Information Asymmetry and the Productivity of Information Workers

David Fitoussi[*], Frank MacCrory[*], Alain Pinsonneault[†]

To understand how IT affects worker productivity we need to understand the factors that shape information worker productivity in the first place. Typical characteristics of information work (in particular, highly intangible output and significant measurement problems) and the managerial response to them are likely to play significant roles in determining information worker productivity. We examine the impact of information asymmetry in a team production environment to develop insights into how team design and monitoring are changing the incentives facing information workers and thus their productivity. Using a detailed dataset of human resources records and timecards from a large multi-national software development firm, we examine the influence of these incentives on novel measures of information worker productivity. We find that skill redundancy reduces individual productivity, and that both team composition and task content have predictable effects on the manager's ability to leverage monitoring effort across several workers. We explore some implications of these results for managing teams of information workers, specifically related to task design elements such as substitutability and complementarity between team members.

(10,002 words)

We are grateful for the contributions of time and expertise from Ken Kraemer and Jason Dedrick in support of this project. Thanks also to Christopher Carpenter, Vidyanand Choudhary, Vijay Gurbaxani and Stergios Skaperdas for helpful comments on a previous draft of this paper. This research was supported in part by National Science Foundation grant SES-0527180.

---

[*] Paul Merage School of Business and Center for Research on IT and Organizations, University of California, Irvine
[†] Desautels Faculty of Management, McGill University, Montréal, Canada

Introduction

As information work has grown to a large share of overall work in the economies of developed nations, workplace changes that affect the productivity of information workers (such as investments in information systems, business process reengineering or offshoring) have also had large impacts on the economy. While a long stream of research has linked information systems investments to increased productivity at the country (Brynjolfsson & Hitt, 1996) and firm (Melville *et al.* (2004) and Tambe & Hitt (2008)) levels, researchers have noted wide variances in the payoffs to these investments (Dedrick *et al.*, 2003). One explanation for these variations is that investments in IT become productive only when they accompany investments in complementary organizational practices. Since such changes directly affect worker productivity, understanding productivity at a more granular level than the country and firm levels is critical but remains underexplored. While there has been some research on worker productivity it has typically focused on production workers (Lazear, 2000) and researchers have pointed out that information workers are fundamentally different from production workers (Davenport *et al.* , 2001).

There are many gaps in our knowledge of what affects the productivity of information workers and knowledge workers. We use the terms information worker and knowledge worker as synonyms, with the understanding that we refer to those primarily engaged in non-routine information work. Although some work has tried to develop measures for the productivity of knowledge workers (see Ramírez & Nembhard (2004) for a review), these efforts represent “instantaneous” measures that do not take into account the economic context in which workers use information, and in particular the incentive effects of team composition and managerial oversight on productivity. The challenge for practitioners is that existing productivity enhancement techniques are based on the characteristics of production workers not information workers. Important differences between the two include intangible output, greater reliance on team (rather than individual) output, and highly-specialized human capital.

Team composition (size of the team, mix of roles on the team, etc.) has a direct effect on productivity in any environment that involves team-level outputs. Since it is very difficult or impossible to identify the individual contributions to the productivity of knowledge worker teams, it is unsurprising that researchers and practitioners have difficulty identifying the ways in which information technology improves individual productivity in teams of information workers. The inability to identify individual contributions also creates an environment vulnerable to moral hazard and free riding (Albanese & van Fleet (1985) and Levine & Moreland (1990)).

Previous research has shown that it is not possible to align incentives between the principal and a team of agents under standard assumptions of microeconomics (Holmstrom, 1982). Conceptually, the solution to this incentive problem is to observe and contract on inputs directly but such monitoring is rarely available for knowledge workers and costly for the firm. The goal of this research is to understand some of the factors that affect knowledge workers' productivity without costly investments in task-level measurement. An important question is how to define, let alone measure, productivity for information workers. It is abundantly clear from taxonomies such as Ramírez & Nembhard (2004) that there is no agreed-upon measure of knowledge worker productivity. Ramírez & Nembhard note that "[m]uch of the literature also focuses on making clear how difficult it is to measure [knowledge worker] productivity but does not provide many recommendations to measure it." We identify theoretical reasons why it is difficult to measure knowledge worker productivity, but we also empirically validate our findings with a novel approach to measure productivity that does not rely on intricate task-by-task performance metrics.

In this study we look at a collection of development teams from a multi-national software developer. Unlike previous software development studies, the teams here are *not* relatively homogenous groups of programmers but include business analysts and managers as well. Because the company's software is generally customized for each client, the productive output of the application developers also depends critically on the contributions client trainers, database designers, subject-matter experts, and technical writers in ways that cannot be split off and analyzed in discrete functional chunks.[1] We follow 143 employees involved with the development, customization, and implementation of complex software products over a 1.5 year period. First, we find evidence of free-rider problems within teams, and show that the magnitude of free-rider losses is influenced by team composition. Specifically, redundancy within the team increases losses due to moral hazard. We find no peer effect on individual productivity, so information asymmetry is driving productivity in this firm rather than identity (Akerlof & Kranton (2005, 2008)). Second, we find that a team-level productivity metric (manager span of control) is affected by task content and team design factors in predictable ways. Specifically, highly related tasks (substitutability or complementarity) increase the efficiency of monitoring the team. For teams with high redundancy in this particular firm, the monitoring effect dominates the moral hazard effect.

We make two contributions to the literature. The first is an empirical analysis of the factors affecting moral hazard in teams and by extension information worker productivity. The second is a pair of novel methods for measuring the productivity of information workers when highly detailed task metrics are unavailable, such as in socially complex software development efforts.

Our findings have several implications for managers. The first implication is that moral hazard lowers individual productivity in a team setting, but the drop can be decreased if the team members are not close substitutes. The difference can be accomplished either through functionally heterogeneous teams ("end-to-end process" teams as opposed to functional teams) or by assigning ownership of specific tasks to specific individuals (so that the manager is aware if a substitute is performing a task). The second implication is that a team manager can leverage her monitoring effort across workers that are highly substitutable or highly complementary, reducing the information advantage of the workers on

[1] Some clients do not require modifications to the software, but the firm is still involved in configuring the software and training end-users.

the team. With this in mind, managers should monitor work-in-progress signals that affect the output of several workers.

The remainder of this paper proceeds as follows. In the next section, we review previous research into knowledge worker productivity. Next, we develop our theoretical model of information worker productivity and generate propositions. The following section describes the data that will be used to test the propositions. After that, results of the empirical tests are presented. The final section concludes with implications for managers.

1. Background

Existing research on the productivity of software development teams focuses on counting techniques based on software engineering methodologies (Kemerer (1993) and Ramasubbu *et al.* (2008)). The output measurement issues in these cases may not be simple, but they are understood. If output can be measured quantitatively, previous research on production worker incentives (Lazear, 2000) offers insight into productivity drivers. Most development efforts, however, like most information work in general, are very difficult to capture with straightforward quantitative metrics (*e.g.*, many database developer tasks produce few if any lines of code or function points; the tasks of technical trainers produce none at all). This lack of measurability has a direct impact on the employer's ability to provide effective incentives in teams. For this reason, alternative incentive systems based on group monitoring, career opportunities and other indirect incentives should play a prominent role in managing knowledge workers' productivity.

