NORTHWESTERN UNIVERSITY

The Impact of Collaboration Networks on Organizational Performance

A DISSERTATION

SUBMITTED TO THE GRADUATE SCHOOL

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS

for the degree

DOCTOR OF PHILOSOPHY

Field of Industrial Engineering and Management Sciences

By

Fang Liu

EVANSTON, ILLINOIS

June 2008

ABSTRACT

The Impact of Collaboration Networks on Organizational Performance

Fang Liu

Operations Management (OM) is concerned with the processes involved in delivering goods and services to customers (Hopp and Spearman 2000, Shim and Siegel 1999). While recent surge in service and professional white collar work has greatly changed the arena of OM practice, OM research has not yet well address the management of white collar work.

This study, drawing on knowledge from fields, such as operations management, economics, sociology, and organizational behavior, aims to (1) build a framework for studying white collar work system by identifying gap between current state of OM research and the needs for organizing white collar work; (2) understand collaboration network formation and its structural properties as a consequence of worker behaviors; and (3) understand the impact of existing collaboration network structures on white collar work performance.

In Chapter 2, we systematically review disparate streams of research relevant to understanding white collar work from an operations perspective.

In Chapter 3 and 4, we seek to understand the formation and structural properties of white collar worker collaboration network as a consequence of worker behaviors. In Chapter 3, we characterize the optimal collaboration network structure of heterogeneous white collar workers based on a mathematical model.

In Chapter 4, we examine the dynamic process of collaborative team formation among knowledge workers. We shows that managers may help improve the process by intervening the decentralized team formation through centralized policies.

In Chapter 5 and 6, we study the impact of existing network structure empirically. In Chapter 5, we examine the impact of network positions and interdisciplinary ties on white collar work performance in academic research environment. Our results show that (1) Eigenvector centrality has an inverted-U shape impact on research productivity and impact ; (2) inter-disciplinary research discussions promote research impact; and (3) peripheral positions in the awareness network tend to promote research productivity and impact.

In Chapter 6, we extend our empirical study on white collar performance to the top 25 engineering schools. we found that having more interdisciplinary collaborators promotes research performance at individual, department, and school levels.

Acknowledgements

I would like to express my gratitude to all those who gave me the possibility to complete this thesis.

I am deeply indebted to my advisors, Dr. Wallace J. Hopp and Dr. Seyed M.R. Iravani, for their guidance and support. I would also like to thank my committee member, Dr. Brian Uzzi, for his insights and comments. I thank Dean Julio M. Ottino, the dean of McCormick School of Engineering and Applied Sciences at Northwestern University, for his support of the McCormick project.

I am grateful for all the professors, staffs, and my fellow students in the Department of Industrial Engineering and Management Sciences, especially my officemates in C229, for their various help, friendship, interest, and valuable hints.

Finally, I would like to thank my husband, Guangming, for his support and encouragement throughout my study at Northwestern. I also thank my first baby girl, Aimee Yu Zhang, who is three month old, for her cooperation during my dissertation writing process. I thank my mother and brother for their unconditional love and support.

Dedication

To my family.

Table of Contents

List of Tables

List of Figures

CHAPTER 1

Introduction

Historically, Operations Management (OM) has its roots in manufacturing-oriented work systems. A large portion of OM research is concerned with the processes involved in delivering physical goods. OM studies mainly focus on task processing characterized by routine and physical work, the so-called ”blue collar” work (Hopp and Spearman 2000, Shim and Siegel 1999). However, the steady shift of economy towards service and professional “white collar” work has dramatically changed the arena of OM research. In white collar systems, work is creative and intellectual and therefore less precisely defined and controlled than in blue collar system. Consequently, the well-known principles in blue collar work systems, such as bottleneck behavior, task sequencing, line balancing, variability buffering and many others (Askin and Goldberg 2002, Hopp and Spearman 2000) cannot be directly applied to help us evaluate, improve and design white collar work systems. This lack of effective management principles in organizing white collar work has made the needs for a science of white collar work immediate and imperative.

In this research study, we examine collaborative behaviors in white collar work systems. Drawing on knowledge from fields, such as operations management, economics, sociology, and organizational behavior, we aim to (1) build a framework for studying white collar work system by identifying gap between current state of OM research and the needs for organizing white collar work; (2) understand collaboration formation and network structural properties as a consequence of worker behaviors; and (3) understand the impact of existing collaboration network structures on white collar work performance.

In Chapter 2, we systematically review disparate streams of research relevant to understanding white collar work from an operations perspective. We propose generic models of white collar work study at individual, team, and organization levels. By exploring the key issues related to operations management, we are able to identify research gaps and propose new directions for developing a operational science of white collar work.

In Chapter 3 and 4, we seek to understand the formation and structural properties of white collar worker collaboration network as a consequence of worker behaviors. In chapter 3, we study the optimal collaboration network structure with heterogeneous white collar workers. We introduce a mathematical model of collaboration, which we term a "hint model" because we view information as flowing among a network of knowledge workers in the form of hints. Workers translate these hints into intellectual property, which in turn generates revenue. We make use of this model to generate insights into the network structure by examining the flow of information that maximizes expected revenue. By disaggregating information into specialties, we are able to show that the optimal network has a well-ordered structure within specialties, such that each worker plays a unique role as a "giver", "taker" or "loner". However, the optimal aggregate network structure can exhibit a wide range of behaviors. By studying multi-specialty systems numerically using linear programming to generate optimal solutions, we conclude that organizational performance is best when creativity and productivity rates are balanced, workers are heterogeneous in their abilities and worker specialization within disciplines is allowed.

In Chapter 4, we examine the dynamic process of collaboration formation among knowledge workers. In contrast to many pervious work, which examine the long-run behaviors of collaboration networks, we study the performance of team formation process within a finite time horizon. We focus on understanding the role of different management policies in fostering efficient work teams. Assuming that individuals may gain information of their potential partners from self experiences as well as through social learning, we model the collaboration decision making as a process combining knowledge obtained through reinforced and social learning while taking mutual trust and informational benefit into considerations. Our results show that management intrusion aims at improving the network connectivity is more efficient than decentralized self-organizing policy. Higher trust level leads to higher productivity and trust is more valuable when teams are formed completely based on agents' own decisions. Taking both productivity and social information benefit into account when making decisions in team formation has different impact on team performance in various types of organizations. It works better than considering productivity only when management intrusion is implemented.

In Chapter 5 and 6, we study the impact of existing network structure on worker performance. In Chapter 5, we examine the impact of network positions and interdisciplinary ties on white collar work performance in academic research environment. We use a social network analysis to examine the role of various types of interactions among the faculty of an American engineering school, ranging from mere awareness to full coauthorship, on academic research productivity (measured by weighted publication rates) and impact (measured by weighted citation rates). Our results suggest that central positions in the discussion network have the most significant impact on individual work performance. However, increasing centrality exhibits diminishing returns, presumably because of the overhead associated with sustaining too many research interactions. Our results also suggest that inter-disciplinary research discussions promote both research productivity and impact. Finally, we observe that peripheral positions in a network that describes awareness of individuals' research activities tends to incur a research productivity and impact advantage, presumably because these indicate innovative domains.

In Chapter 6, we extend our empirical study on white collar performance in Chapter 5 to the top 25 engineering schools. We focus on understanding the impact of interdisciplinary collaboration on research performance. Using the publication and coauthorship between year 2000 and 2005 and two-period linear regression models, we find consistent positive impact of interdisciplinary collaboration on research impact (i.e., based on citations) at individual, department, and school levels. We also find significant positive impact of interdisciplinary collaboration on research productivity (i.e., based on publications) at individual and department but not school level.

CHAPTER 2

White Collar Workforce Management: An Operations-Oriented Survey

2.1. Introduction

Operations Management (OM) is concerned with the processes involved in delivering goods and services to customers (Hopp and Spearman, 2000; Shim and Siegel, 1999). At the core of many of these processes is the workforce. Indeed, the field of OM has its roots in the labor efficiency studies of Frederick W. Taylor and other champions of the Scientific Management movement of the early twentieth century. Because these early studies focused on manufacturing and other physical tasks, the OM field developed a tradition of studying "blue collar" systems. The dramatic improvements in direct labor productivity over the past several decades suggest that this line of research has been highly effective.

However, in recent years, the U.S. economy has steadily shifted toward service and professional "white collar" work (Davenport et al., 2002). Such workers constitute 34 percent of workforce according to the Bureau of Labor Statistics (BLS) category of "managerial, professional, and technical" (Davenport et al., 2002). According to BLS, workers in "management, business, and financial occupations" and in "professional and related occupations" will increase 14.4% and 21.2% respectively from 2004 to 2014, which rank as the 3rd and 1st fastest increased occupations [1]. As a consequence of fast growing white collar work, future economic growth will depend much more on improving productivity of workers in white collar work settings than on achieving further improvements in blue collar productivity.

Despite the obvious importance of white collar work to the economy, it is much less understood in an operations sense than is blue collar work. Well-known principles of bottleneck behavior, task sequencing, line balancing, variability buffering and many others (Askin and Goldberg, 2002; Hopp and Spearman, 2000) help us evaluate, improve and design blue collar work work systems. But in white collar work systems, where tasks are less precisely defined and controlled than in blue collar systems, we do not yet have principles for guiding operations decisions. Fundamental questions remain unanswered. For example: What is the bottleneck of a white collar work system? What are appropriate measures of productivity? How does collaboration affect performance? To answer these and many other questions, we need a science of white collar workforce operations.

A variety of fields, including Operations Management, Economics, Sociology, Marketing, and Organizational Behavior have produced streams of research relevant to white collar work. While these have yet to coalesce into a coherent science, research in these fields has yielded useful insights. In this chapter, we survey a wide range of research that offers promise for understanding the operations of white collar work. Our objectives are to bring together these disparate threads, provide a framework for organizing them, and identify needs and opportunities for developing a science of white collar work.

[1] http://www.bls.gov/emp/emptab1.htm

2.2. Definition of White Collar Work

To achieve these objectives we must first define what we mean by white collar work. Historically, the term "white collar" has been used loosely to refer to salaried office workers, in contrast with hourly "blue collar" manual laborers (Shirai, 1983).[2] Sometimes "white collar" refers to the rank or social status of the worker. For example, answer.com defines white collar worker as "office worker in professional, managerial, or administrative position. Such workers typically wear shirts with white collars.[3]" Other definitions of white and blue collar work are based on whether the worker performs manual work. For example, Prandy et al. (1982) used the term "white-collar" to refer to non-manual labor, e.g., supervisors, clerks, professionals, and senior managers. Still other definition of white collar work focused on job categories. For example, Coates (1986) divided white collar work into three categories: clerical, professional, and managerial. Because of the nature of the work, some scholars have equated white collar workers with knowledge workers (McNamar, 1973; Ramirez and Nembhard, 2004). In this vein, Stamp (1995) summarized eight important aspects of white collar work: "Surfacing and aligning values and vision," "Thinking strategically," "Focusing key resources, at the same time maintaining flexibility," "Managing priorities," "Measuring performance," "Accepting ownership, responsibility and accountability," "Influencing, while maintaining interpersonal awareness," and "Continually improving people, products and processes."

Although these definitions give a general sense of what constitutes white collar work and how it differs from blue collar work, they do not provide a precise or consistent

[2]The root of these terms is the color of the shirts worn by the workers; office workers traditionally wore white shirts, while laborers wore work shirts that were often blue. Relaxation of professional dress codes and colorful trends in fashion have rendered these terms somewhat anachronistic.

[3]See http://www.answers.com/topic/white-collar-worker.

statement that we can use to focus research into the operations of white collar work. For example, Coates (1986) classifies clerical work, such as typing, as white collar work. However, typing does not have any of the eight features of white collar work as defined in Stamp (1995). Moreover, from an operations perspective, typing has much more in common with machining (commonly thought of as "blue collar") than with management (commonly thought of as "white collar"). To study the operations aspects of white collar work, we need a definition that distinguishes white and blue collar work in operationally meaningful ways.

Some researchers have argued that the old white-blue work dichotomy is obsolete (Barley and Kunda, 2001; Zuboff, 1988). While we agree that management practices, such as empowerment and self-directed teams may indeed blur the distinction between white and blue collar work, we believe there remains a fundamental distinction between the two types of work at the *task level*. That is, we focus on the tasks involved in the work, (e.g., financial consulting, operating machine tool) rather than on the workers (e.g., financial advisors, machine tool operators).

Viewed in this way, someone we customarily think of as blue collar worker may perform white collar tasks (e.g., a machinist brainstorms methods for improving the yield of his operation). Conversely, some we normally think of as a white collar worker may perform blue collar tasks (e.g., a professor makes her own photocopies). Hopp and Van Oyen (2004) defined a task as a *process* that brings together *labor*, *entities* and *resources* to accomplish a specified objective. In this highly general definition, labor refers to workers (e.g, machinist, doctor, cashier, banker). An entity represents the job being worked on (e.g., part, patient, customer, financial transaction). Resources include anything used by labor to carry out the activity of the task, such as equipment (e.g., machines, computers), technology (e.g., algorithms, infrastructure systems), and intellectual property (e.g., books, reports, outside expertise).

A task is defined by the three element - labor, entities and resources - as well as the processes that describe how they are brought together. For our purposes, whether a task is classified as blue or white collar depends on how it is characterized along two dimensions:

(1) *Intellectual vs. Physical:* White collar tasks mainly involve using knowledge as a dominant element in generating ideas, processes or solutions (Davenport and Prusak, 2002), while blue collar tasks mainly involve physical labor to perform a mechanical transformation of a material object. For example, data analysis requires the worker to select and/or develop appropriate models specific to each different case by drawing on his/her expertise, statistical knowledge, and prior experiences. In contrast, moving a batch from one machine to another in shop floor requires physical effort but demand a low level of knowledge.

(2) *Creative vs. Routine:* White collar tasks mainly involve generation of novel solutions or combination of previously unrelated ideas (Davenport and Prusak, 2002; Perry-Smith and Shalley, 2003; Shalley, 1995), while blue collar tasks consist primarily of repetitive application of known methods to familiar situations. For example, to formulate a new drug, researchers must design new experiments based on their domain knowledge and creative thinking. Upon completion of each experiment, a new set of data is collected, analyzed, and used to direct new experiments. In contrast, sewing involves repetition of the same actions on each

garment. Because the required actions are repetitive in nature, clear procedures, which govern the work, can be specified in advance of the arrival of the work.

To provide a reasonable correspondence with the colloquial use of the terms "blue collar" and "white collar," we define a blue collar task to be one that is both physical and routine. Any task that is either intellectual or creative, we define as white collar. We illustrate this definition in Figure 1, with some examples of types of work characterized by different positions in this two dimensional space.

It is important to point out that, under this definition, there is no such thing as a pure blue collar or pure white collar job (Ramirez and Nembhard, 2004). For example, driving a lift truck to move heavy parts from one part of the factory to another is generally considered to be blue collar work. However, while driving a lift truck is mainly physical and routine, the driver must sometimes use his creativity to figure out how to efficiently load and unload large items with irregular shapes. So we classify the task of driving parts from point A to point B as a blue collar task, but classify the task of finding a way to transport new or unusual parts as a white collar task. Under our definition, all workers, whether they are conventionally thought of as white or blue collar, do both white and blue collar work (Drucker, 1999). Since, as OM scholars, we are interested in the efficiency of operations, we are more concerned with classifying and analyzing tasks than with classifying people. Models of white collar tasks are the foundation for a science of white collar work.

The above definition raises the question of how white collar work is related to service work. One might be tempted to classify all service work as white collar work because it does not involve heavy physical activity. For example, the tasks carried out by a bank

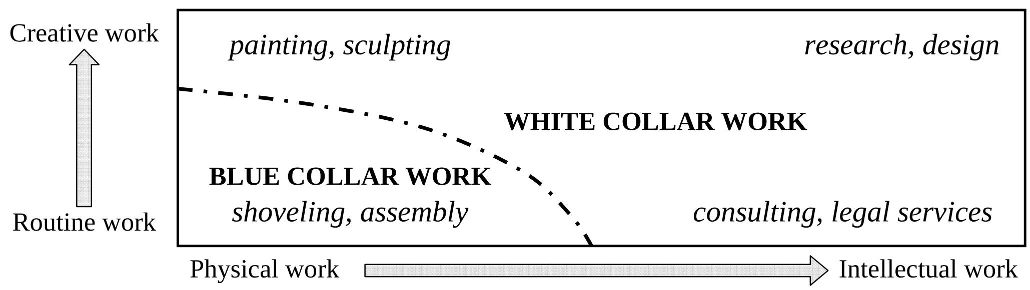


Figure 2.1. White Collar Work vs. Blue Collar Work

teller do not involve significant work in the physics sense. But, since these tasks are highly routine, they are neither intellectual nor creative. Hence, in our framework, tasks such as counting money, entering transactions in a bank book, cashing checks, etc., are predominantly physical and routine and therefore qualify as blue collar work. From an operations standpoint, the work of a bank teller has far more in common with that of an assembly line worker than it does with that of a lawyer or consultant.

A second distinction that is worth making is that between white collar work and knowledge work (Davenport et al., 2002). Roughly speaking, knowledge work corresponds to the right half of Figure 2.1, while production work corresponds to the left half. Any task with a high intellectual content qualifies as knowledge work. Under our definition, this also makes it white collar work. But there are also white collar tasks that are physical and not intellectual in nature. For instance, but they require a high level of creativity and so qualify as white collar work in our framework. Again, the work of a surgeon has more in common with that of a lawyer than that of a janitor, so it makes sense to include surgical tasks in the white collar category.

