all database value represents the sum of q25e and q25f (external databases). The same calculations were performed with respect to proportion of value received measures q26 and q28. Self-reported phone proficiency was measured through q34 "I am highly effective interacting with people on the phone…."; self-reported database proficiency was measured through q35 "I am highly effective at using our in-house proprietary search tools…"

(D.14) I calculated Spearman correlations between performance measures and technology related survey measures. I also calculated correlations between performance measures and survey measures of face-to-face communication and the extent to which recruiters rely on human interaction as opposed to encoded sources of information.

	Correlations between technology and performance measures														
	All					**Consultants**					**Partners**				
	Billing		***Booking***			***Billing***		***Booking***			***Billing***		***Booking***		
	Study	***Yr***	***Study***	***Yr.***	***tech_more***	***Study***	***Yr***	***Study***	***Yr.***	***tech_more***	***Study***	***Yr***	***Study***	***Yr.***	***tech_more***
Phone															
time_phone	0.33 **	0.08	-0.06	0.01	-0.02	0.12	-0.09	0.22	0.26	0.06	0.56 **	0.26	0.17	0.32	-0.39
value_phone	-0.03	-0.21	-0.15	-0.15	-0.16	-0.08	-0.22	0.03	0.02	-0.07	0.00	-0.20	-0.02	0.06	-0.37
relval_phone	-0.33 **	-0.22	-0.14	-0.14	-0.17	-0.14	0.04	-0.17	-0.22	-0.38 *	-0.45 *	-0.38	-0.19	-0.18	0.11
people_day_phone	0.01	0.08	-0.02	-0.01	0.01	-0.01	-0.20	0.09	-0.07	0.06	0.01	0.28	0.14	0.32	-0.15
efficacy_phone	-0.10	0.02	-0.06	-0.08	0.29 *	-0.25	-0.18	0.21	0.16	0.01	0.00	0.25	-0.30	-0.20	0.74 ***
Database															
time_intdb	-0.17	-0.15	-0.33 **	-0.24	0.16	0.05	-0.03	-0.35	-0.29	0.22	-0.38	-0.30	-0.30	-0.15	0.14
value_intdb	0.17	0.14	-0.24	-0.19	0.25	0.62 ***	0.41 *	-0.06	-0.03	0.26	-0.27	-0.20	-0.36	-0.21	0.26
relval_intdb	0.27	0.20	-0.08	0.03	-0.04	0.37	0.27	-0.04	0.08	-0.04	0.24	0.14	-0.31	-0.22	-0.10
efficacy_intdb	0.09	0.33 **	-0.19	-0.23	0.35 **	0.27	0.44 **	0.10	0.05	0.51 **	-0.01	0.25	-0.02	-0.09	0.11
Email															
time_email	0.08	0.22	-0.12	-0.10	0.15	-0.01	0.16	-0.28	-0.21	0.23	0.25	0.29	0.14	0.09	0.01
value_email	-0.03	0.00	-0.24	-0.09	0.14	0.03	0.04	-0.43 **	-0.32	0.22	0.03	0.02	-0.14	0.15	0.03
relval_email	-0.08	-0.21	-0.11	0.00	0.07	0.04	-0.12	-0.21	-0.18	0.14	-0.22	-0.27	-0.28	0.01	0.05
people_day_email	0.14	0.31 *	0.02	-0.01	0.19	0.36	0.34	-0.02	0.00	0.28	-0.06	0.20	0.10	-0.04	0.07
vol_all_study	0.10	0.34 **	-0.14	-0.10	0.21	0.29	0.41 **	0.00	0.17	0.30	0.01	0.29	0.17	0.09	0.15
vol_external_sent_study	0.12	0.33 **	-0.18	-0.17	0.05	0.37 *	0.47 **	0.07	0.22	0.14	0.07	0.28	0.10	0.03	0.05
vol_internal_sent_study	0.04	0.25 *	-0.08	-0.05	0.41 **	0.23	0.32	-0.13	0.01	0.44 **	-0.07	0.17	0.05	0.04	0.27
vol_sent_all_study	0.04	0.31 **	-0.12	-0.09	0.23	0.29	0.37 *	0.00	0.19	0.36 *	-0.10	0.24	0.17	0.04	0.06
Other															
Face-to-Face															
time_ftf	-0.23	-0.11	0.37 **	0.20	0.08	-0.28	0.02	0.34	0.21	-0.12	-0.30	-0.23	0.15	-0.16	0.40
value_ftf	0.03	0.14	0.42 ***	0.32 **	0.28 *	-0.04	0.09	0.49 **	0.40 *	0.21	0.05	0.16	0.22	0.04	0.32
relval_ftf	0.26	0.28 *	-0.01	0.06	0.23	0.31	0.12	0.11	0.18	0.48 **	0.20	0.36	0.08	0.24	-0.16
People vs. Info															
sources_time_people	0.07	0.07	0.27 *	0.20	0.00	-0.08	-0.10	0.28	0.25	-0.08	0.22	0.26	0.34	0.15	0.04
sources_value_people	-0.19	-0.19	0.20	0.17	-0.06	-0.53 **	-0.43 *	0.08	0.17	-0.01	0.14	0.12	0.30	0.07	-0.12
sources_relval_people	-0.24	-0.28 *	0.13	0.11	-0.04	-0.41 *	-0.29	0.05	0.13	0.15	-0.05	-0.19	0.40	0.24	-0.38
sources_relval_info	0.19	0.21	-0.11	-0.10	0.08	0.29	0.25	0.05	-0.03	-0.12	0.13	0.15	-0.56 **	-0.41	0.45 *
General Technology															
tech_more	-0.12	-0.08	-0.09	-0.04		0.04	0.01	0.03	0.09		-0.33	-0.23	-0.39	-0.32	

