Information, Technology and Information Worker Productivity

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We econometrically evaluate information worker productivity at a midsize executive recruiting firm and assess whether the knowledge that workers accessed through their electronic communication networks enabled them to multitask more productively. We estimate dynamic panel data models of multitasking, knowledge networks and productivity using several types of micro-level data: (a) direct observation of 125,000+ e-mail messages over a period of 10 months, (b) detailed accounting data on individuals' project output and team membership for 1300+ projects spanning 5 years, and (c) survey and interview data about the same workers' IT skills, IT use and information sharing. We find that (1) more multitasking is associated with more project output, but with diminishing marginal returns, and that (2) recruiters whose network contacts have heterogeneous knowledge – an even distribution of expertise over many project types – are less productive on average but more productive when juggling diverse multitasking portfolios. These results show how multitasking affects productivity and how knowledge networks, enabled by IT, can improve worker performance. The methods developed can be replicated in other settings, opening new frontiers for research on social networks and IT value.

Key words: Social Networks, Productivity, Information Worker, IT, Multitasking, Dynamic Panel Data, System GMM

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"In the physical sciences, when errors of measurement and other noise are found to be of the same order of magnitude as the phenomena under study, the response is not to try to squeeze more information out of the data by statistical means; it is instead to find techniques for observing the phenomena at a higher level of resolution. The corresponding strategy for [social science] is obvious: to secure new kinds of data at the micro level."

-- Herbert Simon

1. Introduction

Information workers now account for as much as 70% of the U.S. labor force and contribute over 60% of the total valued added in the U.S. economy (Apte & Nath 2004). Ironically, as more and more workers focus on processing information, researchers have less and less information about how these workers create value. Unlike bushels of wheat or tons of steel, the output of most information workers is difficult to measure. Yet, as the information content of work increases, measuring information worker productivity becomes even more critical to our ability to manage individual, group and firm performance.

One of the most hotly debated issues in the design and management of information work is the productivity effect of multitasking – the act of taking on multiple projects or tasks simultaneously (Appelbaum et al 2008).[1] Over the last several decades multitasking has increased in a variety of industries (Spink et al 2008) and speculation about its productivity effects has attracted the attention of managers, academics and the media (Coviello et al 2010). Some claim that multitasking increases productivity by enabling workers to smooth bursty work requirements, realize complementarities across tasks and incorporate relevant information from one task into decision making on other tasks (Lindbeck and Snower 2000). Others claim however that multitasking creates confusion, distraction and cognitive switching costs that reduce workers' intelligence quotient (IQ) and their ability to complete tasks efficiently (Rubenstein et. al. 2001, Rosen 2008). One recent survey conducted by an IT-market research firm claims that multitasking is costing the US economy as much as '$650 billion a year in lost productivity' (Rosen 2008). Unfortunately, little detailed empirical evidence on multitasking and productivity exists to adjudicate these claims.

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[1] We distinguish between multitasking (taking on multiple simultaneous projects) from switching between micro-tasks such as reading email while talking on the phone. We focus on the former.

The rise of multitasking has been accompanied by a simultaneous increase in the flow of information through communication networks enabled by information technology (IT). Email and other technologies support the rapid dissemination of knowledge and information through organizations and are thought to complement systems of organizational practices including decentralized decision making, job rotation and multitasking (Bresnahan, Brynjolfsson and Hitt 2002, Brynjolfsson and Milgrom 2011). IT-enabled communication networks are specifically hypothesized to support 'multitask learning,' the process of applying information and knowledge from one task to improve performance in another (Lindbeck and Snower 2000). Efficient access to useful information should increase productivity by facilitating faster, higher quality decisions and enabling workers to utilize information and skill complementarities between tasks to multitask more productively (Lindbeck and Snower 1996). However, the relationship between information flow in networks and multitasking has never been examined. We therefore econometrically evaluated the effect of multitasking on information worker productivity and assessed whether the knowledge that workers accessed through their communication networks enabled them to multitask more productively.

We analyzed empirical evidence on multitasking, email networks and output for employees at a midsize executive recruiting firm. Accounting records provided data on individual level output, project start and end dates, the number of concurrent projects, and individual effort devoted to each project. With company and employee cooperation, we also monitored email usage to analyze the firm's communication network, conducted field interviews, gathered survey data, and collected independent third party evidence of project difficulty. These micro data allowed us to match individual behaviors to performance and to test dynamic panel data models of the relationships between multitasking, knowledge networks and productivity. Our analysis uncovered two key findings.

First, there is a concave relationship between multitasking and output per unit time. More multitasking is associated with increased project output, but with diminishing marginal returns. At low levels of multitasking, taking on more work enables workers to complete more work per unit time. How-

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ever, multitasking also increases the time it takes to complete each project on average, creating diminishing returns. This argument is robust to several alternative explanations.

Second, multitasking performance improves with access to heterogeneous knowledge made available through IT-enabled networks. There is conflicting evidence on the value of knowledge heterogeneity and diversity (Pelled et al 1999). Some argue that access to diverse perspectives improves problem solving and creativity (Burt 2004). Others contend that networks connecting people with heterogeneous knowledge are costly to maintain (Rodan and Gallunic 2004) and that processing heterogeneous knowledge is more difficult (Reagans and McEvily 2003). The benefits of access to knowledge heterogeneity have been found to be worth their costs in the context of innovation (Hargadon and Sutton 1997). We find the same is true when workers are engaged in heterogeneous multitasking – that act of taking on multiple dissimilar tasks simultaneously. In our setting, recruiters with network contacts who have heterogeneous knowledge are less productive on average, but more productive when juggling diverse multitasking portfolios. This implies that although heterogeneous knowledge accessed through email contacts is costly to process and maintain, it improves the productivity of workers who are responsible for diverse tasks.

Our work has implications for managers responsible for the productivity of information workers. In particular, the concavity of the relationship between multitasking and productivity implies that optimal levels of multitasking could be identified and adhered to in different information work settings. Furthermore, IT investments can be made more productive by encouraging contact between dissimilar employees who juggle diverse multitasking portfolios, while encouraging domain specific communication between specialists. Our research approach also opens a path to studying information flows inside firms and provides a proof-of-concept for using email data combined with individual productivity data to explore relationships between work practices, networks and productivity at the individual level.

2. Research Setting

We studied a medium-sized executive recruiting firm over five years, with fourteen regional offices throughout the United States. The employees occupy three basic positions – partner, consultant and researcher – and our interviews indicate that the contract execution process is relatively standard: A partner secures a contract with a client and assembles a project team (team size mean = 1.9, mode = 2, min = 1, max = 5) by assigning team members to projects. There is some limited room for negotiation in that consultants and researchers can suggest that their inclusion on a project is not a good idea for different reasons. But, typical power politics exist between the partners and lower status employees.[2] Once assembled, the team establishes a universe of potential candidates including those in similar positions at other firms and those drawn from the firm's internal database. These candidates are vetted on the basis of perceived quality, their match with the job description and other factors. After conducting initial due diligence, the team chooses a subset of candidates for internal interviews, approximately six of whom are forwarded to the client along with a formal report of the team's due diligence. The team then facilitates the client's interviews with each candidate, and the client, if satisfied with the pool, makes offers to one or more candidates. A contract is considered complete when a candidate accepts an offer. The period from client signature to candidate signature defines project duration.

The core of executive recruiters' work involves retrieving and understanding clients' requirements and matching candidates to those requirements.[3] This matching process is information-intensive and requires assembling, analyzing, and making decisions based on information gathered from various sources including team members, other firm employees, contacts outside the firm, and data on potential candidates in the internal proprietary database, external proprietary databases, and public sources of information. Recruiters earn revenue by filling vacancies, rather than billing hourly. The speed with which vacancies are filled is therefore an important intermediate measure of productivity. Contract completion implies that the search team has met the client's minimum thresholds of candidate fit and quality, and given controls for differences across contracts (e.g. job type, location), projects completed

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[2] Projects are not likely to be randomly assigned to recruiters in this setting. We therefore test the robustness of our main results to Heckman selection model specifications.

per unit time and project duration are quality controlled measures of worker productivity. They are quality adjusted because the market determines if the match between clients' requirements and candidates' characteristics is of high quality. When a recruiter produces a match, if the client is satisfied with the candidate, they hire the candidate and complete their search. If the match is low quality however, the candidate is rejected and the search continues. Rejections and continuing projects reduce output per unit time by extending the duration of open projects and reducing the number of completed projects. The client therefore vets the output of a recruiter when they decide whether the match is of high enough quality to complete the search.

3. Theory

3.1. Multitasking and Productivity

The organization of work changed dramatically in the late twentieth century. As flexible production replaced mass production and as firms invested heavily in new IT, work organization shifted from Tayloristic practices focused on centralized decision making and specialization to more holistic ones based on decentralization and job rotation (Piore and Sabel 1984). One practice in particular, multitasking, or the act of taking on multiple projects or tasks simultaneously, increased dramatically across industries and geographies during this period (Park 1996). Increasing competitive pressure, the demand for greater product variety and an increasing reliance on IT for internal organization, enabled firms to become more adaptive and inspired them to rely on fewer workers juggling more simultaneous tasks (Park 1996). An important goal for managers and researchers is to understand the effect of this increased multitasking on productivity.