To build toward a science of white collar work, we follow the standard OM approach used to model blue collar systems by starting with a simple structures, such as single-class job, single-server (e.g., simple produce-to-order system) and extending the analysis to more complex structures, such as multi-class, multiple-server systems. To do this, we divide our taxonomy of white collar research into work at the *individual*, *group*, and *organization* levels. This allows us to compare and contrast issues in white and blue collar work systems. In Section 2.3, 2.4, and 2.5, we propose generic models for representing white collar work at individual, group, and organization level and then discuss research relevant to elements of the models. By noting which aspects of the generic models have not been well studied in the literature, we are able to suggest promising avenues of future research in Section 2.6. We summarize our overall conclusions in Section 2.7.

Covering all aspects of white collar work systems, which could include issues as diverse as public policy, education, urban development, etc., is impossible. So we restrict our goals to: (1) identifying key streams of research that are relevant to an operations understanding of white collar work, and (2) highlighting important papers within each stream that will help direct OM researchers to useful sources of literature for understanding white collar work.

2.3. White Collar Work at the Individual Level

The simplest context in which to study white collar work is that of a single person carrying out tasks independently. Examples include a doctor treating a patient, a scientist writing a research paper and a lawyer preparing a case. Although many studies in the OM literature have addressed systems that involve individual work (Buzacott and

Shanthikumar, 1993; Hopp and Spearman, 2000), these often implicitly combine workers with equipment by assuming “workers are not a major factor”, “people (i.e., workers) are deterministic and predictable,” “workers are stationary,” and “workers are emotionless” (Boudreau et al., 2003). While such assumptions may be oversimplifications in blue collar settings, they are completely unrealistic in white collar systems because white collar tasks involve knowledge and creativity, as well as human characteristics like learning, emotion and judgment. So representing these is a key step in modeling white collar work.

2.3.1. A Basic Model

To provide a conceptual framework for representing individual work, we return to the basic representation of a task in Hopp and Van Oyen (2004), which depicts tasks in terms of labor, entities and resources. Since we are talking about individual work, the labor in these systems consists of a single worker. The entities are the logical triggers of tasks. These could be outside requests (e.g., demands from the boss, customer calls for service) or internally generated items (e.g., an idea for a research paper, a plan for improving a system). The resources could include a broad range of physical (e.g., pen, paper, computer) and informational (e.g., books, web sites, personal knowledge, outside expertise) elements. Finally, a fourth element that describes an individual work system is the set of processes that govern how the labor, entities and resources are brought together to complete tasks. These could include sequencing/scheduling rules, incentive policies and a variety of management directives. We illustrate this individual work system schematically in Figure 2.2.

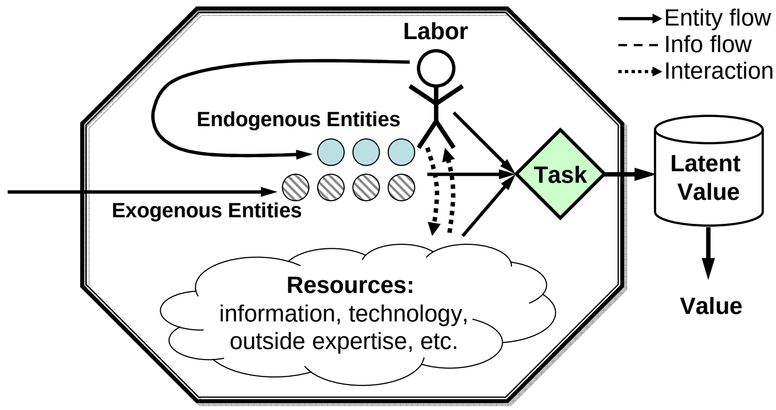


Figure 2.2. White Collar Work at the Individual Level

Note that this model highlights both some similarities and some key differences between white and blue collar work. Similarities stem from the fact that both systems exhibit queueing behavior, in which entities pile up awaiting attention from a worker with finite capacity. This means that variability and high utilization will cause congestion (see Hopp and Spearman (2000) for a discussion). But there are important differences, including:

(1) By our definition of white collar work, the tasks themselves are of an intellectual and/or creative nature. Workers must accumulate sufficient domain knowledge before they can carry out tasks. For example, a risk analyst must master a body of knowledge in order to understand, formulate, and analyze risk problems. Moreover, white collar tasks rarely repeat themselves, which implies that creativity is often important in white collar work. For example, in addition to assessing risks in familiar settings, a risk analyst must evaluate new risk scenarios, which requires a certain amount of creativity.

(2) White collar work systems rely more heavily on knowledge-based resources. While blue collar tasks may require informational inputs (e.g., an instruction sheet showing how parts should be assembled), the standardized nature of the work implies that these inputs will be relatively simple. In contrast, white collar tasks, which involve a higher level of intellectual complexity, may rely on general information that must be processed and synthesized by the worker. For instance, a lawyer preparing a case may have to cull through a vast backlog of precedents and select those relevant to the case at hand.

(3) Learning is slower and more central in white collar systems. The complexity of the resources and the novelty of the tasks mean that white collar workers often have more to learn than blue collar workers. While some models of blue collar work systems involve learning (e.g., by representing workers as growing more productive over time), such learning dynamics are even more important in white collar work systems. Moreover, since the skills involved may be diverse, this learning may be correlated with other things beyond time in the position.

(4) Measurement of output is more difficult in white collar work systems. In blue collar systems the outputs are primarily physical (e.g., completed assemblies, cleaned hotel rooms, painted houses). As such, their value can be measured immediately upon completion of a task. For example, a machining operation could go directly to a test station where it is checked for quality, so that the value created by the machinist could be measured as the rate of acceptable parts produced per day. But in white collar systems, the outputs often have a knowledge component. For example, a consultant writes up an analysis of a management problem

for a client. The value of such outputs is more difficult to measure. Even if client satisfaction (measured via a survey) could be used as a quality measure for the direct deliverables (i.e., the reports), there may be indirect value of the studies. For instance, a consulting job may produce new knowledge that will be valuable to the consulting firm in performing future jobs. These intangible knowledge outputs of white collar work are particularly difficult to value economically until long after the task has been completed.

(5) White collar work systems are much more likely to involve self-generated work. Blue collar tasks (e.g., assembling parts, sweeping a floor, ringing up an order on a cash register) generally address requests from the outside. But, because white collar tasks involve a higher degree of creativity, they are not so easily standardized. Hence, it is common for creative and intellectual workers to define at least some of their own workload. Examples include a poet turning an idea into a poem and a consultant adding a task to a consulting job to address an issue that was revealed by previous work.

(6) Workers tend to have more discretion over processing times in white collar systems. In blue collar systems, tasks are well-defined and so come with concrete completion criteria. A casting must be machined to specified tolerances, a room must be cleaned to stipulated standards, etc. But in white collar systems, where work is intellectually complex and/or nonstandard, detailed specifications are difficult to provide. An engineer tasked with solving a design problem has a general idea of what constitutes an acceptable solution. But he/she must use personal judgment to determine when the task is complete; this decision may depend on

customer needs, as well as the engineer's backlog of other work. Since the amount of time spent on a task is discretionary, system utilization is not exogenously determined in white collar systems as it is in blue collar systems. Hopp et al. (2007a) showed that this implies important differences in the operating behavior of blue and white collar work systems.

(7) Incentives are more critical. As we mentioned earlier, since tasks are intellectual and creative in nature, workers are given more control over task processing. This greater flexibility allows for a large variation in work performance, which suggests that incentives are extremely important in motivating worker behavior. Furthermore, a substantial amount of job satisfaction from white collar work largely is gained through non-pecuniary means, such as peer recognition, task complexity, exposure to smart colleagues, opportunity for self advancement, etc.. Hence, the focus of incentives in white collar work settings should differ from that in blue collar settings. Moreover, due to the difficulty of measuring performance objectively, white collar incentive plans must often be based on subjective measures of performance (e.g., staff evaluations).

By describing the operations of white collar tasks in a manner that highlights the above distinctions from blue collar work, the model in Figure 2 provides a framework for classifying research on white collar work at the individual level. Based on our definition of white collar tasks and the above discussion, some critical aspects of white collar tasks that are distinctive from blue collar tasks are: creativity, discretion, learning, performance measures, incentives, and technology. In the following subsections, we summarize streams of research that have addressed these elements.

2.3.2. Creativity

Creativity generally refers to the ability to generate novel ideas or solutions that are appropriate to the context (Amabile, 1983a, 1996; Amabile et al., 1996; Barron and Harrington, 1981). Early studies of creativity revealed the importance of individual characteristics, such as intelligence, broad interests, intuition, self-confidence, attraction to complexity, etc., to creativity (Amabile, 1983b; Barron and Harrington, 1981; Woodman and Schoenfeldt, 1989; Gough, 1979). More recent studies have emphasized the impact of task processes and organizational and social environments on creativity. One school of thought has argued that work contexts, such as task complexity, deadlines, goal orientations, perceived evaluations, and supervisory styles affect worker motivation and therefore creative performance (Oldham and Cummings, 1996; Shalley, 1991, 1995; Shalley et al., 2000; Chesbrough, 2003). Work from this stream of research suggests that increasing job complexity and enhancing supportive supervisory style can improve worker creativity (Oldham and Cummings, 1996). Another school of researchers have focused on the process of creativity. Fleming and Marx (2006) argued that creativity is a process of combining existing ideas with new ones. For example, research is a creative process implemented by combining existing disparate knowledge streams. MacCrimmon and Wagner (1994) examined creative process through computer simulation. They proposed a creativity model in which the process of creativity can be further divided into "problem structuring, idea generation, and evaluation". A more prevailing view of creativity is to treat creativity as a consequence of social exchange behaviors. Since this view often is examined in the context of organizations, we will extensively discuss it in Section 5.

2.3.3. Discretion

Another core difference between white and blue collar work lies in discretion, i.e., a worker's power to make decisions regarding processing time, task quality, task sequences, etc. Lack of prescribed detailed operational rules requires workers to handle tasks with high degree of discretion. For example, a consultant may determine how much time to spend writing a report based on his/her judgement of quality; a doctor may determine when to release a patient based on the patient's health condition. These discretionary decisions are important because spending extra time and efforts may add value to the output by either improving the quality (e.g., spending longer time may produce a better consulting report (Hopp et al., 2007a)), increasing the quantity (e.g., a doctor may charge more money for extra service (Debo et al., 2004)), or both. Such discretion is less common in blue collar tasks than in white collar tasks because blue collar work is generally straightforward and well defined. Spending extra time beyond a threshold required to complete the task does not significantly change the output. In contrast, in the more complex setting of white collar tasks, discretion is frequently reflected in task selection, prioritization and scheduling, processing time and output quality. The prevalence of discretion in white collar work makes it difficult to apply many results from blue collar research to white collar work systems because most of research on blue collar work systems is built on the assumption that workers are inflexible or have very limited flexibility (Boudreau et al., 2003; Hopp et al., 2007a).

Because task completion criteria in white collar work settings cannot be specified precisely in most cases, workers must rely on their own judgement to decide when a task in complete since task quality is generally nondecreasing in the amount of time spent on the task, this implies a speed versus quality tradeoff. Workers must somehow negotiate this tradeoff, taking into consideration the effect on future work. Hopp et al. (2007a) modeled this problem using an infinite horizon dynamic program with an objective to maximize value produced per unit time. They showed that optimal processing speed increases (and hence average task quality declines) as the number of customers waiting for service increases. Debo et al. (2004) also made the connection between work load and discretionary task completion in a capacited monopoly service expert situation. They modeled the system as a single-server queue with profit as an increasing function of service time spent, and showed the optimal policy is to increase service speed as work load increases.

While discretionary behavior introduces new problems to OM research, it also provides different insights into well understood problems. A general principle of blue collar work systems is that increasing worker capacity always reduces system congestion (i.e., the number of tasks waiting for labor attention). However, Hopp et al. (2007a) showed through simulation experiments that increasing worker capacity may result in higher system congestion when workers choose to use extra capacity to improve task quality instead of reducing congestion.

2.3.4. Learning

Learning plays a critical role in white collar work (Argote and Ingram, 2000). Because scenarios faced in white collar environments frequently evolve rapidly, workers must continually learn new things to perform well. Learning has been studied extensively in the form of "learning curves" in blue collar settings (Sutton and Barto, 1998; Cross, 1983;

Arthur, 1991; Roth and Erev, 1995). The core idea behind using learning curves in production systems stems from the observation that workers gain speed and quality through repetitive task processing. Hence, learning is essentially treated as a by-product of doing (i.e., *learning-by-doing*). Learning curve theory is well suited to blue collar work systems because blue collar work is more routine and stable over time than white collar work. In white collar settings, workers rely on ways other than learning-by-doing to gain knowledge because learning in such circumstances is not simply a by-product of doing (Ryu et al., 2005; Carrillo and Gaimon, 2004). Existing literature has touched on different aspects of learning, such as exploitation vs. exploration (Toubia, 2006), timing decisions (Ryu et al., 2005) and methods of learning (Pisano, 1994, 1996).

Because of the complexity of knowledge involved in white collar work, exploitation and exploration are particularly important activities in white collar learning. Exploitation seeks gradual addition of knowledge and leads to a marginal but certain contribution, while exploitation aims to acquire broader and deeper knowledge, and therefore offers a much less certain contribution (Levinthal and March, 1993; Toubia, 2006). Neither form of learning if without risk. Individuals who are mainly involved in exploitation may fail to achieve needed knowledge, whereas individuals who are exclusively involved in exploration may suffer from obsolescence (Levinthal and March, 1993). Hence, maintaining a balance between exploitation and exploration is critical for effective learning. Toubia (2006) studied idea generation with a two-period two-armed bandit model (Bellman, 1961) and showed that the choice of strategy (exploitation vs. exploration) is contingent on both the certainty of search and the degree of innovativeness required in the idea.

Ryu et al. (2005) studied the interaction between timing and form of learning. They used a model which maximizes the total net profit of knowledge acquisition within finite time periods, where net profit is the difference between total payoff from knowledge acquired and the cost incurred during the learning process. The value of knowledge acquired is measured as the product of knowledge depth and knowledge breadth. Total cost is measured by the cost incurred in the three distinct learning processes: learning-by-investment, learning-by-doing, and learning-from-others. The optimization decision is how to allocate efforts among these three learning processes. Their results characterize the impact of seven environmental factors (discount rate of cost, discount rate of payoff, salvage value of knowledge, initial knowledge, number of group members, productivity of learning-by-doing, and others' knowledge) on learning decisions and suggest an optimal strategy for the timing and type of learning. Pisano (1994, 1996) examined the forms of learning through empirical studies. The author found that learning-by-doing and learning-before-doing are effective ways of learning in different knowledge environments. "In environments where prior knowledge is weak, high-fidelity feedback requires experiments in the actual production environment ('learning-by-doing'). In contrast, when reliable theoretical models and heuristics exist, laboratory experiments, simulation, and other forms of 'learning-before-doing' can be productively harnessed" (Pisano, 1994).

2.3.5. Performance Measures

A key challenge of studying white collar work system is due to the difficulty of measuring work performance (Davenport and Prusak, 2002). In blue collar work, worker utilization, task completion time, output quality and quantity can be objectively measured, while facilitates a number of performance measures for evaluating system performance, including utilization, throughput makespan, failure rate, etc. However, these metrics often do not translate directly to white collar work because the inputs are much harder to measure. For example, using the number of reports a consultant produces within certain period of time (i.e., the throughput) is hardly inappropriate since the quality and complexity of reports may vary greatly. In general since the white collar tasks performed by a single worker often differ significantly (e.g., a lawyer's cases, a doctor's patients and a professor's advisees are all unique), it is difficult to establish uniform metrics of productivity or quality. Finally, white collar work often has a latent impact that can only be measured long after the task is completed. In such cases, fair judgement of output quality upon task completion is almost impossible.

In the literature, there have been a number of efforts to devise simple measures for output evaluation. Gillson et al. (2005) measured latent performance of service technicians by copy machine reliability, which is defined as the average number of copies a machine can make between two customer service calls. Several studies have measured the latent value of academic research publications via delayed recognition in terms of citations (Fleming, 2001; Fleming and Marx, 2006; Toubia, 2006; Almeida and Kogut, 1999). Fleming (2001) and Fleming and Marx (2006) used the total number of citations each patent receives by other patents within a certain period of time as a measure of research performance. Toubia (2006) used the number of times an idea is mentioned in later discussions as a proxy for performance of idea generation.

Ramirez and Nembhard (2004) provided an excellent overview of the literature on productivity measurement in knowledge work. They presented a taxonomy, conceptual models, and methodologies addressing 13 dimensions of performance, including "quantity, economic factors, timeliness, autonomy, quality, innovation/creativity, customer satisfaction, project success, efficiency, effectiveness, responsibility/importance of work, KW's (i.e., knowledge worker's) perception of productivity, and absenteeism." This review reveals that, while researchers have made some progress in approximating or measuring white collar productivity, there has been relative little effort devoted to building general system level models based on specific performance measure. Furthermore, as Ramirez and Nembhard (2004) pointed out we still lack methodologies that integrate and cover multiple performance dimensions.

2.3.6. Incentives

Worker incentives have long been a central issue in operations management. From the piece work systems of the Scientific Management era to the supply chain contracts of the present day, OM researchers have studied the impact of individual motivation on overall system performance. In white collar systems, with their high level of worker autonomy and indirect performance measurement, incentives are particularly important and challenging. More specifically, incentives must motivate learning and creativity, direct discretionary decision making, and enhance adoption and application of new technologies.

Since white collar work is creative and knowledge-intensive, incentives for aligning workers' behaviors with organizational goals should focus on motivating creativity and learning behaviors. Research has shown that means of motivation in white collar work systems go far beyond financial incentives. Previous studies have revealed that task complexity, deadlines, goal orientations, perceived evaluations, and supervisory styles can all be used to monitor worker behaviors (Thompson and Heron, 2005; Oldham and Cummings, 1996; Shalley, 1991, 1995; Shalley et al., 2000; Chesbrough, 2003). Researchers have also shown that non-pecuniary rewards, such as receipt of awards, honorary memberships, and peer recognition promotes worker creativity in a significant manner (Eisenberger and Armeli, 1997; Laudel, 2001). Furthermore, previous research has suggested reward for that creativity in previous task promotes creativity in later tasks and perceived reward for high performance leads to higher perceived self-determination and therefore better performance (Eisenberger and Shanock, 2003; Eisenberger and Rhoades, 2001; Eisenberger and Armeli, 1997).