Table D.22. Correlations between performance measures and technology related survey measures. Correlations with other media and information related survey measures and actual numbers of email messages are also shown.

Results in the table above led me to the pessimistic conclusion that analysis of the survey data is not likely to be sufficient to gain an understanding of relationships between phone and database use and performance. However, a number of correlations may be useful in the context of a more general interpretation of technology related survey measures.

Correlations with the survey question "information technology has increased my ability to handle more projects at the same time" (rightmost column in each set), suggest a pattern consistent with self-efficacy bias. Within the population it is positively correlated with survey questions representing perceived phone efficacy (0.29, $p < 0.10$), perceived database efficacy (0.35, $p < 0.05$) and the value of face-to-face communication (0.28, $p < 0.10$), as well as the actual number of internal email messages sent (0.41, $p < 0.05$). It is not correlated with any of the performance measure at statistically significant levels. Among partners it is weakly negatively correlated with three of the four performance measures at $p < 0.25$.

Among partners, correlations among people vs. information measures suggest higher performing partners favor human information sources. People based sources include project team members, colleagues outside the project team and people outside the company. Information based sources include Web pages, databases (internal and external) and news.[45] Among partners, booking revenue in the study period is negatively correlated with the relative value of information based sources (-0.56, $p < 0.05$). Relative value is calculated as (value received / time spent). An interpretation is that partners who believe their they received relatively more value than time spent from information based sources as opposed to human interactions generated less booking revenue in the study period. Although the other correlations are not statistically significant, the signs are consistent. Partners who spend more time, as well as partners who attribute more value to human based information sources had higher billings and bookings. When a single outlier is excluded (c48), the relative value of time spent with human information sources is also statistically significant

[45] People vs. information comparisons are based on the sum of survey questions (q25a-c) and (q25d-g) respectively. These questions refer to the proportion of time spent and value received from specific sources of information.

among partners (0.62, $p < 0.01$). These results based on perceptual data from the survey are consistent with the theme from the exploration and exploitation hypothesis that higher performing partners rely more on relationships with others.

Among partners, statistically significant correlations between phone-related survey measures and billing revenue in the study period are more difficult to interpret. While the proportion of time on the phone is correlated with revenue from completed billings in the study period (0.56, $p < 0.05$), the perceived value of telephone communication relative to time spent is negatively correlated (-0.45, $p < 0.10$). The interpretation is that partners who believe they spend more time than they perceive as optimal (based on value received) were higher performers in this dimension. It is possible that among partners more phone time may increase completed billings, but could still be looked upon unfavorably if it takes time away from the higher valued activity of landing new contracts.

Among consultants, perceived value from databases and information as opposed to human based sources, as well as the number of external email messages sent are all positively correlated with billing revenue, while the perceived proportion of value received from face-to-face communication is positively correlated with booking revenue. This may reflect task differentiation. The former information sources are used more in tasks related to billings, while more senior consultants tend to have more face-to-face communication with clients.