Multitasking may increase productivity for several reasons. First, taking on multiple simultaneous projects allows workers to utilize lulls in one project to accomplish tasks related to other projects. As is typical in project based work, there are inevitable periods of downtime during projects when em-

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[3] "Client" refers to a firm seeking to hire one or more executives; "candidate" refers to a potential hire; and "recruiter" refers to someone expert in locating, vetting, and placing candidates.

ployees wait to have phone calls returned or tasks scheduled. The non-continuous nature of project work is well suited to parallel processing across multiple simultaneous projects and multitasking creates efficiency by smoothing labor hours over projects with bursty work requirements. Executive recruiters experience downtime while waiting to schedule and conduct interviews and again while clients' conduct their internal reviews. Having multiple projects live at the same time allows them to switch their focus from one project to another during periods of relative downtime, allowing them to use their time efficiently and increasing their productivity.

Second, information and skill complementarities across tasks can increase productivity by enabling workers to use information and knowledge gleaned from one task to help them execute other tasks (Lindbeck and Snower 2000). When a recruiter evaluates ten potential candidates for a job and only one of them is chosen for the placement, they can use information from interviews and due diligence on the remaining nine candidates to help fill other positions. Skill complementarities also enable productivity gains through learning. As workers execute a given task, they develop transferrable skills that help them improve their performance on other tasks. In interviews recruiters reported the importance of learning how to navigate entry into companies and how to evaluate the idiosyncrasies of different markets by working on different types of projects and exchanging knowledge with their colleagues. One recruiter told us that "[c]all penetration can be really hard into private companies so researchers and consultants swap information to get through." The more diverse the procedural information, the more situations in which recruiters can use the information they have to solve procedural problems. Having different information on how to 'penetrate' different private companies can make recruiters more effective at gathering the information and contacts they need to match candidates to clients. These examples suggest that multitasking should increase productivity both by reducing time wasted during natural lulls in bursty work and by taking advantage of information and skill complementarities across projects.

On the other hand, taking on too many simultaneous projects creates congestion. As more projects are attempted in parallel, recruiters face longer delays in getting back to the activities of a par-

ticular project while cycling through activities related to other projects. Excessive delays force recruiters to skip lower priority activities that help fill positions. When employees juggle too many projects, work gets backed up and productivity suffers. The situation is analogous to congestion and throughput processes for queued tasks (Krishnan et. al. 1997). For example, car throughput on a highway initially increases as more cars enter traffic, but eventually congestion increases processing times above arrival rates. Human beings experience an analogous mental congestion. Multitasking is associated with short-term and long-term cognitive switching costs that reduce reaction times and task completion rates and increase error rates (e.g. Rubenstein et. al. 2001). Switching between two or more tasks requires workers to reorient to each new task, which itself takes time and other attentional resources. Overlapping activities create confusion and associative competition, and responses are substantially slower and more error-prone with frequent task switching (Gilbert & Shallice 2002, Monsell 2003). Our interviews corroborate this story. As the CIO of the firm put it "Everyone can only deal with so many balls in the air. When someone gets 'too far in,' [takes on too many projects] they lose touch. They can't tell one project from another."

Most of the limited research on multitasking hypothesizes a linear relationship between multi-tasking and productivity, arguing either for the costs or the benefits of multitasking in isolation (Coviello et al 2010). Considering the costs and benefits together, we hypothesize the relationship is instead concave. The benefits and costs of multitasking are both likely to have non-linear effects on productivity. There are likely diminishing marginal returns to task complementarities and smoothing bursty work because there are only so many hours in a day and a limited amount of overlapping skills and information that can be transferred between projects. There are also likely increasing costs to congestion and cognitive switching as workers take on more simultaneous work. The average time to complete a set of queued tasks is equal to the average number of tasks in the queue times the average arrival rate of new tasks (Little 1961). As the arrival rate increases, the expected completion time goes to infinity. The cognitive costs of multitasking are similarly increasing in the number of simultaneous tasks. Switching

costs, in time and attention required to reorient oneself to one project after having focused on another, increase as more tasks are juggled simultaneously (Rubenstein et. al. 2001, Monsell 2003).

The combination of diminishing marginal benefits and increasing marginal costs to more multitasking will produce a concave relationship between multitasking and productivity. At low levels of multitasking, workers will experience benefits from task complementarities and smoothing bursty work, but will not experience too much cognitive overload. At high levels of multitasking, the cognitive load is higher and the marginal benefits of smoothing work and learning from other projects are smaller. All that is required for concavity is that one of these factors is non-linear. If costs are increasing and benefits are linear or if benefits are diminishing and costs are linear, there will be diminishing marginal returns to multitasking. We therefore expect that *there is a concave relationship between multitasking and output per unit time (Hypothesis 1)*.

3.2. Knowledge Networks and Multitasking

The effective exchange of information and knowledge is critical to work performance (Kogut and Zander 1992), and informal communication networks play a key role in governing the flow of information and knowledge between employees (Hansen 1999, 2002, Reagans and Zuckerman 2001). IT-enabled communication technologies such as email facilitate the rapid dissemination of information and knowledge through informal networks (Sundararajan et al 2010), increase the rate of learning spillovers between workers (Foster and Rosenzweig 1995), and lower the cost of applying information from one task to other tasks (Lindbeck and Snower 2000). In this way, knowledge exchanged through IT-enabled networks is critical to multitasking performance. This is in part why IT investments are theorized to complement multitasking – because they lower the cost of the information exchanges that make multitasking a productive practice (Lindbeck and Snower 2000). However, exactly how IT-enabled communication networks enable multitasking is less well understood.

One key characteristic of information exchanges theorized to affect productivity is the heterogeneity of knowledge accessed through informal communication networks. Social network theories

such as the strength of weak ties (Granovetter 1973) and structural holes (Burt 1992) argue that diverse network structures with ties to disparate parts of a network provide actors with heterogeneous knowledge. As IT lowers the cost of accessing information that is geographically and socially distant (Malone et al 1987, Hinds and Kiesler 2002), it enables access to more heterogeneous information and knowledge outside the recipient's typical domain. Recent research has moved beyond purely structural accounts of this argument by directly measuring the knowledge heterogeneity workers connect to through their social networks (Rodan and Gallunic 2004) and it has recently been shown that diverse IT-enabled network structures actually provide workers with more heterogeneous information (Aral and Van Alstyne Forthcoming). Yet, there are conflicting theories about the performance implications of accessing more heterogeneous information and knowledge.

On one hand, access to heterogeneous knowledge can increase workers' propensity for opportunity recognition and provide information resources that enable brokerage (Burt 1992). Information tends to be locally redundant, meaning ideas and solutions associated with a particular task are most likely already known to those working on that type of task (Dessein and Santos 2006). But, socially distant information can be useful for solving problems that are intractable given only local knowledge (Burt 2004). For example, Hargadon and Sutton (1997) describe how engineers use their connections to diverse engineering and scientific disciplines to broker the flow of information from unconnected industrial sectors, creating novel design solutions. Actors with access to these diverse pools of information "benefit from disparities in the level and value of particular knowledge held by different groups…" (Hargadon and Sutton 1997: 717). Access to heterogeneous knowledge is especially important for job placement (Granovetter 1973). In Granovetter's classic study, information about job openings from diverse social circles was more fruitful because there was less competition in markets that were socially distant from the local pool of competitors. Such opportunities could directly aid recruiters in placing candidates and filling job openings. This leads us to hypothesize that *on average, knowledge heterogeneity among recruiters' contacts is positively associated with productivity (Hypothesis 2a).*

On the other hand, knowledge heterogeneity is costly. Having contacts with heterogeneous knowledge makes it harder to transfer their knowledge effectively (Reagans and McEvily 2003) because of a lack of mutual knowledge among members of the network (Clark 1996). Mutual knowledge, the knowledge that communicating parties share in common and know they share (Krauss & Fussell 1990), is essential for mutual understanding, trust and effective communication and coordination (Cramton 2001). Shared information enables communication partners to 'get on the same page' and to understand the context and perspectives of their counterparts and is therefore considered "a precondition for effective communication and the performance of cooperative work" (Cramton 2001: 349). Recruiters are better able to communicate knowledge about similar projects because they share a common language within particular domains and are aware of the idiosyncratic jargon and recruiting practices in particular industries (Weber and Camerer 2003). For example, recruiters who place candidates in the medical field report relying heavily on their accumulated knowledge of the medical profession to understand client requirements and candidate constraints and to communicate with other recruiters about medical positions. Processing heterogeneous knowledge is more difficult because of the added complexity and interference associated with understanding cognitively dissimilar concepts (Underwood 1957, Darr and Kurtzberg 2000). In addition, there are greater costs to maintaining networks with heterogeneous knowledge (Reagans and McEvily 2003). Such networks require more time and effort to maintain because intellectually dissimilar contacts are more likely to become socially distant or disconnect entirely (Rodan and Galunic 2004). We therefore propose the competing hypothesis that *on average, knowledge heterogeneity among recruiters' contacts is negatively associated with productivity (Hypothesis 2b).*

A priori, it remains unclear which hypothesis, H2a or H2b, should dominate. The net benefits to knowledge heterogeneity are a function of the benefits from opportunity recognition and novel solutions and the costs of maintaining heterogeneous networks and processing unfamiliar knowledge. Existing literature is inconclusive about when the benefits will outweigh the costs and thus the circumstances under which access to heterogeneous knowledge will improve performance. We therefore propose a

mediating concept to predict tipping in this essential relationship. We argue that *task* heterogeneity helps determine the productivity value of *knowledge* heterogeneity.