A critical antecedent to good incentive design is accurate measurement of performance. Although sales revenue is often used to measure the performance of sales managers, such an approximation cannot be readily generalized to many other type of white collar work, especially when the work does not translate directly into financial values and quantity and quality cannot be fairly judged due to the complex nature of the work (e.g., developing a marketing campaign plan). Moreover, the value of many types of white collar work may only be partially measurable upon completion. For example, the value of a new product design may be fully understood only after the product has been on the market for some time. Measurement of such latent value greatly complicates worker performance evaluation. As a result, subjective performance measures (e.g., a manager's rating) are frequently used as bases for incentive plan designs (MacLeod, 2003; Ishida, 2006). Economists have studied incentive plan based on subjective performance measures in repeated games. MacLeod (2003) showed that when an agent's self-evaluation and the supervisor's evaluation (which are both subjective) are correlated, the optimal compensation is only dependent on the principal's evaluation, although the agent's self-evaluation plays a role in the agent's satisfaction. Subjective measures can also moderate the weakness associated with objective performance measures (Gibbs et al., 2004). In a study of department managers in car dealerships, Gibbs et al. (2004) found that using subjective measures in addition to objective measures positively affect managers' willingness to incur intangible risk, as well as managers' job satisfaction. For more discussion of subjective versus objective measures see Bommer et al. (1995).

Another important aspect of incentives in white collar work settings is motivation in a multi-tasking situation. Workers in white collar work settings often perform multiple or multi-dimensional tasks. In these situations, it is important to use incentives to direct workers to allocate their efforts in a manner consistent with the goals of the organization. Datar et al. (2001) studied incentive plans that allocate worker efforts among multiple tasks using relative weights when neither efforts devoted to each task nor the total effort can be observed. Using a linear contract and negative exponential utility structure Holmstrom and Milgrom (1987) showed how optimal weights can be determined and their relationship to workers' sensitivity to performance measures. Lal and Srinivasan (1993) studied incentive issues of a salesforce engaged in selling multiple products. The authors examined the case where sales effort can be modified multiple times within an accounting period depending on the status of sales realization. Assuming that sales history is known to both the salesperson and the firm, the authors showed that "products with higher sales effort effectiveness, lower marginal costs and lower uncertainty in the selling process should be accompanied by a higher commission rate." Feltham and Xie (1994) considered the case where a worker has multiple inter-correlated goals and imperfect performance measures. Using the multi-task framework introduced in Holmstrom and Milgrom (1991), the authors showed that performance measurement in a multi-tasking setting must consider both the expected value of each task itself and the correlations among the tasks.

Instead of evaluating the impact of incentive on the absolute value of performance, some researchers have studied the incentive problem from a goal-setting perspective (Seijts et al., 2004; Locke and Latham, 1990). Presence of goals have been found to positively affect worker performance (Shalley, 1991). Shalley (1995) studied the nature of the effect of goal setting on worker productivity and creativity via experiments and concluded that that the presence of creativity goal promotes workers' creativity but impedes their productivity in a complex work setting. Carrillo and Gaimon (2000, 2004) compared the impact of different goals on a manager's decision to invest in knowledge acquisition. They investigated two types of goal settings. The first was a *target goal*, which requires a target to be met and imposes a cost for exceeding or falling short of the target (i.e., two-side goal). They made use of a model in which the cost is expressed as a function of the variance and showed that, when the perceived uncertainty is high, the decision maker will allocate more resources to the behavior that causes less uncertainty. The second type of goal considered by Carrill and Gaimon was a *threshold goal*. The objective is to achieve a result whose expected value is no less than the desired goal (i.e., one-side goal). Their results suggested that when the decision maker perceives high uncertainty with her effort, she is more willing to pursue risky behaviors under a threshold goal scheme than under a target goal scheme. These results yield important insights for incentive goal design associated with knowledge acquisition. For additional literature related to goal setting in work environments, see Berger (1972), Berger (1991), Mantrala et al. (1994), Locke and Latham (1990), Locke and Latham (2004) and Locke and Plummer (2002).

2.3.7. Technology

Technology is a primary resource in many types of white and blue collar task processing. Often the motivation to use technology is to address tasks for which humans are not intrinsically well-suited. For example, using automated machines to paint cars is a classic use of technology in a blue collar task, while using computers to run a simulation is a prototypical use of technology in a white collar task. The computer revolution has dramatically expanded the range of white collar tasks that can benefit from application of information technology (IT). Moreover, the Internet and various types of knowledge management systems have placed a vast amount of information at the disposal of knowledge workers (Zack and McKenney, 1995). This has resulted in increased processing speed, improved average output, enhanced performance, and more consistent quality (Ebel and Ulrich, 1987; Dvorak et al., 1997; Carrillo and Gaimon, 2004). IT has also played an important role in blue collar work, but in such tasks technology is generally either embedded in the equipment itself (e.g., hardware and software needed to produce a windshield) or used to support established tasks (e.g., computers used to store production data). In either case, the technology stays unchanged throughout the task, that is, no new technology is generated as a result of the task. In contrast, in white collar work, workers interact with technology in a profound manner (Dewett and Jones, 2001). Technology improvement (e.g., more advanced analysis tools) or new technology (e.g., a new patent Fleming, 2001) is often achieved. Furthermore, information technology is also widely used to support decision making and help generate more creative solutions. MacCrimmon and Wagner (1994) showed that using software to generate alternative managerial policies by making connections among problems and internal and external environments leads to the a greater variety of alternatives and therefore potentially better decision making.

As technology assumes an ever greater role in white collar work, new issues associated with technology management (e.g., technology acquisition and implementation) will continue to emerge (Gaimon, 1997; Napoleon and Gaimon, 2004). A related challenge is refining our understanding of the value of output in an IT enabled knowledge sharing environment (e.g., the value of contributions to a data base or knowledge management system).

2.4. White Collar Work at the Team Level

In white collar work settings, tasks often require collective actions by members of teams to achieve designated goals. A team is a social system consisting of two or more people, "which is embedded in an organization (context), whose members perceive themselves as such and are perceived as members by others (identity), and who collaborate on a common task (teamwork) (Hoegl and Proserpio, 2004)" A team can also be defined as "(1) a group of employees that is formally established, (2) which is assigned some autonomy (with different intensities and within different organizational areas), and (3) which performs tasks that require interdependence between members (also with different intensities and areas) (Rousseau and Jeppesen, 2006)." Representative examples of teams engaged in white collar work are product development teams, consulting teams, administrative teams and information system teams (Janz et al., 1997). Teams can be differentiated from organizations by the degree of task interdependence and the degree of reward interdependence. In an organization, people have shared values in general and receive bonuses that are correlated with the success of the firm. But their actions are not closely integrated and their individual success (e.g., who gets promoted) is not highly correlated. In a group assigned to a set of overlapping tasks (e.g., product development team), members' work is more closely connected as are their rewards. In a team assigned to a very specific task, the work of individuals is so closely connected as to be almost indistinguishable (e.g., a group of consultants produces a jointly written report, an assembly team puts together a piece of machinery). When this is the case, rewards almost have to be highly correlated (e.g., if the consulting report is a success, the entire team benefits). Hence, it is critical for teams to "develop a sense of shared commitment and strive for synergy among members" (Guzzo and Dickson, 1996) . For further discussion of important issues related to team management see Kozlowski and Ilgen (2006) and Bettenhausen (1991) for comprehensive reviews.

While team management in production environments has been extensively studied by economists, sociologists, management specialists and OM researchers, much less effort has been devoted explicitly to white collar work systems. Because many white collar tasks are highly collaborative in nature (e.g., engineers designing a product or consultants performing a study), a team focus is very important for white collar work research.

Since teams consist of a collection of individuals, white collar work in teams involves all the issues we discussed at the individual level. In the rest of this section, we focus on the aspects of team work that are central to a framework for understanding white collar work in groups. To provide structure for this framework, we begin by introducing a basic model that captures the major operational elements involved when groups of people work together to carry out white collar tasks.

2.4.1. A Basic Model

Representing white collar work at the group level requires a model with the same basic elements as the model at the individual level. Workers still receive tasks exogenously and endogenously generate self-work. They still make use of and contribute to the growth of resources. The workers still have finite capacity, which leads to queueing dynamics. But, unlike the model at the individual level, we must now account for interaction between team members and the effect on system performance. Conceptually, team performance is determined jointly by the capabilities and efforts of individuals and the synergy between team members. At a more detailed level, team effectiveness is influenced by interdependence (including task interdependence, goal interdependence, and reward interdependence) among team members, team behavior (collaboration, trust), team learning and incentives.

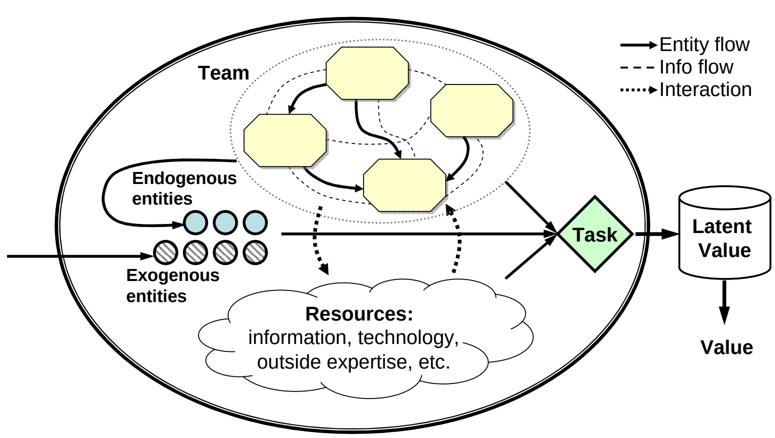


Figure 2.3. White Collar Work at the Team Level

We depict the basic elements of white collar work at the team level in Figure 2.3. The main challenge of modeling white collar work at this level is representing the interactions between team members. While teams are common in both blue and white collar work settings, the nature of interaction is different in the two types of work. In blue collar (production) work, teams collaborate on well-defined physical tasks. This raises many interesting questions about how to match individuals efficiently to each other and to tasks over time (see Hopp and Van Oyen (2004) for a discussion and literature survey). White collar collaboration goes beyond these to include knowledge sharing aspects of joint work.[4]. Specifically, in addition to issues related to white collar work at the individual level, at the team level some important issues to consider include:

(1) Interdependence is of increasing importance. Intra-team interdependence exists in both blue and white collar work teams but in distinct ways. In blue collar work teams, due to the well-defined physical tasks, interdependence among team members is simple and explicit. In contrast, in white collar work teams, workers face complex and loosely defined tasks. Consequently, they rely on frequent interactions with other team members to gain necessary information and work-related knowledge. For example, engineers in design teams exhibit intense interaction, which has been supported in recent years by the proliferation of CAD/CAM technology (Leonard-Barton et al., 1994). In general, interdependence in white collar work involves much more complex and highly implicit activities (e.g., knowledge

[4]Note that workers we think of as blue collar may also engage in knowledge sharing. For instance, two machinists deciding on the best way to cut a part certainly trade expertise and information. But we would classify such work as a white collar task, since it involves both an intellectual and a creative challenge. This type of situation is why we feel it is important to classify work at the task level, rather than at the occupation level.

sharing (Argote et al., 1990)) than does blue collar work. Consequently, it is critical to understand and manage intra-team interdependence in order to achieve desirable team performance in white collar work environments.

(2) Behavioral issues are of paramount importance. The knowledge-based processing involved in white collar work calls for a high degree of team synergy to guarantee collaborations in performing intellectual and creative tasks. Trust, the glue of teamwork, is vital in white collar work and therefore must be incorporated into operations management studies.

(3) Learning is critical for effective and efficient team work in knowledge-based processing. Unlike in blue collar work teams, where team members mainly utilize each other's labor, in white collar work settings, team members also rely on each other as repositories of knowledge and information. Therefore, team structure, composition and processes significantly affect knowledge acquisition, dissemination, interpretation and integration in team work.

(4) Team incentives need to integrate elements promoting creativity, knowledge sharing, and repeated collaborations. As we noted previously, the intellectual and creative aspect of white collar work increases the difficulty in measuring work performance objectively and forces incentive schemes to rely on subjective measures. The increased dependence on team members for knowledge, information, and creative ideas further reduces the feasibility of financial incentives. Consequently, effective incentive schemes may require sophisticated psychological bases and a range of dimensions.

In the rest of this section, we summarize existing literature related to interdependence, team behavior, learning, and team incentives.

2.4.2. Interdependence

Intra-team interdependence refers to the extent to which an individual is affected by his/her team members. It plays important roles in predicting team performance (Van der Vegt and Janssen, 2003; Janz et al., 1997). For example, team members may foster creativity among each other (Uzzi and Spiro, 2005). Interdependence can take various forms, such as task interdependence, goal interdependence, and reward interdependence (Campion et al., 1993). *Task interdependence* refers to the degree to which an individual depends on other team members' skills and efforts to carry out work effectively and efficiently (Van der Vegt and Janssen, 2003; Wageman and Baker, 1997; Wageman, 1995; Campion et al., 1993). It is a combined result of job design and intra-team interactions. *Goal interdependence* refers to the degree to which the achievement of one's goal depends on the goal achievement of other team members (Weldon and Weingart, 1993; Campion et al., 1993). *Reward interdependence* refers to the extent to which one's reward depends on other team members' performance (Wageman, 1995; Wageman and Baker, 1997; Campion et al., 1993).

The research literature has shown that various forms of interdependence affect collaborative behaviors and team performance in different ways. In some cases, they jointly affect performance. For instance, Van der Vegt and Janssen (2003) provided empirical evidence of joint impact of task and goal interdependence. Specifically, they found that, in heterogeneous teams, task interdependence has a strong and positive impact on innovative behaviors when perceived goal interdependence is high, whereas such impact is not found in homogeneous teams. In some other cases, task interdependence has been found to be a significant predictor of collaborative behaviors. For example, Van der Vegt and Van de Vliert (2005) showed in experiments that high skill dissimilarity increases helping behavior in management teams with high task interdependence. Wageman (1995) and Wageman and Baker (1997) studied the interaction between task interdependence and reward interdependence. Wageman (1995) provided empirical evidence that task interdependence promotes collaboration whereas reward interdependence facilitates monitoring of worker effort. Wageman and Baker (1997) found in an analytical model that while both task interdependence and reward interdependence affect performance, increasing task interdependence rather than reward interdependence leads to increased collaboration. They also suggested that higher task interdependence should be accompanied by higher reward interdependence in order to achieve good team performance.

Researchers have used relatively simple measures to represent interdependence. Van der Vegt and Van de Vliert (2005) measured task interdependence in a lab experiment setting by the percentage of tasks for which one has to exchange information or cooperate with others. The same type of measurement was also used in Cheng (1983). Wageman and Baker (1997) modeled the degree of task interdependence in a two-worker team as a scalar between 0 and 1, with a small number indicating one worker's action has little impact on the other's performance and a large number indicating a huge impact. Each worker's performance was then modeled as the weighted average of his own action and the other worker's cooperative action. In a similar fashion, they represented the degree of reward interdependence by a scalar between 0 and 1. Finally, they modeled a worker's reward as a weighted average of his own performance and team performance, with the degree of reward interdependence being the weight. While these simple representations help model and study the impact of interdependence, our understanding of how to measure interdependence in practice is still very limited. Wageman (1995) provided some examples of measuring interdependence empirically, more comprehensive understanding of this manner is needed.

2.4.3. Collaboration

Collaboration is the main purpose for all types of teams. A team's collaborative processes may be affected by many behavioral factors, including team members' attitudes, behavior and emotions (Rousseau and Jeppesen, 2006), team members' perception about other members' competence (Kim, 2003), and team members' proximity over the duration of the task (Hoegl and Proserpio, 2004; Hoegl et al., 2007). Rousseau and Jeppesen (2006) reviewed the impact of three categorizes of psychological factors - "attitudes, behavior, and emotions" - on team performance. They concluded that "team characteristics such as interdependence and team autonomy, and psychological variables such as cohesion, commitment, procedural justice, and potency are generally positively associated." In addition to psychological factors, researchers have found that team members' perception of other members' competence has a significant impact on team performance (Kim, 2003). The reasoning behind this observation is that perceived high competence of other team members may make one feel his/her own contribution is less important and therefore he/she may devote less efforts. Kim (2003) showed that the impact of perceived competence of team members is significant and contingent on the amount of task information shared. That is, perceived high competence leads to worse team performance when task information is partially shared, but it leads to better performance when task information is fully shared. Finally, the proximity of team members has been shown to have a strong association with team performance. For reviews of team collaboration, see Hoegl and Proserpio (2004) and Hoegl et al. (2007).

2.4.4. Trust

Collaboration and team performance are often fundamentally dependent on trust, such that an increase in trust can lead to more collaborations and better team performance (Sirdeshmukh et al., 2002; Nooteboom et al., 1997; Urban et al., 2000; Lewicki et al., 1998). This is particularly true in white collar work settings because tasks are highly dependent, work processes and outcomes are highly uncertain, and measurement of task outcomes is ambiguous (Singh and Sirdeshmukh, 2000). Since team members cannot observe their mates' performance directly, they have no choice but to trust each other if they are to work together effectively. Because of this, research into the concept of trust, impact of trust on team performance, and modeling of the dynamic nature of trust are relevant to a science of white collar work.