Previous research on information worker productivity has searched for situations in which productivity can be distilled to a unidimensional rate such as revenue generated per period (Aral *et al.*, 2007), software function points coded per time period (Kemerer, 1993), or hazard rate of completing a discrete assignment (Wu *et al.* , 2008). Davamanirajan *et al.* (2006) measure transactions per period as well as average cycle time for trade service processors.[2] In these circumstances, researchers are able to identify factors that affect productivity in these well-defined tasks of limited scope. By definition, knowledge workers are those whose jobs consist of more than a collection of well-defined tasks, so it is understandable that situations well-suited to measurement are rare. Ramírez & Nembhard (2004) identify thirteen types of measures used to measure the productivity of knowledge workers including "efficiency" measures such as absenteeism, quantity, and timeliness as well as "effectiveness" measures such as customer satisfaction, importance of work, and project costs.[3]

In the socially complex production environment we study, some of these measures are not comparable across job categories. For example, what is the "quantity" produced by a subject matter expert or the "timeliness" of a technical trainer? Some other measures are observable only at the project level (*e.g.*, costs, customer satisfaction, project success), and rarely are enough permutations of team compositions available to infer individual contributions to these measures.

One noisy measure of productivity that we observe at the individual level is absenteeism, a metric that applies broadly across roles. Absenteeism is an efficiency measure because the firm continues to pay its employees at the same rate but the employee is less productive when home sick (if he or she is doing any work at all),[4] but the productivity effects associated with absenteeism are much more than simply spending time at work or not. While many absences are outside the employee's control (Mowday *et al.*, 1982), previous research has also shown that relatively high absenteeism is associated with low job satisfaction and individual productivity (Porter & Steers, 1973) and this leads to lower firm productivity (Ostroff, 1992). Thus absenteeism is clearly related to both direct productivity (hours worked) and indirect unobservable worker productivity.

---

[2] Davamanirajan *et al.* call the first measure "productivity" and the second one "quality." Each is considered separately in their study.

[3] Ramírez & Nembhard (who looked at information workers more broadly than just software developers) note that most studies use two or three different dimensions to describe productivity.

[4] Efficiency is defined as "hours doing meaningful work divided by hours paid" (Klassen *et al.*, 1998), and sick time increases hours paid with a smaller increase (perhaps zero) in hours doing meaningful work.

There is some evidence in the literature that information worker productivity can be increased by investments in information systems, but the impact is highly dependent on the organizational structures facing those information workers. Bresnahan *et al.* (2002) note that information systems investments are complementary to specific organizational structures, explaining why studies that look only at IT spending encounter such a wide variance in outcomes. Brynjolfsson *et al.* (2005) find that traditional measures of IS investment (spending on IT hardware) represents a small fraction of what firms actually invest in their information systems, the majority of the costs being in software development, business process redesign, testing, deployment and training. Aral & Weill (2007) show that total IS spending explains little of the variation in outcomes, but specific IS investments (IT assets and organizational practices) have significant explanatory power. These firm-level observations are manifestations of the importance of organizational structures in individual knowledge worker productivity. Thus organizational factors such as team composition and monitoring regimes are expected to affect the productivity of knowledge workers.

Previous research has identified the importance of team composition elements such as advice networks and informal communication channels in software development, indicating that organizational factors are in fact important factors in the productivity of individual information workers. Kraut & Streeter (1995) show that the characteristics of software development efforts (especially scale and uncertainty) require informal means of communication because it is simply impossible for managers to be informed about and coordinate everything happening on a project. Yang & Tang (2004) find that even on small software development teams, advice networks and team composition are very important determinants of team-level productivity. Caya *et al.* (2008) find considerable evidence in the literature that team composition and interpersonal processes drive performance in virtual teams while Singh *et al.* (2007) relate the success of open source projects to similar informal communication channels, indicating that the inadequacy of formal communication channels is not an artifact of a single-site corporate environment. Experiments such as Rankin (2004) show that coordination of complementary individual efforts requires rich communication channels when payoffs are based on team output.[5] Underlying all of these findings is that software development teams are composed of information workers whose efforts cannot be completely directed or observed by a central manager. The present study uses detailed individual-level data to focus on this lack of observability to investigate how team design elements affect productivity in a socially complex production setting. To the extent that team dynamics and learning influence an individual's level of productivity, we should observe it in absenteeism figures. Other effects (such as synergies between employees) will not appear in our individual measure of productivity, but they will improve team-level productivity.

The problem of unobservable or hard-to-measure output in teams makes monitoring a critical element of knowledge worker productivity. Besides the internal monitoring within teams, productivity is affected by managers. The harder it is to infer individual effort from output observations, the less effective output-based incentives become (Aggarwal & Samwick, 2003) and the more the manager must rely on other means such as direct monitoring. At the team level of productivity, *ceteris paribus*, a higher-performing team will require less managerial effort per unit of output. That is, managers of high-performing teams will exert a higher span of control. This is an efficiency measure and also a measure of the importance of the manager's work since a manager with a higher span of control is affecting the productivity of more employees.

To summarize, information workers are fundamentally different than production workers in ways that make it very difficult for firms to apply efficient incentives. Previous research has focused on situations in which the measurement issue can be solved, while we believe that our setting of socially complex team production is more typical of knowledge work in general. We propose theoretically

[5] Rich communication is a necessary, not a sufficient, condition for effective coordination. Experiments such as Pinsonneault *et al.* (1999), Chidambaram & Tung (2005) and other show that adding "complementary" inputs to a group can actually decrease performance. In the former case, the coordination process itself is costly. The second case is a result of the 1/N problem described on pages 10-11.

justified measures of productivity measurement that are valid in this general setting, and follow this with empirical validation of the effects predicted by theory. The next section discusses individual worker productivity in the context of a team production model.

2. Model

In practice, identifying the determinants of information worker productivity is challenging because the output is intangible. However, even if this intangible output could be measured with absolute precision, a critical element of knowledge work is that it is team-based and individual output is often inseparable from team output. To examine how this issue affects knowledge worker productivity, we begin with a theoretical model of production that shares this team output feature.

We employ an extension of Holmstrom (1982)'s team production model in which a G groups of N agents have unobservable effort. Each agent i in each group g chooses a positive effort level $e_{g,i}$ with a private cost $C(e_{g,i})$ that is increasing, continuously differentiable, and strictly convex with $C(0) = 0$. Each group's effort is stacked in a vector $\mathbf{e}_g = (e_{g,1}, e_{g,2}, \ldots, e_{g,N})'$, and these groups' efforts are stacked in a matrix $\mathbf{E} = (\mathbf{e}_1\ \mathbf{e}_2 \ldots \mathbf{e}_G)$. The team's productive output is a function of the team's effort $f(\mathbf{E})$: $\mathbb{R}^{GN} \rightarrow \mathbb{R}^1$ which is increasing, continuously differentiable, and strictly concave in each $e_{g,i}$ with $f(\mathbf{0}) = 0$. The payoff to each agent is a share of the output $s_{g,i}\left(f\left(\mathbf{E}\right)\right)$ such that $\sum_{g=1}^{G}\sum_{i=1}^{N} s_{g,i}\left(f\left(\mathbf{E}\right)\right) = f\left(\mathbf{E}\right)$ for any level of output. Holmstrom shows that any Pareto-optimal solution ($\mathbf{E}$, $\{s_{g,i}(\bullet)\}$) is not a Nash equilibrium, even if the function f is deterministic. For ease of exposition, we follow the example of Becker & Murphy (1992), Heywood & Jirjahn (2009), and others by simplifying the sharing rules so that each agent receives an equal share $f(\mathbf{e})/GN$ for all levels of output.[6]

[6] In order to avoid a trivial solution, we must assume that there exists an open set $\mathcal{E} \gg \mathbf{0}$ in GN-space such that the expected value of $f(\mathbf{E})/GN > C(e_{g,i})$ for all $e_{g,i}$ in $\mathcal{E}$. Any reasonable production technology will meet this requirement since otherwise the firm would be unable to hire any employees.