The net benefits of knowledge heterogeneity have been demonstrated in the context of innovation, where the recombination of ideas can stimulate creativity and novel solutions (Hargadon and Sutton 1997, Burt 2004). We propose that knowledge heterogeneity should also complement heterogeneous multitasking. Multitasking can either be specialized or heterogeneous in that workers can take on tasks of the same type or of different types simultaneously. Some recruiters specialize in a particular job category (e.g. nursing or IT) while others work on many different types of projects simultaneously (e.g. nursing, IT, finance, and HR). Knowledge heterogeneity should complement this type of task heterogeneity for several reasons.

First, when knowledge resources fit a worker's task profile, the costs of processing heterogeneous knowledge are offset by opportunities to apply that knowledge productively. The concept of fit or congruence has been applied in organizational theory to explain firm performance, individual performance and knowledge management outcomes (Argote et al 2003). For example, the fit between organizational design and environmental turbulence predicts firms' survival (Sorenson 2003). The fit between the nature of knowledge and the type of tie through which it is transferred affects learning (Uzzi and Lancaster 2003). The fit between task characteristics and problem-solving affects productivity in technical support work (Das 2003). Contingency theory holds that organizational units (e.g. firms, business units and teams) must match their internal complexity (e.g. functional divisions, product release cycles) to the environment's external complexity (e.g. customer segments, industry clockspeed) to achieve the best performance (Morgan 1986; Lawrence & Lorsch 1967). With too little internal heterogeneity, organizations mistakenly process different instances of external heterogeneity in the same way; whereas too much internal heterogeneity relative to the environment is excessively costly. When the complexity of the organization exceeds that of the environment, resources are wasted and the costs of complexity in the solution are born unnecessarily. Empirically, organizations that achieve the best fit between their internal complexity and that of their environment perform best (Miller 1992).

Applying this argument to the relationship between multitasking and knowledge, the costly acquisition of heterogeneous knowledge should produce greater productivity gains when the tasks being attempted are themselves heterogeneous. For executive recruiters, adding heterogeneous project types to their workload necessitates acquisition of more fine grained information and knowledge on a greater number of dimensions. For example, for most project types, understanding generic educational qualifications (which university degrees are more highly respected) is sufficient to screen potential candidates. However, adding projects in the medical, nursing and technology domains, requires recruiters to understand (or connect with colleagues who understand) which universities are highly regarded in a particular specialization (e.g. radiology or geriatric nursing), though they may not be the same institutions that are highly regarded overall. As recruiters add additional project domains – not just additional projects in the same domain – to their multitasking profiles, they require access to a more heterogeneous pool of information to produce the best matches between candidates and open positions.

Second, greater task heterogeneity increases absorptive capacity and enables workers to process heterogeneous knowledge more efficiently. Individuals are better able to understand knowledge in domains with which they have prior experience because we learn by associating new knowledge with what we already know (Cohen and Levinthal 1990). As recruiters are exposed to projects of different types, they become better equipped to efficiently understand and absorb information and knowledge on a greater variety of domains. Knowledge heterogeneity increases the costs of acquiring knowledge due to the lack of a common language with which to communicate ideas efficiently. Greater task heterogeneity increases absorptive capacity and thus reduces these costs. In addition, exposure to a greater variety of task domains also improves our ability to process information and knowledge that is dissimilar to what we already know (Burt 2004, Rodan and Galunic 2004). Processing diversity is itself a learned skill. The greater the diversity of our experience, the more we are able to handle novel ideas to which we have never been exposed. Negotiating task diversity builds these skills and thus enables workers and managers to process novel information and knowledge more effectively (Burt 2007).

Finally, access to heterogeneous knowledge enables workers with heterogeneous tasks to realize synergies across project types through inter-task or multitask learning. IT lowers the cost of multitask learning, the ability to learn how the experience gained from one skill enhances another skill, in order to "exploit complementarities among tasks" by lowering the costs of "providing employees with greater access to information about other employees' work." (Lindbeck and Snower 2000: 355-356) In particular, access to heterogeneous knowledge facilitates applying information gleaned from the execution of a particular task to a different task entirely. For example, when executive recruiters who typically conduct CIO searches begin to take on CEO searches they are exposed to the executives to whom CIOs report. By communicating with other recruiters who are better versed in CEO searches, they learn how CEOs evaluate CIOs and develop a better understanding of the qualities that make a successful CIO. Lessons learned from the CEO search process, through communication with colleagues with this dissimilar knowledge, can then be applied to CIO searches. Such heterogeneous knowledge can also help recruiters understand when and under what circumstances a doctor may, for example, make a good CEO of a medical products company. Communicating with contacts with heterogeneous knowledge thus enables the application of learning from one task to help complete other tasks (e.g. learning how to better fill CIO positions by understanding the CEO's perspective on CIOs) as well as the importation of resources from one task to help complete other tasks (e.g. learning how candidates from one project type can fill positions in another project type).

Task heterogeneity increases the benefits of knowledge heterogeneity by increasing the fit of recruiters' knowledge resources to their tasks, improving multitask learning and increasing the ability recruiters' ability to realize synergies across projects. In addition, task heterogeneity lowers the costs of processing heterogeneous knowledge by increasing recruiters' absorptive capacity. We therefore expect that workers engaged in heterogeneous multitasking benefit most from access to heterogeneous knowledge and hypothesize that *the interaction effect of knowledge heterogeneity and task heterogeneity is positively associated with productivity (Hypothesis 3).*

4. Empirical Methods

4.1. Data

Data for this study include three data sets from inside the firm and one from outside the firm. The first is complete accounting records of: (i) projects completed and revenues generated by individual recruiters, (ii) contract start and stop dates, (iii) projects handled simultaneously, (iv) project team composition and share weighted effort, (v) job levels of recruiters, and (vi) job levels of placed candidates. Accounting data cover the period 2001-2005 and provide excellent output measures.

The second data set covers 10 months of complete email history captured from the corporate mail server during two equal periods from October 1, 2002 to March 1, 2003, and from October 1, 2003 to March 1, 2004. Email data has the potential to overcome bias in survey respondent recall of their social networks (e.g. Bernard et. al 1981) by objectively recording who communicates with whom and when. However, email is not without its own limitations. We therefore took great care in collecting and analyzing our social network data. We designed and developed capture software specific to this project and took multiple steps to ensure data integrity and boost participation while minimizing bias, intrusiveness, and risks to security. We used cryptographic techniques to preserve individual privacy and excluded spam messages by eliminating external contacts who did not receive at least one message from someone inside the firm. The project went through nine months of human subjects review prior to launch. Details are provided in Appendix A and in Van Alstyne & Zhang (2003) and Reynolds, Van Alstyne & Aral (2009). Participants received $100 in exchange for permitting use of their data resulting in 87% coverage of eligible recruiters and more than 125,000 email messages captured.[4]

The third data set contains survey responses on information-seeking behaviors, experience, education, human factors, and time allocation. Survey questions were generated from a review of relevant social network, behavioral and economic literature and more than two dozen interviews with recruiters. Experts in survey methods at the Inter-University Consortium for Political and Social Science

Research vetted the survey instrument, which was pre-tested for comprehension and ease-of-use. Participants received $25 for completed surveys and participation exceeded 85%. The fourth data set, gathered outside the firm, involves independent controls for placement city attributes used to control for project difficulty and described in Section 6 below.

4.2. Measurement

Dependent and Independent Variables

Output. We measured project output as the number of projects recruiters completed per month.[5] To construct monthly measures of the completions for a recruiter, we observe which projects they are working on and the duration of those projects. We amortize the completion of projects uniformly over the projects' life. So for example, if a recruiter is working on only one project which takes 100 days to complete their project completions on each of these 100 days would be 1/100th of a project. We aggregated output to the monthly level by summing output over days in the month. For example, a project that is generating 1/100th of a project in output per day produces 28/100th of a project of output in February. We considered using non-uniform distributions of completions over the life of projects; however we did not have strong evidence to support different distributional assumptions about when work was really being completed during project execution (e.g. front loading or back loading the credit for work done during a project).