Interpersonal Trust. Interpersonal trust among team members can be defined as "the extent to which a person is confident in, and willing to act on the basis of, the words, actions, and decisions of another" (McAllister, 1995, p.25). As such, trust is a multi-dimensional construct that can be classified into *behavior-based trust* and *intention-based trust* (Mayer, 1994). Behavior-based trust refers to the willingness to rely on an exchange partner when that party cannot be controlled or monitored. Intention-based trust may further be classified into *competence-based trust* and *benevolence-based trust*. The former refers to the confidence one party has in the other party's capability and reliability (Lieberman, 1981), while the latter refers to the confidence one party has in the other party's motives and integrity (Mellinger, 1956). Both behavior- and intention-based trust affect team synergy and performance. These constructs of trust have been studied extensively in relational exchange and relational marketing (Morgan and Hunt, 1994; Doney and Cannon, 1997; Crosby et al., 1990).

Trust is both a predictor and a consequence of interpersonal relationships. Trust is a good predictor of individual behavior and performance. A higher degree of trust leads to greater willingness to engage in risk-taking behaviors (Mayer et al., 1995). Trust also predicts openness, communication, higher level of effort and reduced conflict within teams (Boss, 1978; Zand, 1972; Dirks, 1999; Porter and Lilly, 1996). Hence, an appropriate level of trust implies better group performance (Dirks, 1999; Friedlander, 1970). However, a high level of trust may also result in reluctance to allow mutual monitoring in self-managing teams, and which may hurt team performance when individual autonomy is high (Langfred, 2004). In addition to team facilitator of team interaction, trust is also a consequence of teamwork. Empirical study of multi-stage project teams has shown that trust building is dependent on team performance and that high-performing teams are better at developing and maintaining trust (Kanawattanachai and Yoo, 2002). The context and speed of trust building are influenced by the reward structure (Ferrin and Dirks, 2003), as well as satisfaction and interpersonal factors, such as expertise and timeliness (Crosby et al., 1990; Morrman, 1993) and the strength of interpersonal ties (Fleming and

Marx, 2006). Other issues related to trust have been explored in the literature on relational exchange and relational marketing (Morgan and Hunt, 1994; Doney and Cannon, 1997).

Operationalizing Trust. From an operations management perspective, it is important to understand how trust can be measured and incorporated into both analytical and behavioral models. There have been some reviews of the existing literature on the measurement of trust (Lewicki et al., 2006; Dietz and Den Hartog, 2006). Lewicki et al. (2006) examined the trust development from both behavioral and psychological perspectives (which are organized into four categories based on research approaches, one for behavioral and three for phycological) and answered three major questions in each of the categories: how is trust defined and measured, at what level does trust begin, and what factors affect how trust level changes over time. Dietz and Den Hartog (2006) provides a framework for trust measurement and a content analysis of recent empirical measures of trust.

Although there have been many studies on measuring trust, models that take trust into considerations are very limited. The existing literature that explicitly incorporates trust as a factor in collaborative relationships can roughly be categorized into two schools. One school views trust as unchanged in interactions. For instance, Hwang and Burgers (1997) treated trust as a key component between parties who may benefit from collaborations but are also at risk of being taken advantage of if the other party is noncollaborative. They modeled trust as a probability estimation of cooperation by the other party and assumed it remains unchanged throughout the process of collaborations. This enabled the authors to derive some properties of trust in moderating collaborative decision making.

An alternative, and more prevalent view of trust assumes trust to be dynamic and change with interpersonal interactions (Melaye and Demazeau, 2005; Castelfranchi et al., 2003; Quercia et al., 2006; Hopp et al., 2007a). This second dynamic school of thought about trust is of particular interest to OM researchers because operations policies, such as flexible work practices and structured teams, may both affect trust levels and be influenced by the nature of trust within the workforce.

Scholars from Computer Science have pioneered the study of trust dynamics. Castelfranchi et al. (2003) used a simulation model to study the interaction between trust and belief. They discussed the role of different belief sources, such as direct experience, categorization, reasoning, and reputation in trust evolution. Melaye and Demazeau (2005) extended the study of belief and trust in a Bayesian framework. The authors examined the impact of direct experience on trust evolution. In their model, trust level is inferred by the truster's basic beliefs, which come from so-called belief sources. Using simulation, the authors showed the impact of positive and negative observations on trust. They also demonstrated that trust may erode in the absence of new experiences. Besides efforts from the computer science field, scholars from operations management have also started to model the impact of trust. Hopp et al. (2007a) incorporated trust into a multi-period supply chain model by modeling trust as a measure of how much a retailer relies on a salesperson's information in demand forecasting. They showed that the retailer's trust in the salesperson leads to improved supply chain person under different various assumptions about the salesperson's motives.

2.4.5. Learning

White collar tasks often consist of knowledge-based processing, which involves creation, transfer, storage, and utilization of internal and external knowledge. While utilization of internal knowledge is critical, acquisition and application of external knowledge also play important roles in team performance. A team's ability to acquire external knowledge is dependent on properties (e.g., position, tie strength) of the network in which teams are nodes and their work-related communication flows are network ties (Tsai, 2001). However, since we will discuss the impact of these properties at the organization level in Section 5, we will focus on team-specific properties (e.g., structural diversity) in the following discussions.

External knowledge generally refers to task-related knowledge, know-how, information, and feedbacks from outside the team boundary (Haas, 2006). Knowledge acquisition at the team level is affected by team structural diversity (i.e., how different teams members are with respect to their affiliations, roles and positions (Cummings, 2004)). As the diversity increases, team performance due to external knowledge sharing increases because higher structural diversity enables teams to expose to more unique external sources. Schilling et al. (2003) studied the impact of specialization and related work content on learning. Using experiments the authors found that groups working on different but similar tasks over time learn much faster than groups who either are working on specialized tasks or alter between unrelated tasks. Knowledge acquisition is also affected by interruptions, such as "encountering novelty, experiencing failure, reaching a milestone, receiving an intervention, coping with a structural change, redesigning the task, or changing authority" (Zellmer-Bruhn, 2003). By examining data on operational teams in three firms in the pharmaceutical and medical products industries, Zellmer-Bruhn (2003) found that interruptions enhance knowledge transferring, which in turn improves the acquisition of new team routines. The impact of external knowledge acquisition is contingent on the conditions of knowledge utilization (Haas, 2006). Haas (2006) found that when team conditions are favorable, (e.g., when team members can devote more time to work than the minimum requirement, have more prior work experience, and have more collective control over critical decisions), knowledge acquisition enhances team performance in terms of the quality of projects delivered to clients.

2.4.6. Incentive

Just as incentive are critical in promoting work efficiency at the individual level, incentive are vital at the team level in white collar work settings. In addition to the issues we discussed in the context of individual motivation, a core issue of incentive at the team level is motivation of collaborative behaviors among team members. Specifically, an incentive plan for teams should address issues of team synergy, integrated creativity and repeated collaborations.

Due to the difficulty of output measurement in most of white collar work settings, incentive plans based on subjective measures have also been studied at team level (Baiman and Rajan, 1995; Rajan and Reichelstein, 2006). Baiman and Rajan (1995) showed that a discretionary bonus incentive is effective in a two-agent setting. Rajan and Reichelstein (2006) studied a “bonus pool” plan (i.e., the team is informed of how the bonus will be divided based on the realization of noncontractable information). They showed that it is optimal to use a discretionary bonus pool plan when performance can only be measured subjectively. Besides subjective performance measures, another important consideration of team incentives is the impact of repeated interactions among team members. Che and Yoo (2001) studied incentives in a setting of repeated interactions and showed that a joint performance measure (i.e., one in which individual reward is dependent on the performance of others) is desirable because it fosters peer monitoring. Unlike Che and Yoo (2001) who assumed that absolute performance is contractible, Ishida (2006) studied the case when only subjective measures are available and relative team ranking is contractible, and demonstrated the optimality of incentives based on relative performance measures (e.g., awards based on team ranking). This line of research belongs to the literature on relational contracts. For more information please see Baker (1992) and Baker et al. (1994) for related literature.

Besides team incentives based on financial rewards, research has been devoted to understanding nonfinancial incentives. Guimerà et al. (2005) showed a self-assembly mechanism helps teams gain creativity. Others have suggested that the opportunity of being exposed to new collaborators promotes creative team performance (Uzzi and Spiro, 2005). Fleming and Marx (2006) also implied that working with new people provides a level of stimulation not found in solitary work. By working with others, people may gain access to new materials or knowledge that is otherwise unavailable to them. As a result, people enhance their creativity by seeking out new collaborations. For a review of empirical evidence related to the performance of team-based incentive see DeMatteo et al. (1998).

It is worth mentioning that traditionally teams have been located in the same geographical place, so that face-to-face interaction comprises the major form of communications among teams members (Zack and McKenney, 1995). However, as technology advances, new communication channels, such as phone, email, online discussion space, and tele-conferencing, have made it possible for team members to collaborate at a distance. There is huge literature of virtual teams that studies related issues. Constrained by the length of the paper, we direct interested readers to Zack and McKenney (1995), Hoegl et al. (2007), and Martins et al. (2004) for more information on this issue.

2.5. White Collar Work at the Organization Level

An organization is a social system in which teams are embedded. As we noted in the previous section, an organization differs from a team in that both the degree of task interdependence and the degree of reward interdependence are relatively low in organizations compared to those in teams. Formally, an organization is made up of multiple individuals and teams. Therefore white collar work in organizations involve all of the issues noted above for individuals and teams, plus some additional ones. Many of these revolve around communication because this is a much more complex activity at the organization level than at the team level. In teams, shared tasks virtually force communication. But in organizations, many different kinds of communication, both formal and informal, occur. Understanding this communication, how it influences performance, and how it is related to organizational structure and management policies is a central concern in white collar workforce management. Moreover, the interactions between information and task processing have dramatically complicated the work system dynamics. We need to study interactions in order to achieve an understanding of white collar work systems and to develop useful models of them.

2.5.1. The Basic Model

Blue collar production systems are frequently modeled as flow networks by OM researchers (Hopp and Spearman, 2000). This provides a mechanism for linking individual process characteristics (e.g., batching, variability, outages, etc.) to system performance metrics (e.g., throughput, cycle time, cost, quality, etc.). Since organizations performing white collar work also consist of individual processes (i.e., people) who coordinate to complete tasks, it is appealing to view them as flow networks as well.

Unfortunately, a straightforward translation of the production flow network models to white collar work settings is not appropriate due to the differences between blue and white collar tasks we have discussed earlier. Nonroutine intellectual work poses individuals with situations where they must seek out and acquire useful knowledge dispersed among subunits in the organization (Hansen et al., 1999). Hence, in addition to the work flow, which is formal and direct, there is information flowing among different subunits, which is often informal and complex (Huberman and Hogg, 1995).

As shown in Figure 2.4, an organization contains multiple subunits performing white collar work. Each subunit contains a team of one or more workers. Subunits can perform their own tasks, as well as collaborate with other units on more complex tasks. When teams participate in complex task processing, they are linked by either deterministic or probabilistic job flows. These systems can therefore be represented by stochastic networks similar to those used in blue collar work modeling (Adler et al., 1995). When teams perform independent work in parallel, they can be treated as a single team. They can either solve the problem at hand or seek support from other subunits (e.g., searching and acquiring knowledge) or pass it onto to another team that is perceived to have the potential to solve the focal problem.

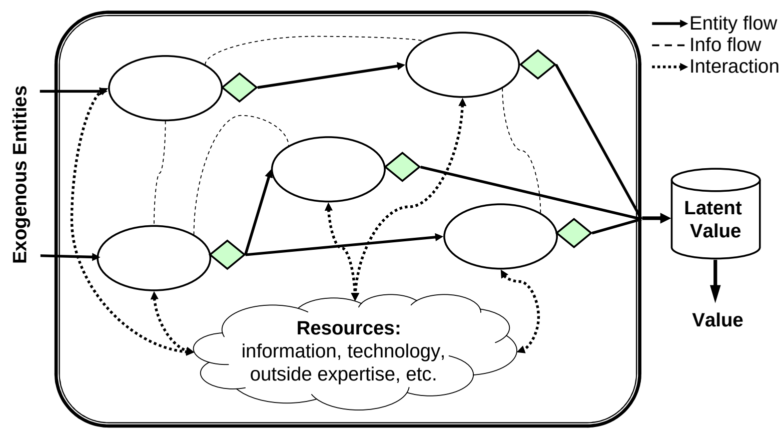


Figure 2.4. White Collar Work at the Organization Level

As shown in Figure 2.4, from a modeling perspective, a white collar work system can be viewed as a superimposed network in which informal networks of information flow are combined with task processing networks. While this conceptual model only lays out the basic dynamics of white collar work systems, it highlights many important issues in studying white collar work at the organization level.

(1) The organizational structures need to address issues created by knowledge-based processing. Since the intellectual and creative content of tasks makes task coordination in white collar work settings fundamentally different from that in blue collar systems, proven methods from blue collar settings, which rely on standard operating procedures and do not take knowledge and information as inputs, cannot be applied directly to white collar work systems. Consequently, we need new

coordination systems which integrate the knowledge and information elements into the task processing framework.

(2) New and more flexible control systems are needed. In blue collar work systems, process control relies largely on standardization and rigid structures (e.g., the serial production line). However, those control systems are generally ill-suited to control white collar work systems because the intellectual and creative content of white collar tasks calls for discretion and flexibility. Hence white collar work requires methods that recognize and enhance the creative and intellectual components of white collar work.

(3) Organizational learning, which involved knowledge seeking and sharing, has become an increasingly important mechanism by which firms can sustain a competitive advantage. Since knowledge-based task processing is highly dependent on knowledge and information input (Grant, 1996), individuals and teams frequently rely on information and expertise located elsewhere in the organizations to perform tasks. A great deal of performance variation is due to a lack of information and not being able to access external expertise in a timely fashion. While an organization may formally design its coordination system and create an infrastructure to support organizational learning, knowledge seeking and sharing largely occur through interactions which are not defined by formal organizational structures. Hence, a science of white collar work requires an understanding of knowledge seeking and sharing via informal channels.

In the rest of this section, we review previous research related to the critical issues of structure, control systems, and learning.

2.5.2. Structure

Knowledge-based task processing is embedded in established organizational structures and communication patterns (Sosa et al., 2003). The most widely studied organizational structures in white collar work environments are hierarchical, modular, and network structures.

2.5.2.1. Hierarchical Structures. Classical centralized coordination is characterized by the hierarchical organization structures, which has a pyramidal form. Many white collar work systems are coordinated with such structures. For example, risk management in investment banking is hierarchical, in which each unit of the firm determines its portfolio of risk activities and the overall level of risk is controlled by the risk managers (Vayanos, 2003).

Garicano (2000) and Garicano and Rossi-Hansberg (2006) studied the optimal organizational structure in the situation where heterogeneous agents face heterogeneous tasks. Heterogeneity among agents is defined according to their different level of knowledge. An agent can handle a task only when her knowledge level exceeds that required for task processing. If an agent fails to solve a task, he/she may choose to acquire knowledge at some cost or to search for help from other agents with a communication cost represented by the reduced production time. Garicano (2000) showed that the optimal structure for such organizations is a knowledge hierarchy, in which the knowledge of each level is non-overlapping and the size of each level decreases as the knowledge level increases. Garicano and Rossi-Hansberg (2006) extended Garicano's findings to characterize the organizational structure by *positive sorting* (i.e., "higher ability agents share their knowledge with higher ability subordinates") and *skill stratification* (i.e., "individuals are segmented by cognitive skills").

Motivated by portfolio formation in investment banks, Vayanos (2003) studied a hierarchical procedure of information processing when communication must occur along hierarchical lines and local information processing by workers is pervasive. Assuming aggregation incurs information loss, Vayanos showed that in the optimal organizational structure all workers have only one subordinate and all workers but one work at their full capacity.

While these studies provide us valuable insights into organizing knowledge-based processing hierarchies, they are limited in two aspects. First, they have ignored the interaction among workers at the same level in performing tasks. Second, and more importantly, they do not account for the fact that smart people often ignore hierarchy because they know that centralized management stifles thinking and hinders diversity of ideas (Goffee and Jones, 2007).

2.5.2.2. Modular Structures. A modular organization is a loosely coupled system consisting of elements that independently perform distinct functions (Sanchez and Mahoney, 1996; Pil and Cohen, 2006) and is an effective means of organizing complex and flexible work systems (Baldwin and Clark, 2000). Research has found that modularity enhances a firm's capability by allowing greater processing flexibility, which improves its fitness in a dynamic environment (Pil and Cohen, 2006). For example, firms may provide a larger variety of product or services through recombinations (Thomke and Reinertsen, 1998). Modularity also promotes a firm's sustained competitive advantage by enabling it to adapt more quickly and act on opportunities more effectively (Pil and Cohen, 2006).

Because of these advantages, white collar work is often organized in modules. Product development teams are a prototypical example of such structure. But since modules can be formed and combined in many ways, this leaves the question of what is the best module structure for a given organization. Moreover, performing tasks assigned to modules often require interactions beyond the boundaries of individual modules. Because of this, a common problem found in modular organization is that they can limit the interdependence among modules and thereby hinder innovation (Fleming and Sorenson, 2001). For an extensive discussion on modularity, see Sanchez and Mahoney (1996).

2.5.2.3. Network Structure. In white collar work systems "the critical input in production and primary source of value is knowledge" (Grant, 1996). Production requires coordination from individuals and teams possessing different expertise (Grant, 1996; Dewatripont and Tirole, 2005). Formal hierarchies and modular structures often fail to promote the timely communication and effective collaborations required for good performance. As a result, informal networks (where workers are represented by nodes and relations among workers are depicted by ties (see e.g., Cross and Borgatti, 2006; Burt, 2004; Cummings, 2004) have been found embedded in many organizations.