Appendix E

Additional Factors Related to Performance

In this appendix, I cover analyses related to factors that may influence individual performance in this setting, but are not included in any of my hypotheses. These include contract selection effects, the percentage of solo searches, information technology use and communication with researchers and staff.

<u>Heterogeneity in projects</u>

Project level variation in search contracts presents a significant measurement challenge. Search contracts vary in revenue, which I observe, and difficulty, which I do not observe. Some searches have a more favorable balance than others. Some recruiters may have more favorable portfolios of searches than others. While part of this variation is random, active selection of more favorable contracts may also play a role.

In such cases, individual performance measures may include components related to the selection of projects, as opposed to skills or effort. This confounding effect makes it more difficult to interpret results. This may be particularly true for research questions that involve effects of social capital. Performance increases may be correctly attributed to social capital effects, but not represent productivity gains when the value of social capital lies in cherry picking more favorable projects. Beyond the dummy variables for industry sector, my base model does not control for potentially non-random variation in the difficulty of searches.

One strategy for addressing this problem is to assume or estimate difficulty levels associated with specific types of searches. These results could be used to introduce an "adjusted" performance measure. However, in the two cases I have considered, involving geographic location and job level variation, relationships between revenue and difficulty appear to be fairly complex. Another strategy, which I have used in previous work, is to use the percentage of searches in a specific category as a control. Given a sound theoretical or empirical argument for controlling for a particular type of contract, I see this is as a reasonable strategy.[46] But given my small sample size, this strategy should be used judiciously if at all.

Geography, a factor recruiters mentioned in interviews, provides an illustrative example of this type of issue.[47] For recruiters, contracts for jobs in locations that combine a high quality of life with high salaries are the most desirable. The former makes it easier to place candidates; the latter generates higher revenues. Interview data suggest recruiters in this study were able to perceive the influence of geography on the cost of a search but that this did not usually lead to a fee adjustment.

This suggests that performance in executive recruiting may be partially related to project selection, as well as talent and effort. Two hypothetical recruiters who are otherwise identical in every respect could produce significantly different levels of output if one conducted searches in San Francisco and the other conducted searches in Akron. The ability to estimate a project selection effect component of performance and its relationship to role of social networks lies beyond the scope of this study. Instead, I use the geography example to motivate a brief analysis of the role of job level variation in search contracts on performance. I focus on this area because of the substantive implications for interpreting results. It is also the area in which the data appear to be most suitable for assessing relationships between revenue and difficulty.

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[46] This assumes that a control is selected on the basis of theory or empirical analysis conducted using observations that are not used to test subsequent hypotheses. Selecting a control on the basis of explanatory power using observations that are subsequently used to test hypotheses is not a valid technique. It is analogous to the use of step-wise regression to select coefficients. Subsequent results from hypothesis tests will not be valid.

[47] I am able to identify the cities associated with a portion of the search records. I could potentially use this data in future work. However, many of the problems associated with estimating the relationship between quality of life indices for specific cities and search difficulty are similar to those I discuss involving job level variation in search contracts.

Job Level Variation in Contracts

In the raw contract data, searches are classified into eight categories based on the type of job they represent. In interviews, recruiters described three job level categories: CEOs, vice president level and others. I was able to interpret the eight types of searches identified in the raw contract data to reflect this three job level distinction.

Job level variation in contract revenues is statistically significant. Contracts landed during the study period had the following average revenues: CEO searches ($81,745); VP searches ($56,900); and Other ($46,203). Job level variation in the types of searches recruiters perform is also related to individual booking revenue. When I add percentages of searches by job level to the base model (two at a time), they explain significant variation in booking revenue ($F > 4$, $p < 0.05$). Their joint influence on billing revenue is not significant ($F = 0.97$, $p \sim 0.39$). Adding the percentages of searches by job level individually to the booking revenue gives the following results.[48]

	B		Std. Error	Beta	t	Sig.
Consultant Booking Revenue						
CEO Search %	368,103	**	139,277	0.70	2.64	0.02
VP Search %	62,065		103,889	0.26	0.60	0.56
Other Search %	-176,542	*	86,245	-0.69	-2.05	0.06
Partner Booking Revenue						
CEO Search %	307,522	**	123,141	0.51	2.50	0.02
VP Search %	-210,169		210,915	-0.35	-1.00	0.33
Other Search %	-380,342	**	169,707	-0.47	-2.24	0.04

n=21 consultants, 22 partners
***p< 0.01, ** p < 0.05, * p < 0.10

Table. E.1 Booking revenue and search percentages by contract job level.