The typical definition of a team in analytical work is that team members' efforts are additive or superadditive (*i.e.*, independent or complementary). In our extension, team members within a group possess similar skills and are somewhat complementary, but each group represents a different set of skills and there is stronger complementarity between groups. For example, a group of business analysts, a second group of application developers, and a third group of end-user trainers.

Teams

To investigate the effects of team composition on unobservable effort decisions (and thus productivity), we examine a single-period game in which workers choose effort under a Cournot conjecture.[7] Under these conditions, each agent maximizes his or her payoff by using the first order condition:

$$\frac{f_{e_{g,i}}\left(\mathbf{E}^*\right)}{GN} - C'\left(e_{g,i}^*\right) = 0 \tag{1}$$

or exerting zero effort in the expectation that others will work. Under the reasonable assumption that a worker exerting **zero** effort would be detected and disciplined with high probability, each worker will maximize using (1).

To see how free-rider problems affect this environment, we consider a specific functional form for $f(\mathbf{E})$, the CES production function which has Cobb-Douglas and purely additive technologies as special cases. The elasticity of substitution between members of the same group is ρ, and the elasticity of substitution between groups is P with $0 < P \leq \rho \leq 1$. This leads to the production function

$$f\left(\mathbf{E}\right) = \left(\sum_{g=1}^{G}\left[\left(\sum_{i=1}^{N} e_{g,i}^{\rho}\right)^{\frac{1}{\rho}}\right]^{\mathrm{P}}\right)^{\frac{1}{\mathrm{P}}} \tag{2}$$

[7] This rules out strategies in which a worker bases his or her effort decision on the effort decisions of some coworkers as in Winter (2005).

Using $C\left(e_{g,i}\right)=\frac{ce_{g,i}^{2}}{2}$ as the cost of effort, the first-order condition becomes

$$\frac{e_{g,i}^{\rho-1}\left(\sum_{j=1}^{N} e_{g,j}^{\rho}\right)^{\frac{\mathrm{P}-\rho}{\rho}}\left[\sum_{h=1}^{G}\left(\sum_{k=1}^{N} e_{h,k}^{\rho}\right)^{\frac{\mathrm{P}}{\rho}}\right]^{\frac{1-\mathrm{P}}{\mathrm{P}}}}{GN}-ce_{g,i}=0$$

which, assuming symmetry across agents, leads to an equilibrium level of effort

$$e^{*}=\frac{N^{\frac{1-2\rho}{\rho}}G^{\frac{1-2\mathrm{P}}{\mathrm{P}}}}{c} \tag{3}$$

As noted by Adams (2006), the 1/N problem manifests whenever ρ > ½. An analogous 1/G problem manifests if P > ½. Groups of similarly-skilled employees naturally fall within the range of ½ < $\rho \leq$ 1. As Levine & Moreland (1990) put it, "[a]s a group grows larger, it also changes in other ways, generally for the worse."

Proposition 1 Individual productivity decreases in larger teams.

The actual level of substitutability is also important, as we would expect free riding to increase if team members were closer substitutes. This is illustrated by how the equilibrium level of effort changes as the elasticity of substitution varies.

$$\frac{\partial e^{*}}{\partial \rho}=-\frac{G^{\frac{1-2\mathrm{P}}{\mathrm{P}}}N^{\frac{1-2\rho}{\rho}}\log N}{c\rho^{2}} \tag{4}$$

If N = 1, the ρ parameter has no effect, but for N > 1, every term in the fraction is positive and the leading negation reverses the sign, so increasing ρ always decreases individual productivity. We are also interested in how this effect operates across different team sizes, which can be shown by taking the derivative of (4) with respect to N.

$$\frac{\partial^{2} e^{*}}{\partial \rho \partial N}=\frac{(2\rho-1)G^{\frac{1-2\mathrm{P}}{\mathrm{P}}}N^{\frac{1-3\rho}{\rho}}\log N}{c\rho^{3}} \tag{5}$$

All of the terms are strictly positive if ρ > ½. Since $\partial e^* / \partial \rho < 0$ and $\partial^2 e^* / \partial \rho \partial N > 0$ in the relevant range,

Proposition 2 Individual worker productivity decreases in homogenous groups (workers have similar skills and roles). The more similar the skills, the less productive each worker is. However, as the group size increases, the effect becomes less pronounced.

The level of complementarity between groups (the value of P) is an empirical question, and therefore we do not have a proposition about it.

Monitoring

A second driver of individual worker productivity in teams is the level of supervision and monitoring exercised by a team manager as worker productivity is clearly affected by managerial supervision. Moreover, managerial supervision is directly related to managerial productivity, a specific case of knowledge work. Finally, managerial time is also an indirect measure of team productivity as it may indicate how effectively the team functions.

For the purposes of our model, the manager's time is a pure overhead cost (*i.e.*, she does not provide her own e_i into the production function). Because the manager's time is overhead, team-level productivity is higher if manager time is lower for the same level of output. Her overhead activity is to audit the work of employees and adjust payouts accordingly. If an employee is audited, the manager receives an accurate signal of that employee's level of effort $e_{g,i}$ and thus his or her productivity.[8] For any given level of managerial monitoring, the probability of being audited by the manager is inversely proportional to team size.

Combining the observation of $e_{g,i}$ and a work-in-progress signal about $f(\mathbf{E})$, the manager receives some information about all other workers that are strong substitutes for or complements to that

[8] If the production technology is stochastic, the signal might or might not include person- and team-level shocks. If the signal includes the shocks, it is a direct measure of individual productivity. If not, it is more properly a measure of effort. Each is a noisy signal for the other, and the difference is not material for our model.

worker. Consider two extreme examples. In the first example, all workers are near-perfect substitutes for one another such as a group of database administrators (conceptually similar to the cashiers in Mas & Moretti (2009)). In the second example, the work is fairly sequential between groups such that the process resembles a Leontief technology.[9]

In the first example, for any given level of team output, a high-productivity signal for one worker indicates that Bayesian updating will lower the manager's opinion of teammates' productivity. The reverse is true if the manager observes a low-productivity signal. In the second example, observing any given $e_{g,i}$ in complete isolation reveals no information at all about coworker's effort. However, the manager can easily observe where the slow-down is occurring because inputs will be piling up at a particular workstation. In both cases, the manager's time in auditing can be leveraged across several workers. This leverage decreases the manager time required, which we have defined as an increase in team-level productivity.