One form of network that has been found to match the communication/relation network in many white collar settings is the *small-work network* (Watts and Strogatz, 1998). For example, this structure has been observed among actors and scientists (Uzzi and Dunlap, 2005). Small-world networks are characterized by high clustering (i.e., the probability a friend's friend is a friend) and small diameter (i.e., the average minimum number of steps between any two nodes) (Watts and Strogatz, 1998; Watts, 2004; Uzzi and Spiro, 2005). Clustering reflects local density and diameter reflects separation (Uzzi and Spiro, 2005). The short average path length implies that information may flow quickly between different clusters and therefore enhance creativity by allowing combination of disparate knowledge. Meanwhile, high clustering allows local sharing and collaboration. See Watts (2004) for an review of the charactersitics and applications of small world networks.

Huberman and Hogg (1995) took a different approach to study network organizations. Instead of matching task types with expertise, the authors focused on hint (an idea that has potential value to the receiver) sharing and helping behaviors among workers using an analytical model. In their model each worker, who performs a multi-step task, chooses either to work by herself or use a hint sent by others at each step. The value of a hint is dependent on both the content of the hint and how fresh it is to the receiver. Nasrallah and Levitt (2001) used a similar framework of hint sharing to examine how timely access affects the probability of successful interaction. These studies are particularly relevant to the operations management field because their use of a flow representation makes them analogous to the flow models prevalent in production and supply chain research.

Since networks are an important form of organizing white collar work, it is very useful to understand how networks form and evolve in various conditions. A intuitive assumption of network formation is decentralized decision making on the part of the workers. Economists have developed models in network formation under this assumption. For example, Bala and Goyal (2000a) studied network formation using a non-cooperative model, in which any individual may initiate a new link with others with by paying some cost. Their results showed that the network converges to an equilibrium social network with simple structures. When formation of a link provides benefits to only one party (e.g., one individual provides expertise to another), the network in Nash equilibrium is either empty or a wheel. When formation of a link benefits both parties (e.g., two individuals collaborate), the final network can be either empty or a star. Many other researchers have formulated network formation models based on probabilistic attachment rules and game theoretic behavior (see Wolinsky (1993), Slikker and van den Nouweland (2001), Jackson (2003), and Watts (2004) for examples and information).

2.5.3. Control Systems

Control systems are mechanisms that clearly specify the appropriate methods, behaviors, and outcomes of the system (Turner and Makhija, 2006). They generally take one of two forms: process-based control and outcome-based control. Process control, often based on work standardization, is widely used in blue collar work systems to achieve superior performance. In white collar work settings, although tasks are nonroutine in nature, appropriately designed process control can still be applied to gain good performance (Nidumolu and Subramani, 2003; Turner and Makhija, 2006).

Since white collar work is knowledge-based, the tradeoff between standardization and discretion processing is of particular importance in designing control systems for white collar work settings. Standardization refers to uniform definition of processing methods and/or performance criteria, while discretion involves the flexibility in making decisions or being evaluated based on different standards (Nidumolu and Subramani, 2003). Nidumolu and Subramani (2003) examined the role of standardization and decentralization in controlling both white collar work process and performance. when they are applied to different targets, (e.g., to task processing or to outcome measurement). By studying software development firms, the authors found that a combination of standardization in performance measures across projects and decentralization in work process decision making enhances performance.

The effectiveness of process control in white collar settings also depends on the features of the knowledge (e.g., codifiability, completeness, diversity) being controlled (Turner and Makhija, 2006). Codifiability refers to the fact that knowledge can be broken down into small and easily understood pieces. When knowledge is highly codifiable, it is relatively easy to break the process and therefore is possible to implement more standardizations in the process control. Completeness refers to the degree to which knowledge necessary for task processing is available to the worker. When knowledge is complete, which indicates less uncertainty involved in task processing, a more standardized approach is recommended. Diversity refers to the breadth and relatedness of knowledge. When knowledge is less diversified, more standardization may be applied to process control.

As we discussed previously, information serves as critical input to white collar task processing. Knowledge of information location, direction, and its integration with entity flows is necessary for designing effective control systems. Unlike in blue collar work system where information flow is sequential (i.e., it flows in a predetermined sequence), information flow in white collar work systems can be sequential or reciprocal (i.e., it flows back and forth and follows no predetermined sequence) (Egelhoff, 1991). Huberman and Hogg (1995) provided an example of integrating information into task processing by modeling hints as "raw materials" for knowledge-based processing.

2.5.4. Learning

Learning in the forms of knowledge seeking and sharing comprise a critical aspect of organization competence. Since white collar workers often encounter work problems that can only be solved with support from others in the organization in terms of information, knowledge or help, the ability to learn (i.e., seek information and share knowledge) is almost always vital to white collar work performance. For example, Burt (2004) showed that a supply chain manager may be able to produce more good ideas if she shares information and knowledge with other supply chain managers. Huston and Sakkab (2006) found that R&D workers at Proctor&Gamble are able to greatly improve their performance by actively sharing information. The knowledge seeking and sharing behaviors are represented in the basic model of Figure 4 as an informal network of informational flow superimposed on a formal task processing network. The entities that flow through the informal network are work-related knowledge and information whose presence may facilitate task processing. Although knowledge seeking and sharing behaviors have become critical to worker performance, there has been little work in the OM community examining such behaviors. Hence, we treat seeking and sharing as two distinct procedures and discuss the impact of various factors on these procedures.

Before we discuss knowledge seeking and sharing, it is necessary to understand different types of knowledge. Based on the difficulty of being codified (Argote and Ingram, 2000), knowledge can be classified into two types: tacit and explicit. *Tacit* knowledge refers to knowledge that is hard or even impossible to codify and therefore is difficult to share through systematic means (Nonaka, 1994; Zander and Kogut, 1995). In contrast, *explicit* knowledge is codifiable and can be easily transferred via "formal and systematic language" (Nonaka, 1994; Zander and Kogut, 1995).

2.5.4.1. Knowledge Seeking. Information or knowledge seeking refers to the activities of locating useful information or knowledge sources (Hansen, 1999; Morten et al., 2005). The decision and efficiency of knowledge seeking within the organization is affected by the informal networks embedded in formal organizational structures, the network within the team, and the competition within the organization. Examples of such networks are the *awareness network* (in which a directional tie represents the former has specific knowledge about the latter), *information network* (in which a directional tie represents the former seeks helps from the latter), and *collaboration network* (in which a non-directional tie represents joint work) (Cross and Cummings, 2004). The most important properties of networks associated with knowledge seeking are network structure (i.e., node position, number of ties, etc.) and tie strength (i.e., the frequency and intensity of interaction). Larger numbers of direct connections implies a higher likelihood of locating the right knowledge source and higher absorptive capacity (i.e., the common knowledge base necessary for absorbing new knowledge) due to past interactions (Hansen et al., 2005) and therefore incurs a lower search cost. However, most research has found node position, rather than the number of direct ties, to be a more significant predictor of searching efficiency. Individuals who occupy positions characterized as "structural holes" or "brokerage positions" are more likely to be exposed to new information and thereby gain timely access to new knowledge more quickly and more frequently (Burt, 1992, 2004; Tsai, 2001). Besides network structure, tie strength is another important factor affecting search efficiency. Weak ties, referring to distant and less frequent relationships, are efficient for knowledge seeking because "they provide access to novel information by bridging otherwise disconnected groups and individuals in an organization" (Hansen, 1999). In contrast, strong ties may impede seeking out new information because people who share strong ties tend to have common friends or tend to have largely overlapped knowledge pools (Granovetter, 1978; Reagans and McEvily, 2003). Hansen et al. (2005) showed that higher network intensity (i.e., the number of established ties divided by the total number of possible ties) within new product development teams leads to less knowledge seeking from outside the teams. They also showed that greater competition among teams leads to higher sharing cost measured by time spent in communicating and gathering new knowledge.

In addition to understanding knowledge seeking behaviors through empirical or behavioral studies, researchers have also modeled knowledge seeking using analytical models, some of which make use of methodologies used to model blue collar work system (e.g., queueing theory). These models provide useful insights into issues, such as task and expertise matching, helping and idea utilization, and efficiency of interaction. For instance, Guimerà et al. (2002b) modeled an organization where heterogeneous tasks and expertise are initially mismatched and tasks need to be delivered to workers with matching expertise. This process is completed via searching and transferring. In their model, the cost of search is proportional to the average distance a task travels before it reaches its destination. In a queueing framework, assuming a task may travel through all possible paths, the authors showed that the congestion (i.e., total task arrival rate) at each node is proportional to the betweenness of the worker (i.e., total number of possible paths a worker occupies) in the informal networks. Guimerà et al. (2002a) considered the same type of organization and incorporated quality of channel into the original model. They modeled the quality of the network tie as the geometric average of the capability (a decreasing function of number of tasks currently at the worker) of the sender and receiver, with higher channel quality indicating faster speed. Their results also characterized the relation between network congestion and network structure.

2.5.4.2. Knowledge Sharing. Knowledge sharing is affected by many factors: the properties of knowledge (i.e., tacitness) (Hansen et al., 1999), the strength of the ties through which knowledge is transferred (Granovetter, 1978), absorptive capacity of the recipients (i.e., "prior related knowledge and diversity of backgrounds")(Cohen and Levinthal, 1990), and mobility of the worker (Jaffe et al., 1993; Almeida and Kogut, 1999). Knowledge sharing is affected by the type of knowledge being transferred. The tacitness of knowledge determines the channel through which knowledge is sought and accumulated. When knowledge is largely tacit, workers rely on complex interactions. For example, Hansen et al. (1999) found that in organizations which provide standard services or product knowledge is mainly shared in codified form, such as person-to-person interaction. Strong personal ties have been found useful in interpreting and absorbing tacit knowledge. This is because strong ties (i.e., ties maintained through frequent and intensive interactions (Granovetter, 1978; Hansen et al., 2005)) promote mutual trust and understanding and therefore facilitate complex knowledge sharing (Krackhardt, 1992; Burt, 1992, 2004; Granovetter, 1978, 1985; Hansen, 1999; Fleming and Marx, 2006; Cross and Borgatti, 2006; Borgatti and Foster, 2003). Moreover, the recipient's relevant knowledge, experiences, and diversity of backgrounds also improves sharing effectiveness (Cohen and Levinthal, 1990; Szulanski, 1996).

Almeida and Kogut (1999) studied the impact of a worker's mobility on knowledge sharing. The authors showed that the mobility path of patent holders leads to inter-firm knowledge spillover. (For a more detailed review of the impact of mobility and research methods using networks see Brass et al. (2004), Brown and Duguid (2001), Tsai (2001), Ibarra and Andrew (1993) and Marsden (1990).) Moreover, information redundancy and timely access to information sources affect knowledge sharing efficiency (Huberman and Hogg, 1995; Nasrallah et al., 2003).

While knowledge sharing is essential to white collar work, it can become a barrier to performance if not motivated appropriately (Lee and Ahn, 2005). One reason is that knowledge sharing is costly. For example, in some cases, people may worry that their work process will be interrupted and therefore may be reluctant to help others when approached for information. In other cases, people may release partial or false information for fear of being outperformed by their peers. Hence, promoting honest and efficient sharing is of great importance to organizations. In the business world, Bain and Company has incorporated how much help a person provides to others into his/her annal compensation (Lee and Ahn, 2005). Unfortunately, research in this area is very sparse and our understanding is still very limited.

In Table 2.1, 2.2, and 2.3, we summarize the literature. We have reviewed above as relevant to white collar work at the individual, team and organizational levels. In addition to organizing the many streams of research by level and topic, this table further breaks them down according to research methodology (i.e., analytic, empirical or behavioral/empirical). By providing a high level summary of the coverage in the literature of the key issues involved in understanding the operations of white collar work, this table provides a platform for identify promising directions of future research.

Table 2.1: White Collar Work at Individual Level

	Analytical	Empirical	Behavioral/Experiments
Creativity		Amabile et al. (1996) Shalley et al. (2000)	Barron and Harrington (1981) Amabile (1983a) Woodman and Schoenfeldt (1989) Shalley (1991) MacCrimmon and Wagner (1994)[s] Shalley (1995) Oldham and Cummings (1996) Shalley and Gilson (2004)
Discretion	Debo et al. (2004) Hopp et al. (2007a)		
Learning	Toubia (2006)	Levinthal and March (1993) Pisano (1994) Pisano (1996)	Ryu et al. (2005)[s]
Performance measure	Ramirez and Nembhard (2004)[r]	Fleming (2001) Gillson et al. (2005) Fleming and Marx (2006)	Toubia (2006)
Incentives *Motivation*		Oldham and Cummings (1996)	Locke and Latham (2004)

		Laudel (2001) Chesbrough (2003) Thompson and Heron (2005) Davenport et al. (2007)	Gottschalg and Zollo (2007)
Subjective Measurement	Feltham and Xie (1994) MacLeod (2003) Ishida (2006)	Gibbs et al. (2004)	Bommer et al. (1995)
Multi-Tasking	Holmstrom and Milgrom (1991) Lal and Srinivasan (1993) Feltham and Xie (1994)[r] Datar et al. (2001)		
Goal-Setting	Carrillo and Gaimon (2004)	Seijts et al. (2004)	Shalley (1991) Shalley (1995) Locke and Plummer (2002)
Technology	Napoleon and Gaimon (2004) Carrillo and Gaimon (2004)	Zack and McKenney (1995)	Dewett and Jones (2001)

s: simulation; *r*: review

Table 2.2: White Collar Work at Team Level

	Analytical	Empirical	Behavioral/Experiments
Interdependence	Wageman and Baker (1997)	Leonard-Barton et al. (1994) Van der Vegt and Janssen (2003) Uzzi and Spiro (2005)	Weldon and Weingart (1993) Campion et al. (1993) Wageman (1995) Van der Vegt and Van de Vliert (2005)
Collaboration		(Kim, 2003) (Hoegl and Proserpio, 2004) (Hoegl et al., 2007)	(Rousseau and Jeppesen, 2006)^r
Trust	Hwang and Burgers (1997) Melaye and Demazeau (2005) Quercia et al. (2006) Hopp et al. (2008)	Morgan (1995) McAllister (1995) Porter and Lilly (1996) Doney and Cannon (1997) Dirks (1999) Kanawattanachai and Yoo (2002) Ferrin and Dirks (2003) Langfred (2004)	Crosby et al. (1990) Lewicki et al. (1998) Lewicki et al. (2006)^r
Learning		Tsai (2001) Hansen (2002) Zellmer-Bruhn (2003) Cummings (2004) Haas (2006)	Schilling et al. (2003)

Incentives	Baiman and Rajan (1995)	DeMatteo et al. (1998)[r]	Cameron and Pierce (1994)[r]
	Che and Yoo (2001)	Fleming and Marx (2006)	Guimerà et al. (2005)[s]
	Rajan and Reichelstein (2006)		
	Ishida (2006)		

s: simulation; r: review

Table 2.3: White Collar Work at Organization Level

	Analytical	Empirical	Behavioral/Experiments
Structure			
Hierarchical	Radner (1993)		Dupouet and Yildizoglu (2006)[s]
	Garicano (2000)		
	Vayanos (2003)		
	Garicano and Rossi-Hansberg (2006)		
Modular		Fleming (2001)	Sanchez and Mahoney (1996)
		Pil and Cohen (2006)	Baldwin and Clark (2000)
Network	Bala and Goyal (2000a)	Uzzi and Spiro (2005)	Watts and Strogatz (1998)[s]
	Dupouet and Yildizoglu (2006)		Slikker and van den Nouweland (2001)
			Watts (2004)[r]
Process Control	Huberman and Hogg (1995)	Egelhoff (1991)	Turner and Makhija (2006)
		Nidumolu and Subramani (2003)	
Learning			
Knowledge Seeking	Guimerà et al. (2002b)	Hansen (1999)	Granovetter (1973)
		Hansen (2002)	Granovetter (1983)
		Reagans and McEvily (2003)	Cross and Borgatti (2006)
		Burt (2004)	
		Cross and Cummings (2004)	
		Hansen et al. (2005)	

		Morten et al. (2005)	
Knowledge Sharing	Huberman and Hogg (1995)	Ibarra and Andrew (1993)	Argote et al. (1990)
	Nasrallah et al. (2003)	Zander and Kogut (1995)	Cohen and Levinthal (1990)
		Szulanski (1996)	Burt (1992)
		Hansen et al. (1999)	Krackhardt (1992)
		Almeida and Kogut (1999)	Nonaka (1994)
		Tsai (2001)	Brown and Duguid (2001)
		Brass et al. (2004)	Borgatti and Cross (2003)^r
		Fleming and Marx (2006)	

s: simulation; *r*: review

2.6. Research Opportunities

The above survey shows that considerable research has been done on issues related to white collar work. But when held against the standard of a coherent science of white collar work, this literature is still fragmented and only loosely connected to operations management. Furthermore, the various research methodologies have been applied unevenly to important problem areas. For example, knowledge transfer has been studied extensively with empirical methods but analytic models of knowledge transfer processes have been rare. As a result, we have not yet incorporated many important insights from the literature into OM models of white collar work.

In this section, we use the survey as summarized in Table 1 to highlight some major gaps and suggest research directions that are fundamental to building a science of white collar work operations.

2.6.1. Performance Measurement

Operations Management is a prescriptive field. The ultimate goal of all OM research is to improve the design and management of operations systems. Hence, an essential element of the science of operations for any class of systems is an accurate characterization of performance. This is certainly true for white collar work systems. Each of the base models presented above include some form of output process, which could be characterized in terms of value, knowledge, customers satisfaction, or other ways depending on the specific environment. To use these models as a framework for developing a operational science of white collar work, we need concrete performance metrics that can be connected to policies.

Unfortunately, accurate measurement of white collar work output is extremely difficult. "Most traditional HR metrics - such as employee turnover rate, average time to fill open positions, and total hours of training provided cannot accurately predict organizational performance" (Bass and McMurrer, 2007). Davenport (2005) suggested that the best way to circumvent this problem is to "Hire smart people and leave them alone". While this might work in some settings, it is hardly a basis for a science of white collar work.