[48] I excluded recruiters who had less than $10,000 in total booking revenue from this analysis. This involves dropping four consultants.

A number of factors could explain these relationships between the percentage of bookings by job level and individual booking revenues. However, my interest in the possibility of contract selection effects led me to consider potential proxies for the difficulty of a search. I identified three ways of analyzing the data that provide some clues.[49] The results suggest that the relationship between the job level of contracts and booking revenue is neither simple nor entirely random.

Based on the assumption that searches that take longer require more effort, differences in difficulty may be related to differences in duration. ANOVA's show no significant differences in average duration between CEO (197 days) and VP searches (196 days). "Other" searches are significantly shorter (184 days).

Based on the assumption that more difficult assignments may involve a more extensive division of labor, recruiters who undertake more difficult searches may be less likely to act alone. CEO searches had the lowest percentage of solo bookings (24.0 percent) and billings (9.6 percent). VP searchers were the most likely to involve solo bookings (39.6 percent) and "Other" searches were intermediate (33.1 percent). "Other searches" were the most likely to involve solo billings (14.3 percent) and VP searches were intermediate (12.2 percent).

Based on the assumption that recruiters who pursue more difficult searches may complete fewer projects, differences in the difficulty associated with either billing or booking particular types of searches might be reflected in relationships between the percentage of searches conducted at specific job levels and total credits received. Scatterplots suggest that it is not unreasonable to assume this variation is random with one exception. Among partners who had some CEO bookings (73 percent), the percentage of CEO bookings is negatively correlated with total booking credits (-0.43, $p < 0.10$); however among all partners, the correlation is positive, but not significant (0.19, $p < 0.40$).[50] This suggests that the lead role associated with

[49] Other data could be used to estimate search difficulty in future work. For example, the number of records consulted in the database or expenses associated with a search. My interest was in using data on hand to take a first cut at the question of how I might be able to identify differences in the difficulty of searches.

[50] The relationship is in the opposite direction for consultants, but is not statistically significant. A possible interpretation is that consultants with more experience landing contracts are more likely to play a more substantial supporting role in landing CEO contracts.

CEO bookings may require more effort.[51] This is consistent with anecdotal evidence and the intuition that competition with other firms involved in landing higher valued contracts is likely to be more intense. However, the results also suggest that with the exception of the lead role in booking, the level of participation on CEO searches is not related to lower output measured in terms of project shares.[52]

The following interpretations are consistent with the preceding analysis of the data.[53] "Other" searches pay less on average, but are completed more quickly. CEO searches pay more, but the booking process is more difficult. However, CEO searches also involve a greater division of labor. This may help explain why CEO and VP searches have similar durations. Recruiters who play the lead role in booking CEO searches may complete fewer projects, but the contracts they do complete have higher revenues. Recruiters who play a supporting role tend to have total higher revenues, although the direction of causality is unclear. In terms of relationships between revenue and difficulty, VP searches more closely resemble "Other" searches than CEO searches.

Unfortunately, these results do not suggest a clear modeling strategy for addressing the effects of job level variation in search contracts. However, they suggest factors that could account for differences in results based on whether the dependent variable is measured as projects or revenues. They suggest the performance of recruiters who play the lead role on booking CEO searches will be higher when measured in terms of revenues and lower when measured in terms of project shares. A scatterplot of the relationship between the two performance measures suggests that recruiters with the greatest differences generally belong to the same group that received the highest proportion of credit for CEO searches. Recruiters who play a supporting role in CEO searches appear to generate higher revenues without necessarily experiencing a compensating reduction in the number of

[51] The lead role in booking a search is observable because recruiters receive 0.5 booking credits for "ownership" of a client.
[52] This is consistent with information from interviews. CEO searches typically involve smaller, more visible pools of potential candidates. Some aspects of the process may be more difficult (e.g. competition for the contract, managing the relationship with a corporate board). Others, such as identifying qualified candidates, may be easier.
[53] I am not controlling for potential variation in the hours recruiters work. This is unobserved, although an email based proxy could potentially be created in future work.

contract shares. One possibility is that they receive more revenue for equivalent effort. In that case, performance measures based on contract shares may be more accurate, while those based on revenues may overstate the contributions of these recruiters. Another possibility is that participation on CEO searches represents a selection effect. Recruiters who lead CEO searches may be able to select their most competent colleagues as teammates.