Multitasking. We define multitasking as the act of taking on multiple simultaneous projects in parallel. We measured individual daily multitasking by the number of projects an employee is working on during any given day. We then aggregated multitasking by averaging the number of projects the recruiter was working on over the days of the month. Figure 1 displays a multitasking profile for one em-

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[4] *F*-tests comparing performance levels of those who opted out with those who remained did not show statistically significant differences. *F*-statistic (Sig): Yearly Revenue 2002 = 2.295 (.136), Yearly Compensation 2002 = .837 (.365), Yearly Multitasking 2002 = .386 (.538). We found similar results for those who opted out of the survey.
[5] We focus on output (projects completed) rather than real output (revenues generated) because reliable deflators for recruiters' real output are not available.

ployee during the period 9/05/2002 to 11/26/2002 and describes how multitasking is indexed for this
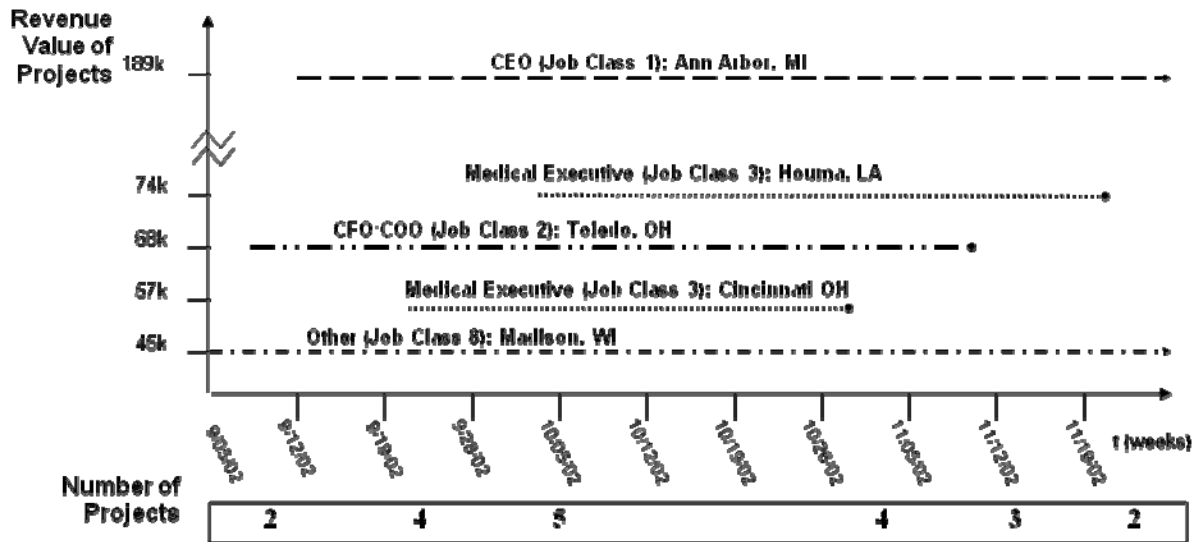
recruiter during this period.

Figure 2. Multitasking Profile of Employee #102 (9/05/2002 – 11/26/2002).

Figure 1. Multitasking Profile of Employee #102 (9/05/2002 – 11/26/2002). A Multitasking Profile displays all of an employee's ongoing projects during a particular period including each project's job class and city. The graphic below the profile displays the employee's number of projects over each day during this period. On September 19th the recruiter is working on 2 simultaneous projects. On October 5th the recruiter is working on 5 simultaneous projects.

Duration. We measured the project duration as the number of days from its start date to the day

the position is filled. Our data record the precise start and completion dates of projects in a uniform way

based on the accounting practices of the firm. To construct the monthly individual duration variable, we

averaged the duration of the projects a worker is working on in each month.

Task Heterogeneity. We measured task heterogeneity using the Teachman/Shannon Entropy

Index. There are eight categorical project types recorded in the firm's accounting records and each

project is assigned to one and only one category. The firm categorizes projects into the following cate-

gories: CEO, COO, CIO, Medical Executive, Human Resources Executive, Business Development Ex-

ecutive, Nurse and 'Other.' We use these categories as the relevant areas of recruiters' expertise.[6] We define the heterogeneity of a recruiter's tasks as follows:

$$th_{it} = -\sum_{c=1}^{8} s_{cti} \ln(s_{cti}),$$

where s_{cti} represents the fraction of recruiter i's projects in job class c at time t. The Teachman Index has been used extensively in the social sciences to measure the diversity of many different variables (Teachman 1980) and is particularly well suited to the measurement of categorical data (Ancona and Caldwell 1992). If a recruiter has no projects in a particular category for a given time period, the value assigned to that category is zero. We calculated the diversity of each recruiter's multitasking portfolio daily because projects can start and end on any day of the calendar month. We then aggregated the diversity of each recruiter's task heterogeneity to the monthly level by averaging daily diversity scores over the days in each month. Task heterogeneity scores in our data range from 0 to 1.87 with a mean of 1.15 and standard deviation of .45. Figure 2 describes how task heterogeneity is calculated.
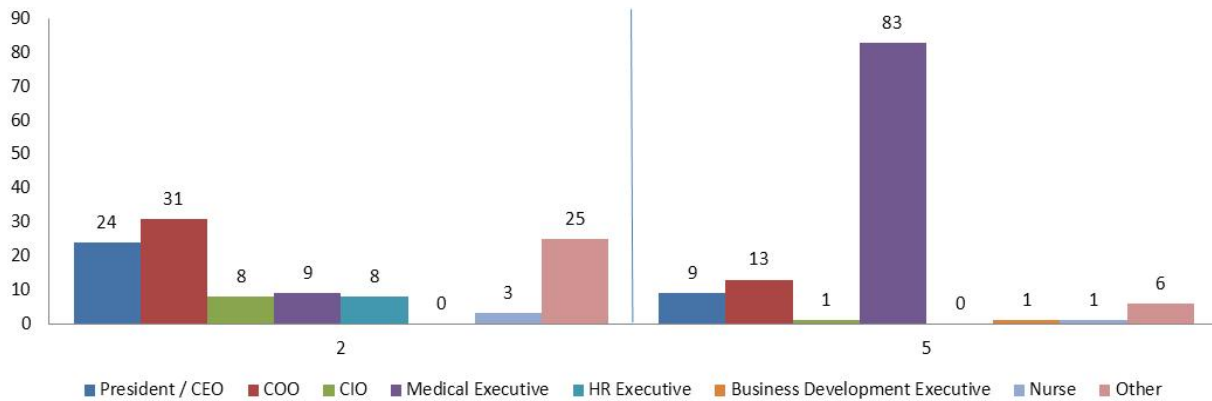

Figure 2. Task Heterogeneity of Two Employees. This figure displays the distribution of two recruiters' projects in a single year over the eight job classes classified by the firm: President/CEO, COO, CIO, Medical Executive, HR Executive, Business Development Executive, Nurse and Other. Although they have almost identical total numbers of projects, 108 and 114 respectively, recruiter #2 has a more even distribution of projects over job classes and thus a higher Task Heterogeneity Index (TH = 1.71) than recruiter #5 (TH = 1.02) who is more specialized.

Knowledge Heterogeneity of Network Contacts (Knowledge Heterogeneity). To measure recruiters' access to expertise and knowledge during the execution of their projects we combined data on the

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[6] We also ran specifications controlling for other categorization schemes and sub-categories of 'Other' jobs clustered by their

email network with data on recruiters' accumulated past project experience. We measure the knowledge heterogeneity of recruiters' network contacts by directly evaluating the diversity of their contacts' expertise accumulated through the history of the projects they have worked on in the past. In this setting recruiters' develop expertise as they complete projects of different types. As there is little in the way of formal training to become an executive recruiter, we do not use recruiters' educational backgrounds but rather the distributions of their prior project experience over project types to measure knowledge heterogeneity. The *Knowledge Heterogeneity* variable is constructed using a Herfindahl Index of the expertise of an actor's contacts in each month, weighted by the strength of the tie to each contact. Since the firm records each employee's effort share on each project, the expertise of a recruiter is share weighted by the amount of effort they recorded against any given project in the accounting data. The measure is

constructed as follows: $KH_{it} = 1 - \sum_{k=1}^{8} \left(\frac{q_{ik}}{q_i} \right)^2$.