To develop rigorous performance measures for white collar work systems, we probably need to look to previous research on blue collar work systems for inspiration. A number of standard performance measures, including throughput, WIP level, utilization, customer satisfaction, etc., are commonly used to characterize blue collar work systems. While some of these may translate directly to white collar settings, many do not. For example, since workers have discretion over the amount of time they spend on a particular task (Hopp et al., 2007a), utilization is a difficult concept to apply in white collar settings. Indeed, it is quite possible that all white collar workers in a system are 100 percent utilized (e.g., a statistician may seem to work all the time: crunching data in a computer, discussing models with peers, etc.). Consequently, the key issue is not how busy workers are, but rather how they allocate their time. New metrics are needed to measure the efficiency and effectiveness with which white collar workers do this. In addition, performance measurement of white collar work is often associated with measuring latent value. For example, the impact of a manager's decision may has consequences beyond his time as a manager (Feltham and Xie, 1994). While latent value is an important feature associated with a variety of white collar work, we have only seen it examined in empirical studies.

There has been almost no analytical modeling work of latent value in operations management studies. Consequently, we have very little knowledge of how the management policies (e.g., incentive plans) should change when latent value measurement is taken into account.

Even measures that do translate from blue to white collar settings may require modification to be useful in white collar systems. For example, customer satisfaction (Lapre and Tsikriktsis, 2006) is appropriate in both blue and white collar settings where customer satisfaction can be measured. In blue collar settings where repetitive products and/or services are provided to customers, simple survey methods can yield reasonable measures of satisfaction. For example, Fornell (2005) measured customer satisfaction at the firm and industry level. But, because important outputs of white collar work (e.g., contributions to organizational knowledge) are not immediately experienced by customers, many white collar work systems cannot be reasonably evaluated in customer satisfaction terms. Nevertheless, when a white collar task is closely connected to a product and/or service, customer satisfaction metrics are key measures of performance. For example, Eisenberger et al. (2007) used customer satisfaction to predict the performance of movie scripts. Straub et al. (1995) studied the role of information technology in measuring system usage and integration of objective (i.e., computer-recorded) with subjective (i.e., self-reported) system measures. Research on the collection, analysis and connection of such metrics to operating policies is essential to the development of a science of white collar work.

2.6.2. Integrated Work and Information Networks

The OM field has developed a rich literature using network flow models to represent the dynamics of blue collar work systems (e.g., Hopp and Spearman, 2000; Buzacott and Shanthikumar, 1993). The flows in such models are physical entities, such as parts, jobs or customers. Such models have also been applied to some white collar work system. For example, Adler et al. (1995) applied the idea of network flow models in a module-based project development management. Their findings suggest that some of the basic principles of blue collar work (e.g., impact of bottlenecks, variability and flexibility) are applicable to white collar work that can be represented as network flows. However, research in this area is till sparse and we do not yet have a good understanding of how broadly these principles apply.

However, in knowledge intensive white collar work systems, information flows are at least as important as physical flows. Research has shown that information sharing is strongly related to ties among workers, which can range from informal to official (Uzzi, 1996; Uzzi and Lancaster, 2003). Hence, methodologies developed in social network analysis offer strong potential for application to OM modeling of systems wehre information and task processing are embedded in work-related social relationships. Analytic and empirical research into models that integrate social networks into task flow models offers a promising avenue for creating a formal platform for representing white collar work systems.

A network representation of white collar work systems raises the issue of how the network is coordinated. In blue work systems, coordination is generally achieved via work process design (e.g., work is organized into a serial production line). In white collar work settings, as information is an important input to knowledge-based processing Grant (1996). For example, a doctor facing a unfamiliar symptom may require advice from more experienced doctors before deciding on a course of treatment. Because the work is less structured than in blue collar systems, it is not usually practical to impose a rigid structure on the work flow. Hence, white collar systems must rely on a mixture of centralized control (e.g., a manager makes task assignments and coordinates dynamic adjustments) and decentralized evolution (e.g., workers direct their own search and collaboration activities). Analytic, empirical and behavioral research into coordination mechanisms is therefore vital to a science of white collar work operations. Of course, to carry out this research we need the previously discussed performance metrics to represent effectiveness.

Finally, the effectiveness of white collar work networks is strongly influenced by the flexibility of the constituent workers. It is well known that flexibility is of fundamental importance in blue collar work system analysis (Sethi and Sethi, 1990; Gerwin, 1993). Cross-training is an effective way to improve system flexibility because cross-trained workers represent capacity that can be shifted to where it is needed most. As such, flexibility can result in increased throughput, reduced work-in-process or improved customer service. In white collar work systems, most workers perform work in a multi-tasking fashion. For example, a consultant communicates with clients, identifies problems, develops strategies, and helps client implement management policies to achieve desirable results. A professor teaches, performs research, and advises students. Obviously, flexibility is a prerequisite for such multi-tasking behavior. From a research standpoint, much remains to do to raise our understanding of the role of flexibility in multi-tasking, white collar environments to that we have attained for flow-oriented blue collar systems.

2.6.3. Bottleneck Analysis

One of the major insights that has come out of network flow analysis of blue collar work systems is the importance of bottlenecks. Because bottlenecks constrain system capacity, they are fundamental in determining throughput, cycle time, customer service and other performance metrics. Similar dynamics apply to some white collar systems. For example, in a multi-step software development project, productivity is constrained by the least productive steps regarding both processing speed and output quality. However, bottleneck analyses are seldom used in white collar systems. The reason is that the standard definition of a bottleneck (i.e., the station with the highest utilization (Hopp and Spearman, 2000)) may be inappropriate in white collar work systems: (a) a white collar worker's time is generally fully utilized, and (b) the quality of white collar tasks can vary greatly, which means that measuring the quantity of tasks completed does not fully capture worker output. Moreover, the knowledge-intensive and non-repetitive nature of white collar tasks also dramatically complicates bottleneck analysis. Hence, basic modeling research is needed to develop a white collar analog to traditional blue collar bottleneck analysis.

2.6.4. Discretionary Decision Making

A key characteristic of white collar work systems that distinguishes them from blue collar systems and complicates modeling and analysis is the high degree of discretion in decision making. Task selection, prioritizing, completion, and self-generated work all require discretionary choices on the part of workers. For example, when helping a customer select a car, a salesperson has the freedom to choose which options to recommend and how to price them (within limits). Similarly, the salesperson may choose to speed up processing of current customer if other customers are waiting. Such discretion makes it difficult to predict the behavior of both individual workers and the overall system. Although there has been limited work to model these systems by using a dynamic optimization framework (Hopp et al., 2007a), our understanding of how these systems actually operate in practice is still very limited. To improve the management of discretionary decision making, we need to: (*i*) identify the areas where discretionary decision making is critical (e.g., task prioritization, time allocation, multi-tasking, information search, etc.) (*ii*) identify the main factors (e.g., tight deadlines, reward structures, nature of tasks) that impact discretionary decision making, (*iii*) develop normative models of optimal discretionary decision making in white collar work settings, and (*iv*) perform empirical studies of white collar workers in various environments to determine how they actually make decisions concerning the discretionary aspects of their work and compare these to optimal strategies.

2.6.5. Trust

Trust is becoming increasingly important due to increased diversity of workforce, participative management style and implementation of work teams (Mayer et al., 1995). It plays critical roles in many aspect of white collar work settings. For examples, trust affects the degree of information utilization (Hopp et al., 2008), worker effort and mutual monitoring in self-directed teams (Langfred, 2004). While trust is of paramount importance to white collar work research, we have seen very few studies that incorporate trust into OM research. As seen in our literature review, research in other fields, such as general management, sociology, and computer science, have provided us with a great deal of insights into factors leading to trust, trust itself, and outcomes of trust. We believe, OM scholars may make use of these valuable results in our own studies. For instance, how does the trust between the manager and the consultants affect the incentive plan design? How does different levels of trust among teams members affect their decisions on from whom or to who to seek or provide help? How does trust monitor collaborative behaviors in repeated settings? A great number of research questions may yield valuable results when trust is taken into consideration and contribute a great deal to the science of white collar work.

2.6.6. Learning

Learning is critical to sustainable competitiveness in both blue collar and white collar work systems. Our literature review reveals that there has been a great deal of research examining knowledge seeking and sharing at the organization level but there have been relatively few studies focused on group learning. Understanding the operations of white collar work at the group and organization level will require more basic research into the mechanisms and support factors for group learning. We need better understanding of issues, such as how teams make learning decisions, how gained knowledge are shared and translated into team routines, and the interaction among knowledge properties (e.g., codifiability, completeness, and diversity (Turner and Makhija, 2006)), team property (e.g., structural diversity) and learning. Moreover, due to the intellectual nature of the work, knowledge depreciation is a factor associated with learning in white collar systems, which can have a significant impact on work productivity (Park et al., 2006). For example, since the new developing tools update very rapidly, software engineers must keep learning those new products in order to work efficiently and collaborate with peers effectively. There has been some research on depreciation rate of technical knowledge (de Holan and Phillips, 2004; Bosworth, 1978; Park et al., 2006), which may be applicable to modeling learning and knowledge depreciation in white collar work systems.

2.7. Conclusion

The past several decades have witnessed a dramatic rise in the quantity and variety of white collar work. The growing need for white collar research has been addressed by scholars from various disciplines, including Sociology, Organizational Behavior, Marketing, Information Systems, and Economics. Although interest in white collar work is also on the rise within the Operations Management community, research into operational issues associated with white collar work is still very limited. Moreover, we lack frameworks for incorporating insights from other fields (e.g., the role of trust, social networks, motivation, learning, knowledge transfer, etc.) into OM models.

In this chapter, we have attempted to address these gaps by providing a survey of the various streams of research relevant to white collar work. We have organized this review by focusing on white collar work at the level of the individual, team, and the organization. To help us classify existing research studies into these categories we have proposed a base model for each level of white collar work. These base models enable us to connect research from disparate fields to OM concerns. Furthermore, they enable us to identify gaps in the research coverage of the three categories of white collar work, and point toward specific research needs that are key to development of a science of white collar workforce management.

We hope that this survey will stimulate fundamental research on white collar work from an Operations Management perspective and provide a reference for scholars seeking to integrate research threads from different fields to improve our understanding of white collar work systems.

CHAPTER 3

Impact of Social Network on Innovation: Hint Model

3.1. Introduction

The dramatic change in the competitive landscape of business wrought by the information revolution is symbolically illustrated by the origins of wealth. As the industrial age came into full swing at the end of the 19th century, the richest man in the world, John D. Rockefeller, owed his fortune to dominance in natural resources (oil) and machines (transportation). At the end of the 20th century, with the information age firmly in place, the richest man in the world, Bill Gates, owed his fortune to dominance in information (software). While information was certainly important in Rockefeller's day, and materials and machines are still important today, the balance has clearly shifted. Creation, diffusion and translation into value of information have become core competitive functions.

Explicit recognition of this reality have stimulated academic inquiry into the role of knowledge in organizations. Such knowledge can be explicitly contained in organizational routines, as well as implicitly embedded in individuals. According to Kogut and Zander (1992) , organizations function as "social communities in which individual and social expertise is transformed into economically useful products and services by the application of a set of higher-order organizing principles". In such communities, social connections among individuals form a network through which people share information in order to complete tasks and create new knowledge. When tasks to be completed is highly creative and intellectual, workers become heavily dependent on each other for job-related information and complimentary expertise. The interdependence among workers gives rise to a work-related network, in which workers may exploit useful resources through direct or indirect links. Such network often is referred to as *knowledge network*.

As the economy steadily shift towards the knowledge era, knowledge network has become an extremely important form of organizing efficient production. Because creative and intellectual work, i.e., knowledge-intensive work, is fundamentally different from what have been well studied in operations literature, which typically are routine, standard, repetitive, and involving less creativity and intellect properties. In contrast, knowledge-intensive work "is based on, in large measure, on either intellectual capital or craft-based skills, both of which have been honed through years of education, training, and experience (Powell, 1990)". Consequently, the assets exist in the mind of talented people whose expertise cannot be easily purchased or appropriated and therefore is largely intangible and highly mobile. Moreover, knowledge network provides an effective form of organizing knowledge-intensive work because for it "create(s) incentives for learning and the dissemination of information, thus allowing ideas to be translated into action quickly; the open-ended quality of networks is most useful when resources are variable and the environment uncertain; network offer a highly feasible means of utilizing and enhancing such intangible assets as tacit knowledge and technological innovation (Powell, 1990)".

Knowledge network has been explored in both industry practice and academic research. In industry, some large companies, including IBM, HP and Intel, have made extensive practical use of a special form of knowledge networks, called *Communities of*

Practice (CoP). Promoting learning among members of CoP's has enabled IBM to greatly "decrease the learning curve of new employees, respond more rapidly to customer needs and inquiries, reduce rework and spawn new ideas for products and services"(Laesser and Storck, 2001). HP has made use of similar methods to implement knowledge management through what they call *knowledge communities*. Intel, has installed and nurtured knowledge networks to expand their access to university faculty experts and thereby improve the productivity of corporate R&D activities (Chesbrough, 2003).

In academia, researchers from various disciplines are exploring the impact of knowledge networks on organizational performance. Much of the existing literature has focused on informal networks that may differ greatly from formal organizational structures. This line of inquiry can be traced back to the early years of the previous century, when it was noticed that formal organizational structure failed to capture many of the important aspects of the communication behaviors (Follett, 1924). More recently researchers have tried to characterize the manner in which informal networks affect the overall performance of organizations (Stevenson and Gilly, 1991; Albrecht and Ropp, 1984).

The goal of this chapter is to study knowledge network formation from a operations perspective by examining the optimal network structure arising from individuals collaborative behaviors. We assume that (i) organization consists of heterogenous individuals who are capable of generating, transferring, and processing ideas into valuable outputs. (ii) idea accumulation, sharing, and processing are time-consuming, (iii) overall network performance is given by the sum of individual performances, and (iv) individual performance is determined by the time allocation between interaction and self-work. Under these conditions, we demonstrate that optimal (i.e., value maximizing) networks for individual specialties exhibit well-defined "giver-taker-loner" structures, but that the aggregate network can take on a wide range of structures. We also investigate the dependence of network performance on agent capability (creativity and productivity), heterogeneity, correlation among agent specialties, and the overall creativity and productivity balance. The results of numerical studies suggest that organizations composed of heterogeneous agents with diverse specialties and with balanced overall creativity and productivity achieve the highest performance.

Our work contributes to the literature by introducing an optimization model to study the dynamic dependence of network structure on individual choices. In contrast to previous research, our work focuses on different forms of heterogeneity. We recognize an individual's capability may vary across different fields and therefore heterogeneity is multidimensional. Within each field, we explicitly consider the production process to include two steps: idea generating and processing, and the outputs produced is limited by an individual's time capacity, which makes a strong connection to the operations management research. We also explicitly allow cost of information transfer increases as distance increases, which represent the general findings from social network literature.

The remainder of the chapter is organized as follows: In Section 3.2 we discuss the connection of our model to the body of network research and to the operations literature. In Section 3.3 we develop our hint model and describe the resulting network structure. In Section 3.4 we use our model to explore some numerical examples and generate managerial insights. We conclude in Section 3.5.

3.2. Related Literature

Researchers have studied knowledge worker productivity from a network perspective. Those work can be classified into two categorizes. The first school of research assumes network formation is exogenous and aims to understand the impact of exogenous network structure on work performance, e.g., role of node position in the network (Burt, 1992, 2004; Ahuja, 2000; Perry-Smith and Shalley, 2003; Cross and Cummings, 2004; Borgatti, 2005), properties of ties (Granovetter, 1978; Ahuja, 2000; Uzzi and Lancaster, 2003), and network structure and evolutions (Fombrun, 1986; Brass, 1995; Borgatti and Cross, 2003; Uzzi and Spiro, 2005; Uzzi and Dunlap, 2005). See Borgatti and Foster (2003) for a review.

The second school of research assumes that network formation is endogenous and focuses on studying what network structures are likely to emerge. The two most prevailing groups of research within this school are random network models (Erdös and Rényi, 1960) and strategic network models (Jackson, 2008). The first group seek to understand network structures and properties stemming from random connections, e.g., the Erdös-Rényi random graph model (Erdös and Rényi, 1959, 1961), small-world networks (Newman, 2000; Uzzi et al., 2007), scale-free networks (Albert et al., 1999) , and non-scale-free networks with preferential linking (Albert et al., 1999). See Vega-Redondo (2007) for a review. The second group of researchers focus on studying network formation and evolution resulted from individual choices and behaviors (Galeotti and Goyal, 2007; Galeotti et al., 2006; Jackson and Wolinsky, 1996; Jackson and Watts, 2002; Jackson, 2003, 2008; Bala and Goyal, 2000a; Watts, 2001, 2002). These research generally specifies a set of individuals(players), who make decisions on link formation by weighing the tradeoff between the cost and the benefit of making a connection. Network forms and evolves as a result of individuals (players) exploiting their network position to their own advantage through such link formation activities. There are several key features of these models: first, individuals(players) are heterogenous; second, link formation is costly; third, an individual's benefits from a connection depends on both the connections of oneself and the connections made by others (Goyal, 2007). The questions addressed by this body of research includes: what is the structure of networks that arise in equilibrium and how are those emerged network structure compared to socially desirable networks. See Jackson (2003) and Goyal (2007) for a review.