So while the probability of a worker being audited is proportional to 1/GN, the probability of the manager gaining information about a worker is directly proportional to his or her connectedness with coworkers (whether as substitutes or complements). If $\partial^2 f\left(\mathbf{E}\right)/\partial e_{g,i}\partial e_{h,j} \neq 0$, each worker's effort functions as a shock to all coworkers' individual productivities.[10] Auditing a worker reveals some information about the shocks experienced by coworkers, which in turn reveals some information about each coworker's productivity. If these shocks are economically significant and workers are risk-averse, the firm can economize on agency costs by using rank-order evaluations (Lazear & Rosen, 1981). Rank-order evaluations are less costly, which leads to a further reduction in monitoring costs.

[9] This Leontif-like technology would eliminate the inter-group 1/G problem, but not the intra-group 1/N problem.
[10] A positive cross-partial derivative is often assumed for team-based production to be efficient (*e.g.*, Kremer (1993)). A positive cross-partial is the *definition* of team-based production in Alchain & Demsetz (1972). In our model, the cross-partial is positive unless workers are near-perfect substitutes *and* the team has significant excess capacity relative to "demand." Even in this inefficient case, the cross-partial would be negative and thus nonzero.

While the information leaked to the manager may not lead directly to the source of a problem, it will give the manager more information than simply observing $f(\mathbf{E})$. The manager can also economize on monitoring with *ex ante* manipulation of the team's task design and also by choosing to monitor those tasks/workers that reveal the most information.

Proposition 3 The level of managerial effort required to direct a team will be lower the more its members' efforts are substitutes or complements. That is, higher substitutability or complementarity will lead to higher team productivity through higher manager efficiency.

Note that Proposition 2 and Proposition 3 give contradictory predictions for teams that exhibit high substitutability. Proposition 2 says that free-riding will increase (which would tend to increase the manager effort required) while Proposition 3 says that the managers of these teams will be more efficient (which would tend to decrease the manager effort required). Which effect dominates is an empirical question.

To verify that our theoretical models reflect important factors in real-world productivity, we apply our models to a detailed dataset for empirical validation.

3. Data

The firm in our study is a large multi-national software developer with over twenty thousand employees in over a dozen countries. The firm provides IT consulting services as well as numerous software solutions. We focus on a specific business unit that provides a complex software product targeted at a specific vertical market segment. The firm's employees configure the software for each client and train the end-users, and in many cases custom code is written by developers to meet specific client requirements.[11]

[11] This business unit's clients are subject to a significant amount of regulation, so the changes are often to meet statutory or regulatory requirements rather than a preference of the customer or to preserve some type of competitive advantage.

For this study, we based all employee-level analysis on the firm's administrative records. We use two data sources: human resources records and timecards. Human resources records allow us to observe demographic information and date of hire. We also observe job titles, base salaries, and performance ratings over time. Timecards record all time off in various categories as well as project/subproject codes and location for all time worked.

Overall the data consist of 5317 person-month-subproject observations and include indicators for person, month, project, subproject, and location plus the number of hours billed and a work type variable coded from free-text descriptions entered into the original timecards. Each observation also includes repeated values for person-level characteristics (such as hire date and gender), person-month characteristics (such as sick time taken and job title), project-month and subproject-month characteristics (such as churn rate and dominant task type), and several calculated variables explained below.

We constructed variants of this dataset for different levels of analysis. First, since each subproject belongs to exactly one project, we constructed a variant of this dataset that includes observations at the person-month-project level (3572 observations). We also constructed other datasets at three other levels of aggregation: person-month (2066 observations), subproject-month (1111 observations), and project-month (318 observations). The human resources dataset contains 306 person-appraisals, but only 169 of these occur during the sample period of the timecard data.

The following table provides summary statistics of data that we use in our empirical investigation of the theoretical model. Note that the values are skewed a bit toward the more experienced employees because they appear in more months.

Table 1: Summary Statistics of Person-Month-Subproject Variables

Variable		Mean	Standard Dev.	Min	Max
Hours on this subproject this month	subprojHrs	59.91	62.55	0.20	352.00
Fraction of time on this subproject[12]	f_subprojHrs	38.86%	36.71%	0.09%	100.00%
Role-group hours[13]	myGroupHrs	307.29	344.64	0.30	1752.70
Fraction of role-group hours[14]	f_myGroupHrs	45.27%	38.77%	0.04%	100.00%
Subproject headcount	Hc	12.97	10.09	1	37
Managers	hc_manager	1.58	1.38	0	8
Nonmanagers	hc_nonmanager	11.39	9.20	0	33

There is considerable heterogeneity in the size of the subprojects and the fraction of a person's time devoted to a particular subproject. A typical person works almost sixty hours on a typical subproject within a month. On average he or she has twelve teammates and works under the supervision of one or two managers assigned to that subproject. About half of the time, this team includes members from two or more of these role groups: application developers, business analysists, database administrators/developers, managers, subject matter experts, technical writers, and trainers. This is evidence of how socially complex the production is in this firm, and why using unidimensional output metrics such as those found in previous information worker research is impractical.

We use two variables, *Job Type Tenure* and *Role Group Tenure* as human capital measures that tend to advance about 1/12 each month, except that they reset to zero if an employee changes roles in certain ways. When an employee's role changes, his or her *Role Group Tenure* and *Job Type Tenure* may start over again at zero. If the employee stays within the same role group, his or her *Role Group Tenure* continues to accrue. If he or she moves into a different role group, then the tenure variable starts again at zero. The variable *Job Type Tenure* is very similar, except that we define only three job types: developers (the first three role groups), managers, and specialists (the final three role groups).

[12] These will add up to 100% within a given person-month.
[13] For example, if an Application Developer 2 is one of four Application Developers that works 10 hours on a project, each would have 40 hours of role-group hours for that project-month.
[14] Continuing the above example, each would have 25% of the role-group hours for that project-month.

These measures of human capital differ only in their level of aggregation, so they are highly positively correlated.

In addition, there are a number of variables that change every month, but not with gradual increases. Examples include the number of subprojects worked in a month and the number of sick time hours taken in a month.

Other variables change over time, but less often than every month. Employees receive performance appraisals approximately annually, and most also receive a wage adjustment shortly thereafter. Analysis of the wage profiles within this firm indicate that wage increases are in percentage terms,[15] so when we control for wages we use the natural logarithm of annual wages.

The following table shows project-month variables used in the Monitoring section. Since all of these are measures of size and complexity, they are all strongly correlated. We use role groups (as defined on page 16) as our proxy for task types in a project. The variable *Count of Task Types* shows how many of the seven role groups are represented in a particular project-month; as can be seen in the table, projects usually have more than one role group working at a time.

Table 2: Summary Statistics of Project-Month Variables

Variable		Mean	Standard Dev.	Min	Max
Manager hours	managerHrs	142.091	365.889	0.0	1905.0
Nonmanager hours	staffHrs	894.282	2490.502	0.5	14139.8
Nonmanager headcount	staffHC	15.852	33.821	1	164
Count of task types	taskCount	2.911	1.647	1	7

Using these data, we next turn to developing measures for productivity, team size, and substitutability that will allow us to test our theoretical framework.

4. Analysis

[15] A hedonic regression of wages controlling for role and performance rating reveals a linear relationship between length of service and the log of annual salary. Other transformations of the wage do not exhibit simple relationships to length of service.