In this measure, $q_{ik} = \sum_{j=1}^{n} w_{ij} P_{jk}$ represents the total amount of prior experience in i's network in project class k, weighted by the strength of the tie to each of i's contacts w_{ij} (the number of email messages exchanged between i and j in a given month) and summed over all of i's contacts j. P_{jk} represents j's prior experience in job class k, where P is an effort share weighted count of the number of projects of class k that j has completed. The denominator, $q_i = \sum_{k=1}^{8} q_{ik}$ represents the total project experience in i's network summed over all project classes. Thus, the ratio $\left(\frac{q_{ik}}{q_i} \right)$ is the share of prior experience in project class k over the total project experience among i's communication network partners. We then construct a Herfindahl Index of this ratio measuring the concentration of expertise across job classes among i's contacts. To measure heterogeneity rather than concentration we subtract this measure of

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project descriptions, which returned similar results. We therefore retained the firm's original classification.

project experience concentration from one. As the expertise in *i*'s network becomes more concentrated in a few project classes, the knowledge heterogeneity measure decreases.[7] Reagans and McEvily (2003) constructed a similar measure of '*expertise overlap,*' although our measure uses accounting records to record project experience (rather than self-reported expertise), and weights the expertise in an employee's network by the strength of their ties to each contact and the effort share of each alter on each project. Our measure of knowledge heterogeneity also changes over time as recruiters complete more projects of different types and as recruiters' communication networks change from month to month.[8]
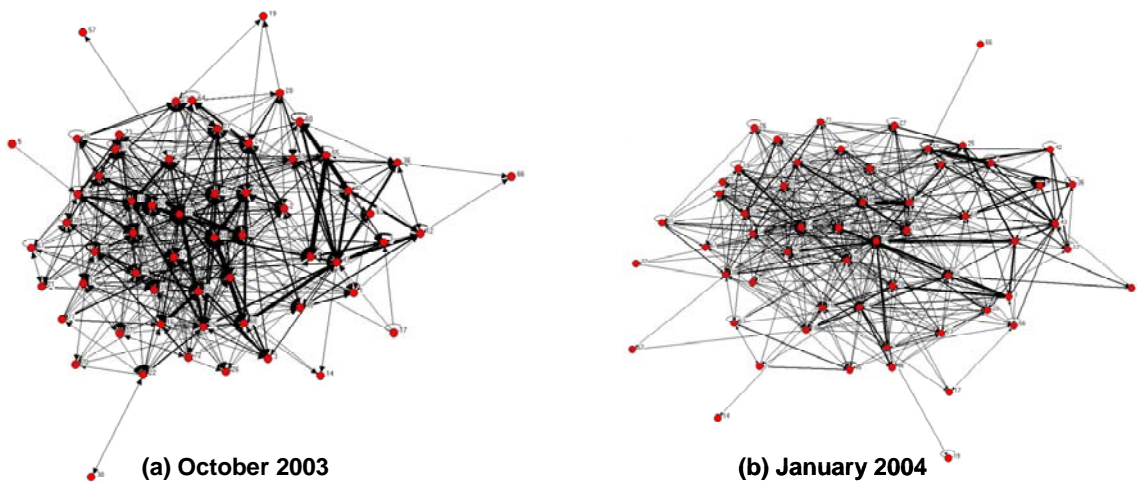

(a) October 2003   (b) January 2004

Figure 3. We use email messages to map the communication network at this firm. Each node represents an individual in our data set, while the thicknesses of the links represent the amount of email traffic.

Control Variables

Our main specification (described in Sections 4.4 and 4.5 below) uses first differences to remove variation due to unobserved individual heterogeneity of recruiters. However, some of our robustness checks do not employ first differences or fixed effects or are performed at the project level, which necessitates controlling for differences between projects. We include the following control variables on

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[7] To normalize the Knowledge Heterogeneity measure to range from zero to one, we scale the measure by multiplying the final

$$KH_i = \frac{8}{7}\left[1 - \sum_{k=1}^{8}\left(\frac{q_{ik}}{q_i}\right)^2\right]$$

metric by (8/7): . This scaling does not affect the distribution of the measure or the outcome of any of our analyses. It simply allows the measure to range from zero to one easing interpretation.
[8] We use the Herfindahl Index to remain comparable to prior research that measures the expertise heterogeneity of network contacts (e.g. Reagans and McEvily 2003), but Teachman diversity formulations produced qualitatively similar results.

individual and project characteristics to control for observables differences between recruiters and projects.

Characteristics of Individual Recruiters. We included controls for traditional demographic and human capital variables (age, gender, level of education, industry experience and managerial level) to control for observable differences in worker education, skill and experience. We also utilize fixed effects specifications to control for unobserved heterogeneity across individual recruiters.

Project Characteristics. Certain positions may be easier or harder to fill. Clients may demand that new CEOs be named quickly. Senior executives also have more experience with recruiters and with job mobility. To control for the effect of *Job Type*, we include a dummy variable for the eight job classes the firm recognizes in its own records.[9] We also control for *Task Characteristics*, measured by survey responses about the routineness and interdependence of tasks for similar reasons. Adding more labor to a project may speed work or slow it down depending on tradeoffs between the complexity of a larger team and the output contribution of additional labor. We therefore also include *Team Size*.

City Characteristics. Crime rates, weather conditions, the cost of living and other city characteristics may affect the attractiveness of a position and influence contract completion due to placement difficulty. To control for these factors we collected data on the 768 cities in which searches took place from the web site Sperling's Best Places.[10] Factor analysis revealed four underlying factors with significance in our models: *cost of living*, *crime rates* (violent and property crime per capita), *weather conditions* (sunny days per annum) and *commute time*. We therefore included these controls in project-level analyses.[11]

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[9] The firm categorizes jobs by the categories: CEO, COO, CIO, Medical Executive, Human Resources Executive, Business Development Executive and 'Other.' We also ran specifications controlling for sub-categories of 'Other' jobs clustered by their project descriptions, which returned similar results. We therefore retain the firm's original classification.

[10] http://www.bestplaces.net/

[11] We collected city level data on *tax rates for sales, income and property, the aggregate cost of living, home ownership costs, rate of home appreciation, air quality, water quality, number of superfund sites near the city, physicians per capita, health care costs per capita, violent and property crime per capita, public education expenditures per capita, average student to teacher ratio, an index of ultraviolet radiation levels, risk indices for earthquakes, tornadoes and hurricanes, average number of sunny, cloudy, and rainy days per year, average number of days below freezing per year* and *average commute time to work*.

Temporal Variation. In our data business exhibits seasonal variation, picking up sharply in January and declining steadily throughout the year. Exogenous shocks to demand for executive recruiting services could drive increases in both the amount of work employees take on (multitasking) and the output they generate. In this case, we could find a spurious correlation between multitasking and output driven by an exogenous increase in demand for the firms' services. There may also be non-seasonal transitory demand shocks in a given year or month of a year. We control for seasonal and transitory variation using dummy variables for *year, month* and *year/month* separately. Table 1 provides variable descriptive statistics and in our analyses, an observation is one person-month.

Table 1. Descriptive Statistics

Variable	Obs.	Mean	SD	Min	Max
Individual Variables (Monthly Data)					
Output (Project Completions)	630	.38	.36	0	1.69
Multitasking	630	5.84	5.21	0	24.96
Average Duration	630	225.23	165.77	0	921.04
Task Heterogeneity	462	1.16	.45	0	1.87
Knowledge Heterogeneity	560	.87	.08	.51	.97
Project Variables					
Team Size	1382	1.98	.60	1	5
Age	1372	45.07	7.77	27	63
Education	1372	17.74	1.02	15	20
Industry Experience	1372	14.47	7.94	1	39
Multitasking	1382	8.86	2.84	1.60	18.31
Project Duration (Days)	1382	206.90	123.69	3	981
Project Revenue Value ($)	1301	56962.50	25780.70	11666	237636
Team Interdependence	1382	1.36	.749	.05	4.65
Task Routiness	1382	1.18	.88	.05	4
F2F Contacts	1382	4.20	8.68	0	75
Phone Contacts	1382	15.76	10.54	1	70
Email Contacts	1382	20.14	18.46	1	100
ESS (Database) Skill	1382	3.10	1.92	.12	9.30
ESS (Database) Use (%)	1382	15.79	14.45	0	80
City Characteristics					
Cost of Living	1187	358.65	144.49	233.60	2059.60
Crime per Capita	1187	6262.40	2648.76	0	14603.80
Sunny Days per Annum	1187	212.15	33.93	23	300
Commute Time (Minutes)	1187	20.22	5.38	9	43

Notes: There are 1382 total projects in the data and 1187 different cities in which projects are conducted. There are 630 total person/month observations.

4.3. Model Specification

In white collar work settings where workers do not bill hourly and in which labor is not compensated by the hour (as in our case), how workers work, for instance whether they take on multiple

simultaneous projects or rather work sequentially, can affect their productivity. If we consider white

collar workers to be managing queued tasks, each with distinct start and stop times, we can measure the

relationship between multitasking and productivity directly. In our production model, employees work

on projects whose number and duration determine total output. A production function to represent in-

termediate processing therefore characterizes output (q_{it}) as a function of the number of simultaneous

projects an individual is working on at any given time (mt_{it}), a quadratic measure of the number of

simultaneous projects to allow for non-linearity (mt_{it}^2), project duration (d_{it}), the task heterogeneity of

recruiters' multitasking portfolio (th_{it}), the knowledge heterogeneity of recruiters' contacts (kh_{it}), and

an error term ε_{it} as specified in equation [1].

$$q_{it} = \alpha + \beta_1 mt_{it} + \beta_2 mt_{it}^2 + \beta_3 d_{it} + \beta_4 th_{it} + \beta_5 kh_{it} + \beta_6 (th_{it} * kh_{it}) + \varepsilon_{it} \qquad [1]$$

This specification is closely related to models of queued task execution in services work (e.g. Adler et.

al. 1995, Hopp et. al. 2007) and models of parallel and overlapping queued task processing (e.g. Krish-

nan et. al. 1997) from the engineering and operations management literatures, which specify the execu-

tion of queued tasks as a function of load (e.g. multitasking) and speed (e.g. duration).[12] In particular,

ceteris paribus, when tasks take longer to complete on average, total output will be reduced, while

doing multiple tasks simultaneously will increase output. Of course, there may be interactions, which is

one of the questions we study in this paper.