Percentage of solo searches

Recruiters acting alone conducted approximately 30 percent of the searches. The percentage of solo searches is positively correlated with both billing revenue (0.28, $p < 0.10$) and billing shares (0.37, $p < 0.01$). The relationship between the percentage of solo searches and individual revenue involves a statistically significant interaction with the dummy variable for partner. On average, partners who conduct a higher percentage of solo searches generate more billing revenue, but less booking revenue.

The proportion of solo searches appears to represent a career progression that is relevant in this setting. As consultants gain experience they begin to land contracts. They often execute some of the contracts they land as solo searches. As partners gain proficiency in landing contracts, they enlist more billing support from consultants. This career progression appears to be related to statistically significant job level differences in proportional information flows (hypotheses group two on exploration vs. exploitation). It also represents a potential explanation for the finding that bookings are negatively related to the bookings of colleagues a recruiter communicates with over email within job levels as well as within the population (hypotheses group three on co-specialization).

Although I did not use the percentage of solo searches in this work, arguments can be made for including this variable and an interaction term as a control. Recruiters who do more work alone may be less likely to rely on their colleagues, so the percentage of solo searches may influence relationships between communication patterns and performance. Because of the role the percentage of solo searches plays in a career progression, it may also represent a site specific proxy for human capital. However, a serious disadvantage is that human capital effects would be confounded with internal and external social capital effects.

While the career progression effect associated with the percentage of solo searches is site specific, it suggests a more general point for future research. It suggests including questions about the specific aspects of career progressions in exploratory interviews. By gaining knowledge of these effects prior to the phase of research design for the collection of quantitative data, researchers may be able to shape the research design to model these effects. How individuals adapt to the specific tasks involved in a career progression may explain significant variation in individual performance.

Information Technology Use and Performance

The literature on relationships between information technology investments and productivity helped motivate my dissertation. However, this literature had less influence on the development of my hypotheses. In this setting, I believe that communication patterns considered collectively are likely to explain more individual variation in performance than technology use related to data processing. However, recruiters answered questions about information technology use as part of the survey and the data suggest some relationships with performance.

Database technology has almost certainly influenced productivity in executive recruiting. By using databases to manage information on candidates, recruiting firms have dramatically reduced the amount of time needed to compile an initial list of candidates for a search. There is some evidence that consultants who are more proficient at using the firm's internal database are more effective at executing searches. For example, an interaction between a consultant dummy and survey question q26e, the proportion of value recruiters assign to the internal database as a source of information explains a statistically significant amount of variation in billing revenue ($t=2.52$, $p < 0.05$). Without the interaction term, the effect is not statistically significant. This is consistent with a general theme from the literature on relationships between information technology investments and productivity that it is not so much the technology itself that influences productivity, but how it is used (Brynjolfsson and Hitt 1998). Influences of information technology may also take the form of complementarities (Brynjolfsson, Renshaw et al. 1997). Teasing out these influences and interactions is a subject for future work.

Relationships Between Performance and Communication with Researchers and Staff

My hypotheses focus on email communication among consultants and partners. These are the revenue generating members of the firm. I used email data on communication with researchers and staff in only one instance – to calculate the proportion of internal messages sent to consultants. Aspects of communication patterns with researchers and staff may be significant omitted variables.

There is some evidence that communication with researchers may be positively related to performance in executing search contracts. The proportion of internal email sent to researchers added to the base model is a statistically significant predictor of billing revenue. ($t=2.54$, $p < 0.05$). A job level interaction term is not significant. In contrast to the value recruiters place on the internal database, this effect appears to apply to both consultants and partners. Correlation analyses suggest that recruiters who communicate more with researchers may be able to handle more simultaneous searches while experiencing fewer perceptions of information overload (survey question, q31, "information overload has caused me to perform at less than my best").

There is also some evidence that aspects of email exchanged with staff may serve as indicators of performance. Statistically significant relationships between communication with staff and performance may well reflect the influence of mediating variables. For instance, a higher administrative load may be causally related to lower performance executing or landing contracts. It may also be correlated with a higher proportion of communication with staff. In this example, it would not be correct to interpret a negative relationship between communication with staff and performance as evidence that this communication degrades performance.

Rather, the correlation would reflect the influence of an unmeasured mediating variable. Analysis of staff communication that includes consideration of likely mediating variables is an area for future work.

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