In our theoretical model, productivity depends on individuals' effort decisions, and these decisions depend on the incentives provided by the firm. The strength of these incentives is necessarily limited by how well the firm can observe individual productivity. In a team production environment, one of the most important factors affecting the team members is the composition of the team itself. Large teams with similar skills create an environment vulnerable to free-riding. Another important factor is the amount and efficiency of monitoring activity that the employees expect.

Taking these factors into account, we construct measures and estimation techniques to empirically test the propositions from our theoretical model.

Teams

Individual productivity depends to a large extent on the employee's level of effort. Although employees are getting paid but generally not doing work while out sick, we are primarily using absenteeism as a noisy signal of lower productivity even on days the employee is working (Ostroff, 1992).[16]

A review of absenteeism research by Harrison & Martocchio (1998) finds that the two most common measures of absenteeism are frequency of absences and time lost per period. Driven by data availability, we use hours of reported sick time in a person-month as our measure of absenteeism because this is the same timescale as our assignment data, and we believe that assignments' effects on absenteeism are contemporaneous.[17]

In order to perform our analysis we calculated measures for team size and employee contribution to a subproject (as a proxy of substitutability with other team members). Summary statistics for these derived measures are presented below in Table 3.

[16] Of course, other factors may affect effort. For example, an employee's spouse may become unemployed, which would induce an employee to exert higher effort in an attempt to avoid any possibility of losing one's job at this firm. These events are presumably rare, and definitely outside the manager's control, so we treat them as noise.

[17] Harrison & Martocchio (1998) indicate that "job satisfaction" affects absenteeism over a medium term of months to a year, but we are measuring more immediate responses to job conditions that change more rapidly than this.

We measure team size in two ways, consistent with our theoretical model on page 10. Our measure for *Team Size* is the number of people who worked on the same subprojects as the focal employee in month t (equivalent to GN in the model). The variable *Group Size* is defined analogously except that it includes only people in the same role group as the focal employee (equivalent to N in the model).

While we do not observe a direct measure of substitutability between group members, we do observe how billed time is divided among a group. From this we form an inverse proxy for substitutability that we label *Contribution*. The variable *Contribution* is based on the assumption that if all persons in the same role group g on the same subproject s in the same month t are substitutes for one another, then their time will be split more or less evenly. Conversely, if the time primarily accrues to one or a few members then they possess scarce skills. To get a measure of how scarce person i's skills are in group g in month t, *Contribution* is calculated as the weighted average of *Fraction of Role-Group Hours* on each subproject, weighted by hours billed to each subproject.

Table 3: Summary Statistics of Derived Person-Month Variables

Variable		**Mean**	**Standard Dev.**	**Min**	**Max**
Team Size	teamSize	24.718	16.211	1	89
Group (subteam) Size	groupSize	7.506	5.621	1	37
Contribution to subprojects	Contribution	46.14%	30.21%	0.09%	100.00%

One way to conceptualize absenteeism is a normative standard level of productivity minus actual productivity. However, since productivity and payoffs are continuous, it is entirely possible that a worker would choose to work more than is expected. Such a situation would result in "negative absenteeism" that we cannot observe.[18] Because our response variable conceptually could be positive

[18] The sample consists primarily of salaried employees, so "overtime" is not actually evidence of trying to secure a higher paycheck.

or negative, but we can only observe nonnegative values, we employ a Tobit regression technique treating our observations as censored from the left at zero.[19]

To account for intrinsic differences across workers, we would prefer to include fixed effects for each worker. Unfortunately, opportunities for free riding are not fixed over time, and including fixed effects adds considerable instability to a Tobit regression (Greene, 2004). For this reason we include instead worker-level random effects. Our empirical model is

$$toSick^*_{i,t} = \alpha_0 + \alpha_1 teamSize_{i,t} + \alpha_2 groupSize_{i,t} + \alpha_3 contribution_{i,t} + \boldsymbol{\beta}'\mathbf{z}_{i,t} + \varepsilon_{i,t} \tag{6}$$

$$toSick_{i,t} = \max\left[0, toSick^*_{i,t}\right] \tag{7}$$

where $toSick^*_{i,t}$ is the intended or latent time-off for sickness for person i in month t, $toSick_{i,t}$ is the observed time-off for sickness, $\mathbf{z}_{i,t}$ is a vector of controls, $\varepsilon_{i,t}$ is a random-effects error term, and the other variables are defined earlier in this section.

Monitoring

The amount of time needed to monitor a team is an inverse measure of team-level productivity, but from a different perspective it can also be used as a measure of the manager's productivity (the manager is herself a knowledge worker). A manager's span of control is an efficiency measure that we define as the number of staff hours controlled by each manager hour. Since all managers work roughly the same number of hours each month, higher span of control is also an importance measure. To support our analysis we also calculate measures of project-level task concentration, manager experience, nonmanagers' depth of experience, and nonmanagers' breadth of experience. Summary statistics for these derived measures are presented below.

[19] The traditional R^2 metric is not valid with the random-effects panel Tobit estimator, but a goodness-of-fit measure is desirable for comparison. The pseudo-R^2 from McKelvey & Zavoina (1975) is valid for Tobit models (Veall & Zimmermann, 1994 & 1996).

For monitoring we use project-month (as opposed to subproject-month) observations to improve the precision of our observations. The subprojects of a project are highly interrelated, and it seems inefficient to force managers to apportion every moment to precisely the correct subproject. In fact, there are many small subprojects to which no manager time is billed at all, but it is obvious from conversations with development personnel that these small teams are in fact directed by managers.[20] Focusing on the project level therefore reduces the noise of mis-allocated manager time. Therefore, we measure span of control at the project-month level as the proportion of managerial time *vs.* non-managerial time.

The observed span of control will depend largely on the structure of the project and the staff assigned to it. One important part of the team composition is the size of the team which we define as the sum of staff (nonmanager) hours billed to the project in a month.

Independent of project composition, we expect productivity to improve with the accumulation of experience. The experience level of the manager and the staff are both important, so we will control for them in our empirical model. Human capital theory posits that employees become more productive through learning-by-doing, and Boh *et al.* (2007) find evidence that this theory can explain productivity improvements in software developers. Human capital is not perfectly general; for example some of what an employee learns may be specific to his or her employer and useless if he or she changes jobs. Huckman *et al.* (2009) take this one step further and investigate whether some human capital is task-specific, so we measure human capital using *Role Group Tenure* in the same seven categories listed above. A person's "depth" of experience is his or her experience in his or her current role group. The sum of all other experience is his or her "breadth" of experience. The *Staff Experience Depth* variable is

[20] A handful of project codes are not associated with any management time. The free-text descriptions for many these observations indicate that they are recording travel, recruiting, or off-site training. Such project-months yield an undefined quantity for *Span of Control* and are thus systematically excluded from the sample.

the weighted average of all nonmanagers' "depth" (using time billed to the project as the weight). Similarly, *Staff Experience Breadth* is the weighted average of all nonmanagers' "breadth."

From our theoretical model, we expect managers' productivity to increase when staff tasks are homogenous (high ρ in the model). To measure the diversity of tasks on a project, we use the *ex post* division of labor within a project-month to determine the tasks involved. If a project-month includes 100 man-hours of Business Analyst time and 50 man-hours of Subject Matter Expert time, that project-month is treated as two-thirds Business Analyst tasks and one-third Subject Matter Expert tasks. To generate a measure of task diversity, we calculate a Herfindahl concentration score of task division. In the above example, the two-thirds/one-third split would result in a task concentration score of approximately 0.556. Our theoretical model also predicts that managers' productivity will increase when staff tasks are highly complementary (very low ρ which we do not observe, but we do observe teams with high G or P).