4.4. Estimation Procedures

We estimated the model specified in equation [1] using monthly panel data. The relationships

between output, multitasking, duration and other independent variables are likely endogenous. We

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[12] Using the multiplicative model $Q_{it} = MT_{it}^{\beta_1} * D_{it}^{\beta_2}$ and the log reduction
$\log(Q_{it}) = \alpha + \beta_1 \log(MT_{it}) + \beta_2 \log(D_{it}) + controls + \varepsilon_{it}$ produces nearly identical statistical results, with $\beta_1 <1$ also indicating concavity.

therefore estimate the model using the Arellano-Bover (1995) / Bundell-Bond (1998) system GMM estimator as follows:

$$q_{it} = \alpha + \beta_1 mt_{it} + \beta_2 mt_{it}^2 + \beta_3 d_{it} + \beta_4 th_{it} + \beta_5 kh_{it} + \beta_6 (th_{it} * kh_{it}) + \gamma_t + \eta_i + v_{it} + u_{it} \qquad [2]$$

The error term ε_{it} from equation [1], is decomposed into several components: γ_t is an intercept reflecting common temporal productivity shocks, η_i is an unobserved individual effect, v_{it} is a residual productivity shock and u_{it} represents serially uncorrelated measurement errors.[13]

There are several difficulties in estimating this specification that must be overcome to obtain robust parameter estimates. First, the right hand side variables are assumed to be endogenous. As causality may run in both directions, for example from multitasking to output or from output to multitasking, the regressors may be correlated with the error term. Second, time invariant characteristics of individual recruiters such as their age, experience, tenure, education as well as other unobserved heterogeneity could bias parameter estimates. The system GMM estimator uses a system of two equations – the original equation [2] and one transformed by first differencing [3] – and controls for endogeneity by using lagged values of the differences and levels of endogenous variables as instruments to identify parameter estimates (Arellano and Bover 1995, Bover and Bond 1998).

$$\Delta q_{it} = \alpha + \beta_1 \Delta mt_{it} + \beta_2 \Delta mt_{it}^2 + \beta_3 \Delta d_{it} + \beta_4 \Delta th_{it} + \beta_5 \Delta kh_{it} + \beta_6 \Delta(th_{it} * kh_{it}) + \Delta\gamma_t + \Delta v_{it} + \Delta u_{it} \; [3]$$

The system GMM estimation procedure controls for endogeneity and also eliminates bias from unobserved heterogeneity. First differencing removes the η_i and thus eliminates potential bias from observed or unobserved individual characteristics. The estimator addresses endogeneity in the regressors by instrumenting differences with available lags of levels and variables in levels with suitable lags of their own first differences.

The model assumes that the remaining measurement error u_{it} is i.i.d, which in our case may not be true as individual recruiters work together, making it likely that the errors in their output are corre-

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[13] Tests reveal no serial correlation in the residual productivity shocks as shown in the results tables.

lated. To account for this potential correlation, we adapted a two-step adjustment from spatial econome-

trics designed to filter out dependencies between non-independent observations prior to the application

of dynamic panel data models (Badinger et al 2004). Following (Getis and Ord 1992), we applied a

commonly used spatial filter to remove correlations between non-independent observations in the first

step and then estimated the model using the system GMM estimator in the second step. The filtering

process typically uses a decreasing function of distance to remove correlations between regions that are

connected in some way (e.g. they exchange goods, labor or foreign direct investment). We applied a

similar procedure but estimated correlations between individual workers using the number of projects

that they worked on together. The logic of the filter is that correlations of the output (or the multitask-

ing) of two individual workers will be increasing in the number of projects they work on together in a

given period. To remove these correlations we calculated filtered measures of output (and other va-

riables) q_{it}^* by adjusting q_{it} using the weighted output of i's coworkers as follows, where weights

w_{ijt} are the number of projects i and j worked on together in time t:

$$x_{it}^* = \frac{x_{it} \times \left(\sum_{j=1}^{N} w_{ijt} \Big/ (N-1) \right)}{G_{it}}, \text{ where} \qquad [4]$$

$$G_{it} = \sum_{j=1}^{N} w_{ijt} x_{jt} \Big/ \sum_{j=1}^{N} x_j \qquad [5]$$

Since our data are also heteroskedastic, we estimated standard errors using the Windmeijer (2005) cor-

rection. Thus, we estimated the following dynamic panel data model using network autocorrelation fil-

tered variables and the system GMM estimator with robust standard errors:

$$q_{it}^* = \alpha + \beta_1 mt_{it}^* + \beta_2 mt^2{}_{it}^* + \beta_3 d_{it}^* + \beta_4 th_{it}^* + \beta_5 kh_{it}^* + \beta_6 (th_{it}^* * kh_{it}^*) + \varepsilon_{it}^* . \qquad [6]$$

Section 5 presents results from our main specification and estimation procedure. We also examined the

robustness of our results to several different model specifications and estimation procedures and tested

for selection effects in the assignment of greater multitasking as described in Section 6.

5. Results

Two primary results emerged from our estimation of equation [6]. First, there is a concave relationship between multitasking and output per unit time. More multitasking is associated with more project output to a point, after which there are diminishing marginal returns to increased multitasking. The results in Table 2 show that on average, a one standard deviation increase in multitasking (taking on five more projects) is associated with a nearing doubling of output per month. The coefficient on the multitasking squared term is negative and significant implying a concave relationship. Although more multitasking is associated with greater project output, there are diminishing marginal returns to increased multitasking. Increases in average project duration are also associated with decreases in output per unit time. A one standard deviation increase in average project duration (an additional five and a half months to complete a project on average) is associated with a 50% decrease in output per month.

Table 2. System GMM Dynamic Panel Data Estimates of Output		
Dependent Variable	**Output**	
	1	**2**
Multitasking	.39**	.36**
	(.08)	(.07)
Multitasking Squared	-.11*	-.08**
	(.06)	(.04)
Average Duration	-.12**	-.18**
	(.04)	(.06)
Task Heterogeneity		.02
		(.07)
Knowledge Heterogeneity of Contacts		-.27**
		(.11)
Task Heterogeneity x		.22**
Knowledge Heterogeneity of Contacts		(.11)
Temporal Controls	Month	Month
AR(1)	.13	.10
AR(2)	.41	.12
Hansen Test (p-value)	.20	.57
Difference in Hansen Test (p-value)	.21	.75
Observations	630	431
Notes: This table reports dynamic panel data models using network autocorrelation filtered variables and the system GMM estimator with robust standard errors. Significance levels are as follows: **p<.05; *p<.10.		

We believe these results demonstrate a fundamental tradeoff between the benefits and efficiency costs of additional multitasking. As workers take on more simultaneous projects they see benefits

from smoothing busty work requirements and from cross-task complementarities, but each additional

task creates switching costs, mental congestion and a loss of efficiency. To test this explanation, we

examined the relationship between multitasking and duration directly. Table 3 shows results of dynamic

panel data estimates of the relationship between multitasking and average project duration, estimated in

the same way as the main specification in equation [6]:

$$d_{it}^* = \alpha + \beta_1 mt_{it}^* + \beta_2 th_{it}^* + \beta_3 kh_{it}^* + \varepsilon_{it}^*. \tag{7}$$

Results show that multitasking has a significant positive association with average project dura-

tion supporting the interpretation that while more work is getting done as recruiters multitask more,

each project is taking longer to complete. A one standard deviation increase in multitasking (taking on

five more projects) is associated with projects taking an additional 48 days longer to complete on aver-

age. Together these results provide a plausible explanation for the concave relationship between multi-

tasking and output - workers produce more output per unit time as they multitask more, but are less ef-

ficient per task due to switching costs, overload and congestion. As the costs are increasing and the

benefits are decreasing with more multitasking, the relationship between multitasking and output per

unit time is concave.

Table 3. System GMM Dynamic Panel Data Estimates of Project Duration

Dependent Variable	Duration
Multitasking	.29** (.14)
Task Heterogeneity	-.04 (.16)
Knowledge Heterogeneity of Contacts	.50 (.37)
Task Heterogeneity x Knowledge Heterogeneity of Contacts	-.44 (.32)
Temporal Controls	Month
AR(1)	.41
AR(2)	.43
Hansen Test (p-value)	.68
Difference in Hansen Test (p-value)	.50
Observations	431

Notes: This table reports dynamic panel data models using network autocorrelation filtered variables and the system GMM estimator with robust standard errors. **$p<.05$; *$p<.10$.