Our work falls closely to this second line of research. We aim to understand the network structure arise endogenously from individual choices. Our model assumes that individuals are heterogeneous in terms of their capability of generating ideas and producing ideas into measurable output. Individuals seek to improve their productivity by forming links with people who have complimentary capabilities and make linking decisions by weighing the trade off between the cost of communication and benefits of productivity improvement. However, our model is different from this body of research in that we do not solve for the equilibrium that arises from individual choices. We seek the optimal network structure obtainable through central management. We are interested in understanding resource allocation among individuals. In this sense, our work is closely related to network models in operations literature (Jackson, 1957; Buzacott and Shanthikumar, 1993; Altiok, 1997; Hopp and Spearman, 2000) as well. The existing research closely related to our work is Huberman and Hogg (1995). Like ours, Huberman and Hogg (1995) study the collaborative performance and dynamic consequences of a group of people who interact to share work-related knowledge and experience. In their model, tasks are completed through a series of steps, with decisions at each step of whether to perform self-work or share hints (i.e., beneficial information that can be transferred and used by others) in order to optimize the network performance. Similarly, our model assume task complete through idea generating and processing two steps and individuals may choose to whether to help or request help from others. Same as Huberman and Hogg's model, we define the overall network performance as the sum of the performance by the individuals in the organization, measured in terms of value produced. Our model differs from Huberman and Hogg's model in that we decompose the network into sub-networks of unique specialties (Campbell, 1969). We allow information from indirect sources (i.e., from neighbor's neighbor) to be used in the production process whereas their model considers only hint from direct sources.

3.3. Hint Model General Formulation

To formulate a hint model, we assume that knowledge production consists of two phases: *creation* and *processing*. Although in practice a hint might derive from either an external input or an internal idea, for purposes of modeling we will act as though all hints are the result of ideas. In this context, hint(idea) creation is the (time consuming) process used by agents to develop a complete and potentially valuable thought by applying his/her knowledge to the available information. From a modeling perspective, "hint(idea) borrowing" from a source outside the system is very similar to "hint(idea) creation" so we will not distinguish between the two activities.

Processing refers to the (primarily mental) activity that transforms hints into intellectual properties (such as executable plans, designs, patterns, etc.). Hints being processed may be borrowed or self-generated. For the purposes of our model, we assume that the hints borrowed will not be processed the hint sender and that the economic value of intellectual properties can be measured.

To illustrate the mechanics underlying our model we consider a management consulting firm example. The firm provides professional advice to companies on problems in specific areas (e.g., strategy, operation, marketing). The agents in this system are consultants who generate IP (i.e. solutions to problems) that is encapsulated in reports submitted to clients. These reports have concrete value, which is considered by the consulting firm partner in negotiating a price for the services. In other knowledge systems, such as the previously mentioned design process that created the iPod, the value of IP is not captured until it is translated into a physical product, manufactured and sold.

We assume that agents are capable of both generating and processing hints and that individuals have intrinsic capacities for each activity. Furthermore, we consider a simplified environment in which there is one-to-one correspondence between hints and outputs (i.e., each hint is capable of being transformed into a separate piece of IP). We define an agent's *creativity* as his/her idea generating rate (i.e., expected number of hints generated per unit time) and *productivity* as his/her processing rate (i.e., expected number of hints transformed into value per unit time). As a result, agents can work alone, by independently creating self-hints and processing them into intellectual properties. They can also collaborate with other agents by giving or taking hints. Depending on agents' relative creativity and productivity rates, it may be more effective for agents to collaborate than to work alone.

The outcomes of interactions between agents depends on more than their capacities. The likelihood of one agent's hint helping another agent generate value is also affected by how well they communicate. We define the *communication efficiency* between any pair of agents as the expected rate of successful hints transferred per unit time. This is determined by both the speed (expected number of hints transferred per unit time) and accuracy (% of successfully shared hints) of their communication.

For example, in the case of a consulting firm, consultants assigned to particular client will communicate their ideas on how to solve problems via email and direct conversation. The rate at which they generate hints is a function of their creativity, while the rate at which they translate these hints into useful advice for the client is a function of their productivity. The fraction of suggestions (hints) that get translated into solutions is a function of communication efficiency. Note, however, that in the consulting example, IP is not packaged and sold on an individual hint basis, but instead is compiled into a report that addresses multiple issues. In this regard it represents a more complex environment that the one we will consider with our model.

In most environments, hint flows are complicated because the information shared between agents can be of many types. For instance, a consulting project might involve making use of hints related to market research statistics, human resources, product design, and strategic positioning.

For modeling purposes, we assume that hints can be classified into mutually exclusive, collectively exhaustive *fields*, which may also be referred to as unique expertise. Hints in the same field are equally valuable. Furthermore, agents have creativity and productivity rates within each field, which may or may not be correlated. The overall flow of hints between agents can therefore be viewed as the superposition of the flow of hints within fields. For instance, three types of expertise are generally considered important in software development team: "technical expertise (knowledge about a specialized technical area), design expertise (knowledge about software design principles and architecture), and domain expertise (knowledge about the application domain area and client operations) (Faraj and Sproull, 2000)."

In real-world systems, hints and other information are combined in complex ways to complete tasks. Furthermore, generating value may require completing and coordinating many tasks. The number of patterns in which value can depend on hints is virtually unlimited. Moreover, the definition of productivity becomes complex if IP outputs depend on hints in complicated ways. Hence, describing the patterns for various knowledge network environments is an important research issue, but one that is beyond the scope of this initial effort at developing a hint model. For our purposes, we assume that hints are processed individually into value and that the overall value generated by the network is given by the sum of the value produced by each individual agent.

To develop an explicit formulation of our hint model we make use of the following notation for a system with N agents and K fields:

Parameters:

T^g_{nk}	expected time for agent n to generate an idea in field k.
$\lambda_{nk} = 1/T^g_{nk}$	rate of idea generation by agent n in field k.
T^p_{nk}	expected processing time of a hint by agent n in field k.
$\mu_{nk} = 1/T^p_{nk}$	rate of hint processing by agent n in field k.
T^t_{mnk}	expected time to transfer a hint from agent m to agent n in field k.
S_{mnk}	percentage of acceptance of hints transferred from agent m to agent n in field k, $S_{mnk} \in (0, 1]$.
V_k	expected value of a processed hint (a piece of IP) in field k.

Decision Variables:

$\mathbb{X}$	$= [\mathbf{X_1}, \ldots, \mathbf{X_N}]^T$, the matrix of decision variable, where $\mathbf{X_n} = [X^g_{nk}, X^p_{nk}, X^t_{n1k}, \ldots, X^t_{nNk}, X^t_{1nk}, \ldots, X^t_{Nnk}]$, $n \in \{1, \ldots, N\}$
X^g_{nk}	the number of ideas generated by agent n in field k.
X^p_{nk}	the number of hint processed by agent n in field k.
X^t_{mnk}	the number of hints transferred from agent m to agent n in field k.
Π	total profit (value) of the network

We can now express the problem of maximizing value per unit time subject to constraints on flow balance (i.e., the total number of hints processed and given out equal to the number of hints that are self-generated and borrowed.) and time capacity (i.e., total time agents spend cannot exceed 100% of their available time) in an N-agent network with K fields as follows:

$$\max \qquad \Pi = \sum_{k=1}^{K} \sum_{n=1}^{N} X^p_{nk} V_k$$

$$
\begin{aligned}
s.t. \qquad X^g_{nk} - X^p_{nk} + \sum_{m \neq n} s_{mnk} X^t_{mnk} - \sum_{m \neq n} X^t_{nmk} &= 0 \ \forall\ n, k \text{ Flow Balance (FB)} \\
\sum_{k=1}^{K} \left[X^g_{nk} T^g_{nk} + X^p_{nk} T^p_{nk} + \sum_{m \neq n} X^t_{nmk} T^t_{nmk} + \sum_{m \neq n} X^t_{mnk} T^t_{mnk} \right] &\leq 1 \ \forall\ n \text{ Time Capacity (TC)} \\
X^g_{nk}, X^p_{nk}, X^t_{nmk}, X^t_{mnk} &\geq 0 \ \forall\ m, n, k
\end{aligned}
$$

Note that in the FB constraint the number of hints an agent *accepts* often is not equal to that he/she receives because the received hint may be discarded due to various reasons, such as, incompatible with the receiver's knowledge, already known to the receiver, hard to understand, and etc.. Therefore only partial (S_{mnk}) of the hint is kept in the IP creation process (Huberman and Hogg, 1995). In the TC constraint the time each agent spends includes time in idea generation, in hint processing, and in communication and it cannot exceed the total time available to the agent, which is normalized to 1.

Note that this model treats all allocation of agent time to creation, transfer, and production as decision variables. Hence, the solution it yields represents the optimum that could be achieved through complete central control. Of course, such control is not feasible (or even desirable) in realistic settings. But it provides us with a benchmark against which to compare outcomes that result from decentralized decisions on the part of the agents and their management.

3.3.1. Characteristics of Agents in Single-Field Model

We begin our analysis of the above model by considering the case of a single-field network. Because agents can be rank ordered according to their creativity and productivity within a single field, we can show that unidirectional hint sharing is better than bidirectional sharing. Furthermore, if communication between any pair of agents is equally efficient, (i.e., all communication efficiency coefficients are identical), we can show that indirect transfer (i.e., through a third agent) of a hint is never optimal. To do this let us first define the following (Since $K = 1$ the subscript k is omitted for conciseness):

Definition 1. *Let the agent of concern be agent* n. *Then a* **giver** *is an agent who gives hints but does not receive them (i.e.,* $\sum_{m \neq n} X^t_{nm} > 0, \sum_{m \neq n} X^t_{mn} = 0$*), a* **taker** *is an agent who receives hints but does not give them (i.e.,* $\sum_{m \neq n} X^t_{nm} = 0, \sum_{m \neq n} X^t_{mn} > 0$*), a* **loner**

is an agent who neither gives nor receives hints (i.e., $\sum_{m\neq n} X^t_{nm} = 0, \sum_{m\neq n} X^t_{mn} = 0$*), and a* **transmitter** *is an agent that both gives and receives hints (i.e.,* $\sum_{m\neq n} X^t_{nm} > 0, \sum_{m\neq n} X^t_{mn} > 0$*).*

Using these classifications we can describe the optimal flow in a single field knowledge network. We begin with the following:

Lemma 1. *In an N-agent hint model, agent idling is not optimal.*

Proof see appendix.

Lemma 2. *Increasing the percentage of hint acceptance between any two collaborating agents improves their joint performance.*

Proof see appendix.

Lemma 3. *In an N-agent (*$N \geq 2$*) single-field network, each agent either works as a loner or performs unidirectional hint sharing.*

Proof see appendix.

Having ruled out bidirectional sharing, the optimal network only has agents who either works as loner or share hints unidirectionally. we now turn to the question of transmitters.

Lemma 4. *In an N-agent* ($N \geq 2$) *single-field network, no transmitter exists in the optimal solution when communication efficiency is the same for all pairs of agents, i.e.,* $S_{mn} = S \in (0, 1]$ *and* $T^t_{mn} = T$ *for all* (m, n)*.*

Proof see appendix.

Lemmas 3 and 4 permit us to fully characterize the optimal hint flow in N-agent single-field networks with uniform communication efficiency.

Theorem 1. *In an N-agent single-field network with the same communication efficiency, (i.e., $S_{nm} = S$ and $T_{nm} = T$ for all (n, m)) throughout the network, each agent must either be a giver, a taker, or a loner in the optimal solution.*

Proof: The proof is the direct results of Lemmas 3 and 4. ∎

After identifying the optimal structure of single-field network we now consider a special case of network structure, in which all agents have the same relative ability of generating and processing hints.

Proposition 1. *In a single-field network, it is optimal for all the agents to work independently (as loners) if the ratio of hint processing time to hint generating time is the same for each agent, i.e., $T_n^p/T_n^g = r, \forall\ n$.*

Proof see appendix.

3.3.2. Characteristics of Agents in Multiple-Field Model

Although the structural results are very sharp for single field knowledge networks, most real-world networks contain multiple fields. For example, professors in an Industrial Engineering department at a research university do research in a variety of fields (optimization, stochastic modeling, simulation, statistics, supply chain, ergonomics, industrial psychology, etc.). Within fields, it is not unreasonable to assume that faculty can be rank ordered according to expertise. (Note that this is almost tautological if we define fields narrowly enough.) For instance, the simulation specialist is likely to dominate the other faculty in the department with respect to simulation questions. Division by field doesn't mean that faculty are restricted to working in a single field. Indeed, it is quite possible that the simulation specialist may also be one of the most knowledgeable statistics researchers in the department. Whether expertise in the various fields is positively or negatively correlated depends on the department, but either case is possible.

While the overall behavior of a multi-field knowledge network may be complex, behavior within fields follows that shown earlier for single field networks.

Theorem 2. *In an N-agent ($N \geq 2$) multi-field network with uniform communication efficiency, then in each single field an agent must assume the role of either: giver, taker, or loner in an optimal solution.*

Proof: We show that a N-agent multi-field network can be expressed as independent N-agent single-field networks. Therefore the results in single-field network apply.

Suppose the optimal solution is $\mathbb{X}^* = [\mathbf{X_1^*}, \mathbf{X_2^*}, \ldots, \mathbf{X_N^*}]$. Define $\delta^*_{n(k)} = 1 - \sum_{l \neq k}(X^{g*}_{nl}T^g_{nl} + X^{p*}_{nl}T^p_{nl} + \sum_{m \neq n} X^{t*}_{nml}T^t_{nml} + \sum_{m \neq n} X^{t*}_{mnl}T^t_{mnl})$. Then optimized multi-field problem can be expressed as:

$$
\begin{array}{lrcl}
\max & \displaystyle\sum_k \sum_n V_k X^{p*}_{nk} & & \\
s.t. & X^{g*}_{n1} - X^{p*}_{n1} + \displaystyle\sum_{m \neq n} S_{mn1} X^{t*}_{mn1} - \sum_{m \neq n} X^{t*}_{nm1} & = & 0 \ \forall \ n \\
 & X^{g*}_{n1}T^g_{n1} + X^{p*}_{n1}T^p_{n1} + \displaystyle\sum_{m \neq n} X^{t*}_{nm1}T^t_{nm1} + \sum_{m \neq n} X^{t*}_{mn1}T^t_{mn1} & \leq & \delta^*_{n(1)} \ \forall \ n \\
 & \vdots & & \vdots \\
 & X^{g*}_{nK} - X^{p*}_{nK} + \displaystyle\sum_{m \neq n} S_{mnK} X^{t*}_{mnK} - \sum_{m \neq n} X^{t*}_{nmK} & = & 0 \ \forall \ n \\
 & X^{g*}_{nK}T^g_{nK} + X^{p*}_{nK}T^p_{nK} + \displaystyle\sum_{m \neq n} X^{t*}_{mnK}T^t_{mnK} + \sum_{m \neq n} X^{t*}_{nmK}T^t_{nmK} & \leq & \delta *_{n(K)} \ \forall \ n
\end{array}
$$

Since the feasible region of the problem can be completely decomposed into K fields, solving the multi-field network problem is equivalent to solving the following K separate single-field problems:

$$\begin{aligned}
\max \quad & \sum_n V_k X^p_{nk} \\
s.t. \quad & X^g_{nk} - X^p_{nk} + \sum_{m \neq n} S_{mnk} X^t_{mnk} - \sum_{m \neq n} X^t_{nmk} = 0 \\
& X^g_{nk} T^g_{nk} + X^p_{nk} T^p_{nk} + \sum_{m \neq n} X^t_{nmk} T^t_{nmk} + \sum_{m \neq n} X^t_{mnk} T^t_{mnk} \leq \delta^*_{n(k)}
\end{aligned}$$

Therefore, results of Theorem1 apply, which proves the theorem. ■

Decomposing a multi-field knowledge network into its underlying single-field networks is conceptually useful. But to be of practical use, we must be able to say something about the fully superimposed network, since that is what can be observed in the real world. For example, information flow could be measured via email traffic, a survey of the agents or collaborations on outputs (e.g., papers or patents).

To investigate the connection between basic parameters and overall structure we consider a network with three independent fields. Figure 3.1, 3.2, and 3.3 illustrates the different network structures when communication efficiency and time are the same for all the agents but correlation among fields vary. In Figure 3.1 the rightmost figure shows the superimposed network, while the other three figures show the networks for fields 1, 2, and 3. The superimposed network under these conditions is highly connected with a small world structure. Figure 3.2 shows the same network with the three fields perfectly correlated. Note that this results in a loosely braided network structure. Positive correlation in agent creativity and/or productivity across fields makes the aggregate network resemble the loosely connected single-field networks. No correlation or negative correlation across fields leads to a highly connected network. However, correlated fields are not the only environmental conditions that yield a highly connected optimal network. Figure 3.3 displays the single- and multi-field network for a case where agents are highly differentiated

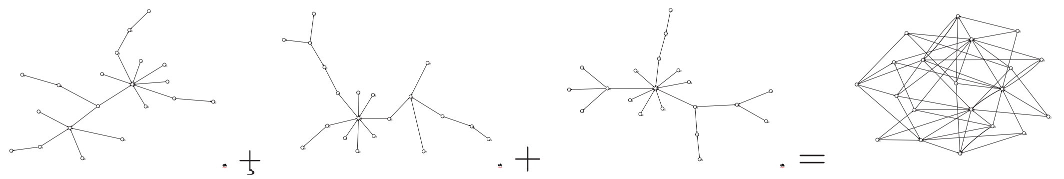


Figure 3.1. When Fields are Independent

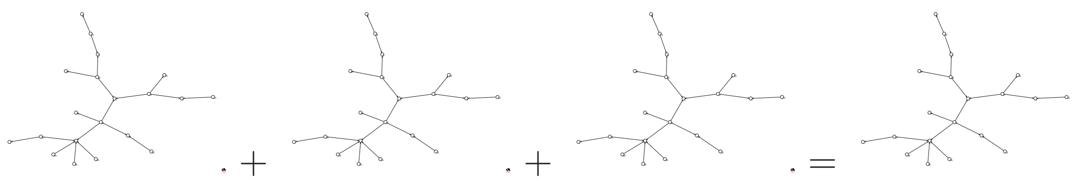


Figure 3.2. When Fields are Perfectly Positively Correlated

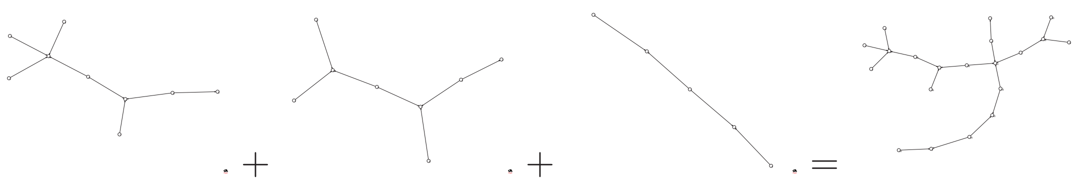


Figure 3.3. When Fields are Highly Negatively Correlated

(i.e., agents' creativity rates are very different in various fields). The highly connected aggregate network looks very similar to that when fields are highly correlated. Evidently there is a limit to what we can conclude about the micro-level characteristics of a network from its macro-level structure. In the next section, we use numerical examples to examine what extra information is needed to evaluate network behavior and the environmental factors that achieve the best performance.