Table 4: Summary Statistics of Derived Project-Month Variables

Variable		Mean	Standard Dev.	Min	Max
Span of control	projSpan	7.428	12.122	0.000	68.000
Task concentration	taskConcentration	0.650	0.286	0.229	1.000
Manager experience	managerDepth	0.387	0.649	0.000	3.814
Staff experience depth	nonmanagerDepth	2.393	0.944	0.030	4.830
Staff experience breadth	nonmanagerBreadth	0.083	0.255	0.000	1.719

Our empirical model is

$$projSpan_{p,t} = \gamma_0 + \gamma_1 staffHrs_{p,t} + \gamma_2 taskCount_{p,t} + \gamma_3 taskConcentration_{p,t} + \boldsymbol{\delta}'\mathbf{z}_{p,t} + \eta_{p,t} \qquad (8)$$

where $projSpan_{p,t}$ is the observed span of control for project p in month t, the next three variables are from Table 2 and Table 4, $\mathbf{z}_{p,t}$ is a vector of controls, and $\eta_{p,t}$ is an error term clustered at the project level. Using these methods, we uncovered several interesting empirical results reported below.

5. Empirical Results

Teams

According to our theoretical framework, we expect individual productivity to decrease in larger groups and in more homogenous groups. We find that both effects are present and in the hypothesized directions as shown below in Table 5. The panel pseudo-R^2 measure for Model I(b) is 0.4147, which is impressive for predicting an activity that must remain undetected to be effective.

The effect of *Total Headcount* is positive on absenteeism, supporting Proposition 1. The negative effect of *Total Team Hours* represents the relative visibility of the subproject and is plausibly related to the level of attention paid by management. The negative effect of contribution indicates that workers with scarce skills (those for whom substitutability is difficult) have lower levels of absenteeism, supporting Proposition 2.

Table 5: Effort Estimation Results (N = 2048)

	Model I(a)	Model I(b)
Estimation Method	Random Effects Panel Tobit	
Dependent Variable	Sick Time (in hours)	
Observation	Person-Month[21]	
Team size		-0.168*** (0.064)
Group (subteam) size		0.390** (0.192)
Contribution	-5.071*** (1.875)	-4.152* (2.268)
Rating	-1.839** (0.924)	-1.707* (0.916)
Length of service	-0.059 (0.170)	-0.052 (0.165)
Hourly employee	8.144*** (3.170)	8.248*** (3.077)
Intercept	-4.478 (3.822)	-4.223 (3.979)
σ_u	8.930	8.567
σ_e	13.141	13.161
$\rho = \sigma_u^2 / \left(\sigma_u^2 + \sigma_e^2\right)$	0.316	0.298
Panel pseudo-R^2	0.330	0.415

Note: Standard errors in parentheses. * indicates $p < 0.10$, ** indicates $p < 0.05$, and *** indicates $p < 0.01$

A one standard deviation increase in *Group Size* increases reported sick time by 2.19 hours, which is economically significant since this affects *each coworker* in the focal employee' role group. It also happens to be bigger than the mean reported sick time (1.98 hours) once outliers are removed. Decreasing *Contribution* from 1 to 0.5 without affecting the hours worked (that is, splitting a unique contributor's work across two people) increases sick time by 2.08 hours for both workers and increases the *Group Size* by one for each, indicating a net increase of 4.932 hours. This clearly illustrates the substitutability effect in Proposition 2.

[21] Person-month observations with 40 or more hours of sick time are excluded from the sample since such absences need to be justified on medical grounds, and they are highly influential outliers if they are included.

If there was already more than one person in that role group, the drop in *Contribution* from adding one more would be smaller. In this situation, the increase in observed sick time would be smaller, consistent with the last part of Proposition 2.

The positive coefficient on *Team Size* indicates that complementarity between groups (P in the model) is high enough to overcome the $1/G$ effect.

Monitoring

In our theoretical model, a manager's monitoring becomes more efficient as her team's work becomes more substitutable or complementary. Taking auditing as an overhead activity, this means that team-level productivity increases when the nonmanagers' work is substitutable or complementary. Although we cannot measure complementarity directly, we find a strong negative impact on the observed level of monitoring effort as substitutability among workers increases.

Our main measure of managerial efficiency is *Span of Control*. This quantity is a ratio, so we first wish to establish that the numerator (*Nonmanager Hours*) and denominator (*Manager Hours*) tend to move together *ceteris paribus*. We then include our variables of interest to establish that the relationship between numerator and denominator changes in response to these variables. Our empirical model for the first column of Table 6 is

$$mgrHrs_{p,t} = \kappa_0 + \kappa_1 staffHrs_{p,t} + \kappa_2 staffHrs_{p,t}^2 + \boldsymbol{\lambda}'\mathbf{z}_{p,t} + \zeta_{p,t} \tag{9}$$

where $\mathbf{z}_{p,t}$ is a vector of controls, and our empirical model for the remaining columns is

$$\begin{aligned} mgrHrs_{p,t} = \kappa_0 + \kappa_1 staffHrs_{p,t} + \kappa_2 staffHrs_{p,t}^2 + \kappa_3 taskCount_{p,t} + \kappa_4 taskConcentration_{p,t} + \\ \kappa_5 \left(staffHrs_{p,t} \times taskConcentration_{p,t} \right) + \boldsymbol{\lambda}'\mathbf{z}_{p,t} + \zeta_{p,t} \end{aligned} \tag{10}$$

Again we cluster the error $\zeta_{p,t}$ at the project level.

Table 6: Manager Time Estimation Results (N = 305)

	Model II(a)	Model II(b)	Model II(c)	Model II(d)
Estimation Method	OLS with errors clustered on projects			
Dependent Variable	Manager hours			
Observation	Project-month			
Nonmanager hours (Hrs)	0.172*** (0.023)	0.170*** (0.024)	0.175*** (0.027)	0.282*** (0.010)
Nonmanager hours squared	-2.75×10^{-6} (2.03×10^{-6})	-2.60×10^{-6} (2.06×10^{-6})	-2.90×10^{-6} (2.21×10^{-6})	-5.91×10^{-6}*** (1.50×10^{-6})
Number of groups			0.777 (8.778)	1.077 (8.230)
Task concentration (TC)			39.413 (36.237)	62.050* (31.146)
TC × Hrs				-0.259*** (0.080)
Manager experience	98.480*** (18.363)	101.077*** (18.112)	108.434*** (17.190)	107.435*** (16.694)
Staff experience depth		-10.423** (4.513)	-10.788** (4.576)	-10.662** (4.631)
Staff experience breadth		-31.643* (15.795)	-26.835 (16.147)	-28.406* (14.486)
Intercept	-13.858** (6.464)	7.687 (12.016)	-31.163 (41.563)	-42.339 (33.637)
Project type dummies[22]	Yes			
R^2	0.965	0.966	0.966	0.969

Note: Standard errors in parentheses. * indicates $p < 0.10$, ** indicates $p < 0.05$, and *** indicates $p < 0.01$

In the first column of Table 6, Model II(a) shows that *Manager Hours* is linear in *Nonmanager Hours*. Each hour of manager labor directs about six hours of nonmanager labor. The strength of this relationship indicates that the ratio is likely to be valid across different team compositions, a requirement for the span of control model to be identified. There is also a positive relationship between manager experience and manager labor, perhaps indicating that more experienced managers are assigned the more difficult projects.