However, we also considered three alternate explanations and let the data speak to which is the most likely. First, correlated differences between individual workers and their project portfolios could produce the concave relationship between multitasking and output. For example, new inexperienced workers may take on fewer less valuable projects, while the most experienced consultants take on the largest number of projects. These two clusters could explain the first and last third of the concave relationship while partners' social and organizational power (e.g. Pfeffer 1981) could enable them to take on a relatively small number of high value projects, creating a relationship between leisure (less multitasking) and output in the partner strata of our data. This explanation is consistent with incentive theories of deferred compensation, where workers are underpaid early on in their careers (e.g. [Pay=f(revenues)] < marginal revenue product) and paid more than their marginal revenue product later on (Lazear 1979).

Second, there may be unobservable drivers of both multitasking and output that create the concavity. For instance, productive workers may spend time on other tasks we don't observe that allow them to work on fewer projects simultaneously while producing more output. If these productive workers worked on slightly more projects than inexperienced new workers, but fewer projects than experienced workers who did not spend time on these unobserved tasks, a concave relationship between multitasking and output could be observed.

Third, there could be exogenous temporal variation. Clients may hire top management teams in groups, creating temporal clusters of contracts that are both few in number and high in revenue value (and thus priority). If this type of turnover happens seasonally – for example, near the beginning or end of the fiscal year – then temporal clusters of fewer high value projects could create a concave relationship. Exogenous transitory shocks to client demand could also inspire ramping up of production, or large simultaneous layoffs in low revenue value positions.

While the alternate explanations conform to theory and could explain the concave relationship between multitasking and output, our specifications suggest they are unlikely. Our estimates of the rela-

tionship between multitasking and output are robust to specifications controlling for unobserved heterogeneity across individuals, holding constant variation driven by status, organizational power or career tenure, as well as unobservable practices or characteristics. Our controls for temporal variation (both seasonal variation and exogenous shocks to demand) also discount explanations based on temporal clusters of projects of different types. As our quantitative and qualitative data discount the alternative explanations, we are drawn to interpret the results in Tables 2 and 3 as evidence of a tradeoff between the increasing marginal costs and decreasing marginal benefits of multitasking.[14]

The second primary result of our analysis is that recruiters with network contacts who have heterogeneous knowledge are less productive on average, but more productive when juggling diverse multitasking portfolios. This implies that although heterogeneous knowledge accessed through email contacts is costly to process and maintain, it improves the productivity of workers who are responsible for diverse tasks. Holding multitasking and the degree of own specialization constant, communication with contacts whose expertise is diverse is correlated with lower productivity. This suggests there are costs to greater knowledge heterogeneity among network contacts.

However, a plausible alternative explanation is that recruiters who specialize do so by focusing on projects that are inherently easier and therefore have a significantly lower mean duration. If specialists specialize in easier projects and have contacts with lower knowledge heterogeneity, this might explain the negative relationship between knowledge heterogeneity and productivity. To test this alternative explanation we first examined whether specialists were focused on particular job classes and then estimated whether these job classes had lower project duration on average. Our tests revealed that only one job class was positively associated with specialization at greater than a .05 correlation - business development jobs (pairwise correlation = .31, p < .05). The rest were either not correlated or negatively correlated with specialization, meaning specialists tended to specialize in business development jobs (though not exclusively). However, the average duration of business development projects (m = 199

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days; S.D. = 97) was very similar to the average project duration across all projects (m = 207 days; S.D. = 124). As expected, t-tests showed this difference was not statistically significant (t-statistic = -.77, N.S.). Specialists were not specializing in particularly easy jobs. We therefore interpret the negative association between knowledge heterogeneity and output per month as evidence of real costs to accessing and maintaining networks with heterogeneous knowledge.

Finally, the interaction term between task heterogeneity and knowledge heterogeneity has a positive and significant association with output per unit time. When heterogeneity is needed (i.e. when task diversity necessitates access to knowledge heterogeneity), having access to heterogeneous knowledge improves performance. Better fit between task requirements and knowledge resources, increased absorptive capacity and multitask learning are all plausible theoretical explanations for the positive effect of the interaction of task heterogeneity and knowledge heterogeneity on productivity.

6. Robustness

Although the GMM estimator addresses potential bias from unobserved heterogeneity and endogeneity, we tested the robustness of the main findings to several alternate specifications and estimation procedures. First, it is likely that project assignment is not random in this setting. For example, it could be that recruiters who are better able to multitask are more likely to choose to take on more simultaneous projects or are assigned to more simultaneous projects. To test the effects of selection on our results, we estimated the relationship between multitasking and output using a Heckman two-step selection model. We estimated multiple versions of this model including but not limited to those reported in Appendix B Table 1. We collected new data from the Bureau of Labor Statistics on the levels and growth of statewide employment and GDP in the states where the firm operates (both in states where they have offices and in which they have clients) for sectors of relevance to their work (executive recruiting, professional services, education, and health care, and overall levels and growth of statewide employment and GDP in these states). We weighted these variables by the number of projects a recruiter had in each state. These data capture exogenous shocks to demand for the recruiters' services and

represent valid exclusion restrictions because their effect on output can only come through increased multitasking (increased multitasking in this one firm is unlikely to move statewide employment or GDP, but changes in aggregate demand can create exogenous shocks to demand for the firm's services) (see Levitt 1996). We also include more traditional observable characteristics of recruiters in these models (e.g. age, gender, industry experience, firm tenure, position within the firm, as well as the primary city in which recruiters work) to control for selection bias based on observables. In all models the relationship between multitasking and output remained concave and highly significant and duration was negatively associated with output, corroborating our main results.

Second, although our models of duration, which capture the loss of efficiency caused by additional multitasking, control for observable and unobservable time invariant characteristics of recruiters through first differencing, they may not completely control for differences between projects. So, we checked the robustness of our duration results by specifying a hazard rate model of project completion as a function of multitasking, project characteristics and team member characteristics and estimated the model using data on projects over the five year period. The team level multitasking variable captures the extent to which team members have other commitments during a project measured as the number of other projects recruiters on a team take on during any given project. The results, shown in Appendix B, Table 2 indicate that an additional project taken on by a team member slows the project completion rate by approximately 15% corroborating the efficiency loss from multitasking. We also assessed alternative specifications of time horizons by estimating standard FGLS, fixed and random effects specifications on daily data. The results also corroborated our findings regarding multitasking, duration and output.[15]

7. Discussion and Conclusion

As more and more fine-grained data become available on organizational information flows, practices, and performance – researchers are better able to understand the nature of knowledge work.

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[15] These results are available from the authors.

Our analysis of detailed data on work practices, email, and output among a group of executive recruiters offers two main insights. (1) Recruiters who multitask more produce more project output, but only up to a point, after which there are diminishing returns. Thus our findings bridge and explain the conflicting evidence on multitasking. While multitasking increases confusion, distraction, and task switching costs (Rubenstein et. al. 2001, Rosen 2008), its beneficial effects on throughput push knowledge workers to absorb these costs up to the point of diminishing returns. (2) Recruiters whose network contacts have heterogeneous knowledge are better able to cope with heterogeneous multitasking. For reasons of combinatorial synergy, goodness of fit and increased absorptive capacity, knowledge heterogeneity can interact with task heterogeneity to increase productivity. These two insights reinforce each other in both theory and empirical evidence. In turn, our research findings have at least three important implications for research and practice.

First, multitasking is a topic of serious debate among practitioners and academics. Some believe it helps productivity while others believe it hurts productivity. Combining the two lines of argument produces a theoretical prediction that the relationship should be concave. At low levels of multitasking, workers will experience benefits from task complementarities and smoothing bursty work, leading to increased output from multitasking. However, at high levels of multitasking, the cognitive load is higher and the marginal benefits of smoothing work and learning from other projects are smaller. All that is required for concavity is that one of these factors is non-linear, yet theory suggests both might be non-linear. Indeed, this is consistent with our empirical findings. The implication for managers is that there are likely to be optimal levels of multitasking in different information work environments. Managers can potentially discover these optimal conditions through systematic trial and error and experimentation.

Second, our findings contribute to the growing literature on how changes in work organization complement IT investments to improve firm performance. Although most of the current literature considers broad aggregates (see Brynjolfsson and Milgrom (2011) for a review), we provide a micro level explanation for why a particular work practice, multitasking, complements IT. IT reduces the costs of

exchanging information, which enables workers to cope with more diverse multitasking portfolios. Diverse portfolios are necessary, along with job rotation and team work, to support a firm's ability to deal with greater demand for product and process variety, and manufacturing flexibility. More precisely, we shed light on the process through which technology helps workers access the diverse knowledge they need to cope with diverse project multitasking. In our setting, recruiters with network contacts who have heterogeneous knowledge are less productive on average, but more productive when juggling diverse multitasking portfolios. This implies that although heterogeneous knowledge accessed through email contacts is costly to process and maintain, it improves the productivity of workers who are responsible for diverse tasks.