In the second column, Model II(b) shows that project teams with more experienced staff require less manager labor. A one-standard-deviation increase in *Staff Experience Depth* decreases the requirement

[22] Project types are customization, development, maintenance, training, and mixed. Some charged time is also for nonproject work such as hiring; all such time is coded as a "project type" of its own.

for manager labor by 9.8 hours per month, or a little over one manager-day per month. There is also a marginal effect from *Staff Experience Breadth*, with a one-standard-deviation increase also saving about one manager-day per month. The effects of nonmanager labor and manager experience are qualitatively unchanged.

In the third column, Model II(c) adds the number of role groups (*G* in the model) in the project that month as well as *Task Concentration*. Neither of these is significant, and the only qualitative change to the other explanatory variables is that *Staff Experience Breadth* goes from marginal to insignificant.

In the fourth column, Model II(d) adds an interaction of nonmanager time and task concentration. The main effect of *Nonmanager Hours* is now slightly less than linear. The main effects of nonmanager time and task concentration are both positive and significant while the interaction is negative and significant.

Having confirmed that manager time responds to our variables of interest, we turn to our main dependent variable, *Span of Control*, for Table 7. Unlike Model II, here a higher number is more desirable. Model III(a) has the same explanatory variables as Model II(d). Unfortunately, the models' predictive power for this ratio is less powerful and colinearity masks the influence of some variables. In Model III(b) we drop the quadratic and interaction terms to clarify the small negative effects of team size.

Table 7: Span of Control Estimation Results (N = 169)

	Model III(a)	Model III(b)
Estimation Method	OLS with errors clustered on projects	
Dependent Variable	Span of control	
Observation	Project-month	
Nonmanager hours (Hrs)	-0.004 (0.003)	-0.001** (0.000)
Nonmanager hours squared	-0.148×10^{-6} (0.099×10^{-6})	
Number of groups	2.249* (1.110)	1.904* (1.078)
Task concentration (TC)	26.626*** (5.678)	27.530*** (5.680)
TC × Hrs	0.004 (0.006)	
Manager experience	-13.719*** (3.126)	-13.733*** (3.103)
Staff experience depth	0.322 (1.199)	0.325 (1.190)
Staff experience breadth	0.032 (2.083)	0.294 (2.138)
Intercept	2.498 (6.853)	3.361 (6.695)
Project type dummies	Yes	
R^2	0.424	0.418

Note: Standard errors in parentheses. * indicates $p < 0.10$, ** indicates $p < 0.05$, and *** indicates $p < 0.01$

In both versions of Table 7's Model III, *Span of Control* is positively influenced by *Task Concentration*. Since no significant interaction effect is present to complicate the relationship, this is direct evidence in support of Proposition 3.

6. Concluding Remarks

In this study we analyze the comparative statics of a common theoretical model of team production, developing several refutable predictions relevant to the productivity of information workers. We also demonstrate two methods for measuring the productivity of information workers in teams that do not rely on the detailed task-level metrics required by other methods. These measures are used to test the predictions of our theoretical model, and we find support for all three of our propositions.

Our results show that pooling information workers into teams can lower individual productivity by increasing shirking, perhaps outweighing the purported benefits of forming the team in the first place. An interesting implication is that managers can mitigate this drop in productivity by decreasing the substitutability of team members from the manager's point of view. While it is desirable for a manager to have several team members who could perform a task (this reduces the impact of environmental and personnel risks), it may increase the difficulty to measure the contribution of each individual to the team output.

Assigning "ownership" of tasks to individual employees would reduce substitutability (the responsibility for the task cannot be replicated) which would increase individual productivity by making output more observable at the individual level, confirming the intuition in Albanese & van Fleet (1985). However, if a manager habitually redistributes un-started tasks to balance workloads, there may be little or no benefit. In most environments, managers cannot rely on output counts (lines of code, closed tickets, etc.) because individual tasks vary in difficulty and overreliance on count measures would create perverse incentives against high-quality work.

There is more to the productivity of a team than simply summing the productivities of the individuals in it. The managerial implication of our team-level Monitoring results is that high interdependence among team members allows the manager to leverage her monitoring effectively across more employees, lowering overhead and thus increasing the team's productivity. This is analogous to a key performance indicator (KPI). A KPI represents an in-process or output measure that reflects the team's effect on the utility of several customers. Here the indicator reflects one's effect on several coworkers. While it is obvious that the socially complex production environment we observe is full of interdependencies and complementarities to assist auditing, it is not obvious that managers would also be able to leverage auditing effort across groups of similar employees. In this setting at least, the leverage effect dominates the free-riding effect such that large interdependent teams are feasible.

This study, of course, has limitations. By employing measures that would be broadly applicable, we necessarily sacrifice precision. In addition, our analysis assumes that each employee performs a single task according to his or her role at the time of working on a project. Future research could incorporate a more realistic model in which employees perform multiple tasks with varying levels of observability. Fitoussi & Gurbaxani (2008) show that providing effective incentives in such a situation is considerably more complex.

Future work may investigate measures beyond absenteeism and span of control that broadly capture effort and can be applied to the same population at the same time. For example, in a future study with the same focal firm, we will investigate turnover as a concept complementary to absenteeism. Absenteeism and turnover are related to affective commitment to the firm (Mowday *et al.*, 1982), and our new data will include the time at which the focal firm began offshoring some of its knowledge work. We expect this organizational change to impact long-term incentives by altering the availability of promotions, and it may also have affected affective commitment via feelings of job insecurity or psychological contract breach. Affective commitment can have a significant impact on how much the worker values continued employment with the firm, which is critical because the incentives facing information workers are largely based on continuing the employment relationship (as opposed to production workers, which usually have incentives including explicit monetary rewards).

As information work continues to displace production work in developed and developing economies, it is vital that we understand the incentives facing these employees and how to measure their impacts on employee productivity. The theoretical insights and empirical methods used here should form the basis of discovering means of identifying incentives and effects and their impact on information worker productivity.

References

Adams, C. (2006). Optimal Team Incentives with CES Production. *Economics Letters , 92* (1), 143–148.

Aggarwal, R., & Samwick, A. (2003). Performance Incentives within Firms: The Effect of Managerial Responsibility. *Journal of Finance , 58* (4), 1613-1649.

Akerlof, G., & Kranton, R. (2005). Identities and the Economics of Organizations. *Journal of Economic Perspectives , 19* (1), 9-32.

Akerlof, G., & Kranton, R. (2008). Identity, Supervision, and Work Groups. *American Economic Review: Papers & Proceedings , 98* (2), 212-217.

Albanese, R., & van Fleet, D. (1985). Rational Behavior in Groups: The Free-Riding Tendency. *Academy of Management Journal*, *10* (2), 244-255.

Alchain, A., & Demsetz, H. (1972). Production, Information Costs, and Economic Organization. *American Economic Review , 62* (5), 777-795.

Aral, S., & Weill, P. (2007). IT Assets, Organizational Capabilities, and Firm Performance: How Resource Allocations and Organizational Differences Explain Performance Variation. *Organization Science , 18* (5), 763–780.