Third, the findings clarify how social networks create value. Seminal social network theories such as the strength of weak ties (Granovetter 1973) and structural holes (Burt 1992) are predicated on the argument that ties to disparate parts of a network provide access to heterogeneous knowledge. Most such research assumes knowledge heterogeneity adds more value than cost but this presumption can often be false. More recently, research has moved beyond purely structural accounts of this argument by directly measuring the knowledge heterogeneity workers connect to through diverse social networks (Reagans and McEvily, 2003, Rodan and Gallunic, 2004) and it has recently been shown that diverse network structures actually provide workers with more heterogeneous information (Aral and Van Alstyne, Forthcoming). Prior work assumed that knowledge heterogeneity always helped improve performance. In this paper, we show that the link to performance is contingent on the degree to which the individual needs diverse information. Drawing on theories of common knowledge (Clark 1996, Cramton 2001, Reagans and McEvily 2003) and organizational fit (Morgan 1986; Miller 1992), we hypothesized that networks with heterogeneous knowledge have costs that can reduce performance. But we also found that when heterogeneity is needed, i.e. when task diversity necessitates access to knowledge heterogeneity, having access to heterogeneous knowledge improves performance.

In sum, the combination of data on individual worker project completion, email messages, and work practices reveals a pattern of relationships among multitasking, technology use, and output. The

findings can help managers design optimal information work production processes – specifically the degree to which workers should multitask and the circumstances under which putting them in touch with diverse communication partners helps or hinders their multitasking and productivity. Our results suggest that managers should match the complexity of knowledge flows to the complexity of task assignments. When adding new tasks, keeping them similar enables workers to rely on existing information and knowledge flows to raise productivity. But when adding dissimilar tasks is unavoidable, matching the heterogeneity of tasks to that of the information accessed through IT-enabled communication raises productivity. Job rotation systems that simultaneously increase contact and task heterogeneity can therefore increase productivity.

There remain some important limitations to our analysis. While we were able to use the Sys-GMM approach to sort out some issues of causality and endogeneity, this is an imperfect technique. An ideal research design would include a randomized controlled experiment with some, but not all of the information workers getting changes in email access and workloads, in order to tease out the causal relationships. Such experiments are the gold-standard in medicine and other sciences and we do not think they are out of reach in organizational settings, although due to costs, they have necessarily been rare (e.g. Aral & Walker, Forthcoming). In contrast, the increasing ubiquity of fine-grained measurement and abundant data on information flows, work practices and performance will open up far more opportunities for studies such as this one. Companies are gathering petabytes of data via their digital communications systems, performance measurement systems, enterprise information systems, and customer networks and supply chains.

We are particularly optimistic that the techniques developed during this research can be applied to other project-level information work involving information flows among workers, a category which encompasses a large and growing share of most twenty-first century economies. Instead of relying on coarse data at the industry- or firm-level, researchers can exploit the large quantities of data being created at the level of individual workers and even individual tasks and messages. As fine-grained data

increasingly become available, such analyses portend a substantial improvement in our understanding

of the relationship between information, technology, and value creation.

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Online Appendices

Appendix A: Email Data Collection Methods

Email data provides advantages over survey self reports in that direct observation of communications traffic avoids biases in respondent recall of social networks (Marsden 1990, Reagans & McEvily 2003). Securing access to complete email communications required us to develop original software tools, coded specifically for this project. A more complete description is provided in Van Alstyne & Zhang (2003) and Reynolds, Van Alstyne & Aral (2009). Here we summarize our methods, and describe the problems we confronted while collecting email data and our approaches for resolving each as a means to ensure data completeness and validity. Study participants who allowed use of their email data received $100 in Amazon gift certificates in compensation. Email coverage of eligible employees exceeded 87%.

The code developed for email capture runs on a Microsoft Exchange™ server, under a standard email configuration. It downloads all messages from the exchange server (storing To, From, CC, BCC, Subject, Body, and Attachments fields) and provides secure backup and nightly export of encrypted data to servers outside the research host site. Due to the potential intrusiveness of email capture, the research underwent three rounds and nine months of human subjects review by the University of Michigan IRB and two rounds and five months of human subjects review at MIT prior to launch. We addressed several data completeness and validity issues as follows.

1. *Privacy*: Potential invasions of privacy raised two concerns for data validity. First, the human subjects boards required voluntary participation of all study participants. Voluntary non-participation might therefore have reduced the representativeness of our data sample if too many employees had chosen to opt out. Second, among remaining employees, privacy concerns could cause them to change their communication behaviors. To address these issues, we developed a data masking and encryption algorithm that permits analysis of header information and content but prevents reading of any individual message. The hashing algorithm and the information theoretic and statistical properties for granting privacy protection are not part of this article but are described in Van Alstyne & Zhang (2003), Reynolds, Van Alstyne & Aral (2009), a provisional patent application dated 2003, and in a master's thesis we supervised at MIT (Farrokhzadi 2007). Privacy assurances, however, are a primary reason why more than 87% of employees chose to remain in the study.

2. *Data Bias*: Different people exhibit different patterns of behavior with respect to retaining and deleting email. This risks introducing data bias in the volume and frequency of communication, and in the shape of egocentric social networks. To prevent deletion bias, administrative switches in the Exchange email server and email capture code recorded properties of deleted messages for a period of 24 hours before details were expunged.

3. *Load Balancing*: Significant data processing – necessary for capturing data, privacy sanitization, and secure data export – introduced risk of increased load on the email server and decreased user responsiveness. Poorer system performance, in turn, could also have influenced user behaviors. To ensure compliance with all normal functions on the Microsoft Exchange email server, we tested our software at a Microsoft research facility in Redmond, WA and received a clean bill of health. This also provided assurance that data intended for capture was correctly recorded. To minimize interference at the research site, we captured daily increments of email communications, and exported sanitized encrypted data to university servers at 03:00 am local time at the research host, utilizing a lull in normal activity immediately after normal backup operations.

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Appendix B. Robustness Checks

Table B1. Heckman Selection Model of Multitasking and Output			
Dependent Variable	**Output**		
Model	1	2	3
Multitasking	.36**	.36**	.36**
	(.02)	(.02)	(.02)
Multitasking Squared	-.08**	-.08**	-.08**
	(.01)	(.01)	(.01)
Average Duration	-.15**	-.14**	-.14**
	(.02)	(.02)	(.02)
Rho	.13	.05	.01
Sigma	.21	.19	.19
Lambda	.03	.01	.002
Observations	630	450	450

Notes: This table reports results of a Heckman two-step selection model in which the first stage regression predicts multitasking as a function of several observable characteristics of recruiters and the regional economic climate in which they operate. In model 1, we estimated the first stage of the model by predicting the level of multitasking using observable characteristics of recruiters including age, gender, industry experience, firm tenure, position within the firm, as well as the primary city in which recruiters work. In model 2, we predicted multitasking using data on exogenous shocks to recruiters multitasking collected from the Bureau of Labor Statistics on the levels and growth of statewide employment and GDP in the states where the firm operates (both their offices and the cities in which they have clients) for sectors of relevance to their work (which include executive recruiting, professional services, education, and health care as well as overall levels and growth of statewide employment and GDP in these states). We weighted these variables by the number of projects a recruiter had in each state. In model 3, we predicted multitasking using all of these variables. Significance levels are as follows: **$p<.001$; *$p<.05$.

Table B2: Hazard Rate Analysis of Multitasking and Project Completion Rate

Dependent Variable	Project Completion Rate		
Variables	**Model 1**	**Model 2**	**Model 3**
	RSE-c	RSE-c	RSE-c
nMultitasking	.858**	.843**	.851**
	(.030)	(.029)	(.030)
IT Controls			
nFTF Contacts	1.002		1.015
	(.027)		(.029)
nPhone Contacts	1.109		1.073
	(.061)		(.062)
nEmail Contacts	.974		.958
	(.043)		(.046)
nESS Use		1.118**	1.114**
		(.035)	(.038)
nESS Skill		.947	.949
		(.051)	(.060)
Team Controls			
Team Size	.854**	.820**	.842**
	(.067)	(.067)	(.071)
Industry Experience	.989**	.990**	.991**
	(.004)	(.005)	(.005)
Task Controls			
nRoutineness	1.003	1.074	1.042
	(.042)	(.043)	(.047)
nInterdepend.	.980	.957	.979
	(.038)	(.034)	(.041)
Job Class Controls?	YES	YES	YES
City Controls?	YES	YES	YES
Log Likelihood	-7080.3	-7077.6	-7076.03
X^2 (d.f)	185.07*** (19)	193.16*** (18)	196.79*** (21)
Obs.	1180	1180	1180

***p<.001; **p<.05; *p<.10. RSE-c = Robust Clustered SE (n = 505 Clusters)

Notes: Team size and industry experience are associated with longer project duration and slower completion rates. Teams with more members may take longer to execute projects due to the added complexity of coordination, or the firm may resort to 'throwing more labor at' difficult jobs or jobs that are taking longer to complete than expected. Controlling for team size therefore may also account for differences in project difficulty not picked up by controls for job type, task, and city characteristics. Industry experience also corresponds to longer project duration perhaps because less experienced employees receive less demanding work. Cost of living, crime rates, and greater commute times all reduce the project completion rate on average, meaning these characteristics may be less attractive to potential candidates, while good weather is associated with increased completion rate. Routine tasks consistently finish faster, and greater interdependence among team members is associated with slower completion rates. Significance levels are as follows: **p<.001; *p<.05.