Aral, S., Brynjolfsson, E., & Van Alstyne, M. (2007, June). *Information, Technology, and Information Worker Productivity: Task-Level Evidence*. Retrieved August 13, 2009, from http://www.nber.org/papers/w13172.pdf

Becker, G., & Murphy, K. (1992). The Division of Labor, Coordination Costs, and Knowledge. *Quarterly Journal of Economics , 107* (4), 1137-1160.

Boh, W., Slaughter, S., & Espinosa, J. A. (2007). Learning from Experience in Software Development: A Multilevel Analysis. *Management Science , 53* (8), 1315–1331.

Bresnahan, T., Brynjolfsson, E., & Hitt, L. (2002). Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-Level Evidence. *Quarterly Journal of Economics , 117* (1), 339-376.

Brynjolfsson, E., & Hitt, L. (1996). Paradox Lost? Firm-Level Evidence on the Returns to Information Systems Spending. *Management Science , 42* (4), 541-558.

Brynjolfsson, E., Fitoussi, D., & Hitt, L. (2005). The Information Technology Iceberg. Working paper.

Caya, O., Mortensen, M., & Pinsonneault, A. (2008). *Understanding Virtual Team Performance: A Synthesis of Research on the Effects of Team Design, Processes, and States*. Retrieved February 23, 2009 from http://ssrn.com/abstract=1282095.

Chidambaram, L., & Tung, L. (2005). Is Out of Sight, Out of Mind? An Empirical Study of Social Loafing in Technology-Supported Groups. *Information Systems Research*, *16* (2), 149-168.

Davamanirajan, P., Kauffman, R., Kriebel, C., & Mukhopadhyay, T. (2006). Systems Design, Process Performance and Economic Outcomes. *Proceedings of the 39th Hawaii International Conference on System Sciences*, (pp. 1-10). Kauai, HI.

Davenport, T., Harris, J., De Long, D., & Jacobson, A. (2001). Data to Knowledge to Results: Building an Analytic Capability. *California Management Review , 43* (2), 117-138.

Dedrick, J., Gurbaxani, V., & Kraemer, K. (2003). Information Technology and Economic Performance: A Critical Review of the Empirical Evidence. *ACM Computing Surveys , 35* (1), 1-28.

Fitoussi, D., & Gurbaxani, V. (2008, April). IT Outsourcing Contracts and Performance Measurement. Working paper.

Greene, W. (2004). Fixed Effects and Bias Due to the Incidental Parameters Problem in the Tobit. *Economietric Reviews , 23* (2), 125-147.

Harrison, D., & Martocchio, J. (1998). Time for Absenteeism: A 20-Year Review of Origins, Offshoots, and Outcomes. *Journal of Management , 24* (3), 305-350.

Heywood, J., & Jirjahn, U. (2009). Profit sharing and firm size: The role of team production. *Journal of Economic Behavior & Organization , 71*, 246–258.

Holmstrom, B. (1982). Moral Hazard in Teams. *Bell Journal of Economics , 13* (2), 324-340.

Huckman, R., Staats, B., & Upton, D. (2009). Team Familiarity, Role Experience, and Performance: Evidence from Indian Software Services. *Management Science , 55* (1), 85–100.

Kemerer, C. (1993). Reliability of Function Points Measurement: a Field Experiment. *Communications of the ACM , 36* (2), 85-97.

Klassen, K., Russell, R., & Chrisman, J. (1998). Efficiency and Productivity Measures for High Contact Services. *Service Industries Journal , 18* (4), 1-19.

Kraut, R., & Streeter, L. (1995). Coordination in Software Development. *Communications of the ACM , 38* (3), 69-81.

Kremer, M. (1993). The O-Ring Theory of Economic Development. *Quarterly Journal of Economics , 108* (3), 551-575.

Lazear, E. (2000). Performance Pay and Productivity. *American Economic Review , 90* (5), 1346-1361.

Lazear, E., & Rosen, S. (1981). Rank-Order Tournaments as Optimum Labor Contracts. *Journal of Political Economy , 89* (5), 841-864.

Levine, J. & Moreland, R. (1990). Progress in Small Group Research, *Annual Review of Psychology*, *41*, 585-634.

Mas, A., & Moretti, E. (2009). Peers at Work. *American Economic Review , 99* (1), 112-145.

McKelvey, R., & Zavoina, W. (1975). A Statistical Model for the Analysis of Ordinal Level Dependent Variables. *Journal of Mathematical Sociology , 4*, 103-120.

Melville, N., Kraemer, K., & Gurbaxani, V. (2004). Review: Information Technology and Organizational Performance: An Integrative Model of IT Business Value. *MIS Quarterly , 28* (2), 283-322.

Mowday, R., Porter, L., & Steers, R. (1982). *Employee-Organization Linkages: The Psychology of Commitment, Absenteeism, and Turnover.* New York: Academic Press.

Ostroff, C. (1992). The Relationship between Satisfaction, Attitudes, and Performance: An Organizational Level Analysis. *Journal of Applied Psychology , 75*, 963-974.

Pinsonneault, A., Barki, H., Gallupe, R., & Hoppen, N. (1999). Electronic Brainstorming: The Illusion of Productivity. *Information Systems Research*, *10* (2), 110-133.

Porter, L., & Steers, R. (1973). Organizational, Work, and Personal Factors in Employee Turnover and Absenteeism. *Psychological Bulletin , 80* (2), 151-176.

Ramasubbu, N., Mithas, S., Krishnan, M. S., & Kemerer, C. (2008). Work Dispersion, Process-Based Learning and Offshore Software Development Performance. *MIS Quarterly , 32* (2), 437-458.

Ramírez, Y., & Nembhard, D. (2004). Measuring Knowledge Worker Productivity: A Taxonomy. *Journal of Intellectual Capital , 5* (4), 602-628.

Rankin, F. (2004). Coordinating Effort under Team-Based and Individual Incentives: An Experimental Analysis. *Contemporary Accounting Research , 21* (1), 191-222.

Singh, P., Tan, Y., & Mookerjee, V. (2007). Social Capital, Structural Holes and Team Composition: Collaborative Networks of the Open Source Software Community. *Twenty Eighth International Conference on Information Systems*, (pp. 1-16). Montréal.

Tambe, P., & Hitt, L. (2008, May). Information Technology Employment and Productivity, 1987-2006. Working paper.

Veall, M., & Zimmermann, K. (1994). Goodness of Fit Measures in the Tobit Model. *Oxford Bulletin of Economics and Statistics , 56*, 485-499.

Veall, M., & Zimmermann, K. (1996). Psuedo-R^2 Measures for Some Common Limited Dependent Variable Models. *Journal of Economic Surveys , 10* (3), 241-259.

Winter, E. (2005, August 31). Co-location and Incentives. Working paper.

Wu, L., Waber, B., Aral, S., Brynjolfsson, E., & Pentland, A. (2008). Mining Face-to-Face Interaction Networks Using Sociometric Badges: Predicting Productivity in an IT Configuration Task. *Twenty Ninth International Conference on Information Systems.* Paris.

Yang, H.-L., & Tang, J.-H. (2004). Team Structure and Team Performance in IS Development: A Social Network Perspective. *Information & Management , 41* (3), 335–349.