3.4. Numerical Analysis

The above analytical insights give us an idea of what kind of knowledge network to expect to be optimal for a given set of conditions. But they don't tell us what conditions

Table 3.1. Design of Experiments in Single-Field Network

Factors to study	**Levels**
Ratio of the means=productivity/creativity (A)	0.2, 0.5, 1
Correlation between creativity and productivity (B)	Negative(-1), 0, Positive(+1)
Coefficient of variation of creativity (C)	0.25, 1
Coefficient of variation of productivity (D)	0.25, 1

are preferable from a performance perspective. Since managers can influence the underlying characteristics of a knowledge network, it is important to understand witch system parameters offer significant leverage. Specific question of interest are:

(1) Will increasing heterogeneity in agent capability (creativity and productivity) help or hurt organizational performance? The variability law for production systems (Hopp and Spearman, 2000) shows that introducing variation in processing time degrades performance. Does a similar logic apply to variation in creation and processing times in knowledge systems?

(2) Which type of organization achieves higher performance, one consisting mainly of specialists or generalists?

(3) Should total creativity be balanced or unbalanced to maximize performance?

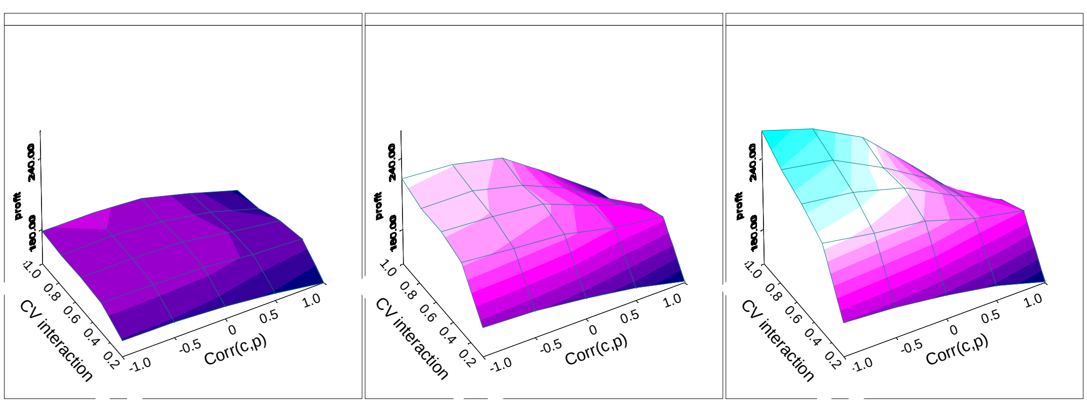
(4) If agents share hints based on partial information about other agents, how well or poorly do the emergent networks perform compared with the optimal structure?

Table 3.1 summarizes the experimental settings for our numerical studies of single-field networks. Factors considered are (a) the ratio of the productivity to creativity, with a ratio of 1 indicating a balanced network, (b) correlation between creativity and productivity, with negative correlation indicating a high level of specialization, and (c) coefficient of variation (CV) of creativity and (d) CV of productivity, where higher values of CV's indicating greater heterogeneity. We study three levels of the first two factors and two levels of the last two factors using a full factorial design. For each of the 36 ($3 \times 3 \times 2 \times 2$) settings we tested four replicates. All of the networks tested consisted of 300 agents.

Rates of idea generation and hint processing of those agents are generated from Weibull distributions. We use the Weibull distribution because with three parameters the Weibull can have many different shapes, symmetric, right, or left skewed, and small probability of generating negative random numbers when CV is high. Although other distributions, for example, the truncated normal, may be used for generating positive numbers, they do not have the desirable shape flexibility of the Weibull. Communication time (T_{nm}) is fixed to 0.000001/unit throughout the network and communication efficiency (S_{nm}) was set to 1 for all cases.

3.4.1. Heterogeneity

We studied two types of heterogeneity, creativity heterogeneity and productivity heterogeneity, with both characterized by CV. Our tests considered a low CV, 0.25, which represents organizations with homogeneous agents and a high of CV, 1, which represents organizations with heterogeneous agents. The results are summarized in Figure 3.4.



$\frac{\bar{\mu}}{\lambda} = 0.2$ $\frac{\bar{\mu}}{\lambda} = 0.5$ $\frac{\bar{\mu}}{\lambda} = 1$

Figure 3.4. Summary Plots of Numerical Studies

The graphics in Figure 3.4 show that when the CV of creativity is low increasing the CV of productivity from low to high improves performance. However, when CV of creativity is high, increasing the CV of productivity does not affect performance. The reason for this is that, for fixed average creativity and average productivity, increasing variability results in some agents who are either highly creative or highly productive. By taking advantage of these high performers, the network can produce more output. However, we must temper this conclusion with the observation from Figure 3.4 that CV interacts with the correlation of creativity and productivity. If this correlation coefficient is high, then increasing the CV of creativity and productivity will not improve performance because the highly creative agents are also the highly productive ones. Hence, the network cannot make use of specialization to increase output.

The practical insight from these result is that diversity in agent skill and specialization is beneficial to organizational performance. This result agrees with the social capital literature (see **?**Pelled, 1996). Research on teams and networks has found that teams consisting of members from diverse demographic categories perform better because "such teams generate links between people with different skills, information, and experience." And "therefore enhance team (network) capacity for creative action" (Reagans and Zuckerman, 2001).

3.4.2. Effect of Specialization

To understand the effect of specialization we examined the impact of correlation between an agent's creativity and productivity. We tested three levels of correlation: highly positive (1), none (0), and highly negative (-1). Positive correlation represents the situation where agents are either good or bad at both creation and processing. Zero correlation represents the situation where creativity is not related to productivity. Negative correlation denotes the situation where agents are either good at generating ideas or turning hints into value but not both.

Table 3.2. Experimental Results of Single-Field Network

Source of Variation	Sum of Squares	Degrees of Freedom	Mean Square	F_0	P-Value
A	34115.100	2	17057.600	4560.050	0.000
B	35895.900	2	17947.900	4798.070	0.000
C	17574.200	1	17574.200	4698.170	0.000
D	8313.900	1	8313.900	2222.580	0.000
AB	7917.800	4	1979.400	529.170	0.000
AC	2639.300	2	1319.700	352.790	0.000
AD	3827.500	2	1913.700	511.600	0.000
BC	4724.600	2	2362.300	631.520	0.000
BD	5354.600	2	2677.300	715.730	0.000
CD	9352.000	1	9352.000	2500.090	0.000
ABC	2270.300	4	567.600	151.730	0.000
ABD	1840.600	4	460.200	123.020	0.000
ACD	906.800	2	453.400	121.210	0.000
BCD	6737.300	2	3368.600	900.550	0.000
ABCD	1236.400	4	309.100	82.630	0.000
Error	707	189	3.7		
Total	136550.9	224			

Table 3.2 shows the effect of correlation levels is significant and is negative. From Figure 3.4 it is obvious that positive correlation leads to the worst performance and negative correlation leads to the best performance, indicating that specialization benefits performance. The explanation for this result is that when correlation between creativity and productivity is negative, agents can specialize in the function in which they are most proficient, either creating ideas or processing hints. Hence, given the same level of total creativity and productivity, resources can be better used when agents can be specialized.

The practical insight from these results is that organizations are better off hiring complementary specialists rather than generalists in order to maximize total organizational output and encourage current employees to acquire special knowledge in order to maximize the organizational performance.

3.4.3. Capacity Balance

In production systems, balancing capacity between workstations in a line is important for avoiding wasted capacity. So the question arises as to whether knowledge systems could similarly benefit from balancing capacity between idea generation and hint processing, since these represent successive steps analogous to steps in a production line. To answer this question we let $\bar{\lambda} = \frac{1}{n}\sum_{n=1}^{N} \lambda_n$ and $\bar{\mu} = \sum_{n=1}^{N} \mu_n$ denote the average creativity and average productivity, respectively, in a single-field network. We then define the following:

Definition 2. *A single-field network is* **balanced** *if $\bar{\lambda} = \bar{\mu}$. Otherwise it is* **unbalanced**. *Furthermore, a multi-field network is said to be balanced if each single-network contained in it is balanced, otherwise the network is unbalanced.*

We then examined the impact of the ratio of average creativity to average productivity. A value of 1 represents a balanced system, while the distance of the ratio from 1 measures the level of unbalanceness. Because with $S_{nm} = 1$, for all n, m, creativity and productivity play symmetric roles in the LP formulation. Switching them merely changes the direction of information flow but does not impact total profit. Hence, testing the ratio of r is equivalent to testing the ratio of $\frac{1}{r}$ with regard to the network performance. Therefore we only test values of $r \leq 1$.

We define $\bar{\lambda}$ and $\bar{\gamma}$ to be the average creativity in the balanced and unbalanced systems respectively. Similarly $\bar{\mu}$ and $\bar{\tau}$ denote average productivity in the balanced and unbalanced systems. We tested three levels r: 0.2, 0.5, and 1. When $r = 1$, the system is balanced and $\bar{\lambda} = \bar{\mu} = 1$. The two unbalanced systems were generated with mean creativities $\bar{\gamma} = \frac{3}{4}, \frac{3}{5}$ and mean productivities $\bar{\tau} = \frac{3}{2}, 3$. In order to keep total capacity fixed, the balanced and unbalanced systems are related by the following equation:

$$\frac{1}{\bar{\lambda}} + \frac{1}{\bar{\mu}} = \frac{1}{\bar{\gamma}} + \frac{1}{\bar{\tau}}$$

Table 3.3. Examples of Error Caused by Incomplete Information

	Example 1				Example 2			
	Field 1		Field 2		Field 1		Field 2	
	A1	A2	A1	A2	A1	A2	A1	A2
Creativity ($\frac{1}{T^g}$)	99	98	1	99	50	50	1	99
Productivity ($\frac{1}{T^p}$)	1	2	99	1	50	50	99	1
Heuristic	Reverse flow is *NOT* allowed				Reverse flow is allowed			
Output	2.97				50			
Optimal	99				99			
Loss	97%				49.5%			

where $\bar{\lambda} = \bar{\mu}$, $\bar{\gamma} = \bar{\lambda} + a$ and $\bar{\tau} = \bar{\mu} - \frac{\bar{\lambda}a}{\bar{\lambda}+2a}$.

Figure 3.4 shows clearly that the highest profit is attained when the system is balanced. As unbalance increases, the total profit decreases. Hence, we observe the same behavior as in production line balancing. The practical insights is that organizations should balance the total creativity and total productivity in order to maximize collective performance.

3.4.4. Incomplete Information

The previous numerical studies considered only single-field networks. Since virtually all real-world knowledge systems involve multiple fields, we extend out analysis to multi-field networks in this section. The primary questions of interest are: (1) how is network performance affected by incomplete information on the part of agents?, and (2) what settings achieve maximum profits in multi-field networks?

Before we can examine the effect of incomplete information, we must first specify how agents behave under these conditions. We do this by means of a pair of examples, which are illustrated in Table 3.3. In these examples, we assume that field 1 is observable and field 2 is not. Furthermore, we assume that an optimal communication network is formed for field 1 in both examples. But in Example 1 we assume that the sharing connections for field 2 are the same as those for field 1, while in Example 2 we assume that the links for field 1 constitute sharing options (in either the original or reverse direction) for field

2. These examples represent a situation when the agents have had time to explore each others capabilities and arrive at an effective solution for working in field 1 but must "guess" about capabilities in field 2. Example 1 models the heuristic in which agents assume that capabilities in fields 1 and 2 are perfectly correlated. Example 2 models a process by which agents restrict their communication in field 2 to channels already established for field 1. We allow reverse flows in field 2 because if agents A and B are communicating in field 1 which A as giver and B as taker, they have established a relationship, which would presumably allow B to act as giver and A to act as taker in field 2.

Using the data from Table 3.3 and assuming communication time is negligible we find that the optimal profit for Example 1 is 2.97 (both agents work in Field 1, one as giver and the other as taker: $\frac{1-(1/99)(2)}{1/99+1/1}+2$), while that for Example 2 is 50 (both agents work in Field 1 a loner: $\frac{2}{1/50+1/50}$). Since the optimal profit for the full information case is 99, the loss due to incomplete information is 97%. In Example 2, the loss is 49.5%. These examples illustrate how inefficient it can be to form a knowledge sharing network based on incomplete information. Although these are highly simplified cases, there is no question that similar heuristics find wide use in practice. For instance, a successful collaboration is likely to prompt two researchers to collaborate again, even if the network of the second project is not as conducive to success (e.g., it is in a slightly different field).

We can bound the profit loss from using information about one field to form a knowledge network in a multiple-field systems.

Definition 3. *The upper bound on the percentage performance drop is defined as* $\Pi_d = \frac{\Pi_b - \Pi_w}{\Pi_b}$, *where* b, w *refer to best and worst scenarios respectively.*

Proposition 2. *If* $\sum_{n=1}^{N} \frac{1}{T_{nk}^{g}} = \sum_{n=1}^{N} \frac{1}{T_{nk}^{p}} = c_k$ *(a constant),* $V_k = V$ *forall* k *and* $N \geq 2K$, *then*

$$\Pi_d = \frac{\sum_{k=1}^{K} c_k - \frac{c_1}{2}}{\sum_{k=1}^{K} c_k}.$$

Proof: First we consider the best scenario, where full information of each single field is available. In this case, the profit attainable in each single field (Π_k) is bounded above by the minimum of total creativity and total productivity. The upper bound can be attained when agents are extremely specialized in either hint generating or hint processing when hint transferring time is negligible, i.e.,

$$\Pi_k \leq \min\{V \sum_n 1/T_n^g,\ V \sum_n 1/T_n^p\} = c_k V.$$

Since the profit produced by the network (Π) is the sum of the profits in all single fields, network profit is bounded above by $\sum_k \Pi_k$. A special case where the maximum network profit is attained is illustrated below (where c stands for creativity and p for productivity):

	Field 1		Field 2		$\cdots$	Field K	
Agent	c	p	c	p	$\cdots$	c	p
1	c_1						
2		c_1					
3			c_2				
4				c_2			
$\vdots$					$\vdots$		
2K-1						c_K	
2K							c_K
$\vdots$							$\vdots$

Now consider the worst scenario, where agents' capability in other fields cannot be accurately inferred based on the experience in field 1. Since the network can be formed optimally with full information in field 1, the lower bound on the objective in the worst case is the optimal objective in field 1 when it is optimized as a single-field network.

Therefore, $\Pi_w \geq \Pi_1$. Since the all loner solution yields the lower bound on the objective function, the lower bound on Π_1 can be achieved when all agents work as loners, which is $\Pi_1 = \sum_n \frac{1}{T^g_{n1}+T^p_{n1}} \cdot V$. Therefore,

$$\Pi_w \geq \Pi_1 \geq \frac{c_1 V}{2} \text{ and}$$

this holds with equality when

$$T^g_{n1} = T^p_{n1} = \frac{1}{c_1 N} \; \forall \; n$$

Hence, the upper bound on the percentage performance drop with incomplete information is

$$\Pi_d = \frac{\sum_{k=1}^{K} c_k - \frac{c_1}{2}}{\sum_{k=1}^{K} c_k}. \qquad \blacksquare$$

Finally, we consider the question of what settings maximize profit in a multi-field system. We address this with the full-factorial experimental design shown in Table 3.4. We made a single replication at each of the 256 (2^8) settings. Each network in this set contained two fields and 100 agents. Table 3.5 presents the results from the experiment. The main effect on each factor was significant. From these results we conclude that high variation among agents and independence of creativity and productivity in different fields.

3.5. Conclusion

In this chapter we have appealed to similarities and differences between knowledge and production networks to introduce framework for modeling knowledge networks. We

Table 3.4. Design of Experiments in Multi-Field Network

Factors	**Levels**
CV of creativity in field 1 (A)	0.25, 1
CV of productivity in field 1 (B)	0.25, 1
CV of creativity in field 2 (C)	0.25, 1
CV of productivity in field 2 (D)	0.25, 1
Correlation between creativities in fileds 1 and 2 (E)	0, positive(+1)
Correlation between productivities in fileds 1 and 2 (F)	0, positive(+1)
Correlation between creativity in filed 1 and productivity in field 2 (G)	0, positive(+1)
Correlation between productivity in filed 1 and creativity in field 2 (H)	0, positive(+1)

Table 3.5. Experimental Results of Multi-Field Network

Factor	Effect	Coefficient	Standard Error	T	P-value
A	7710	3855	371.3	10.38	0.00
B	9007	4503	371.3	12.13	0.00
C	7514	3757	371.3	10.12	0.00
D	6819	3409	371.3	9.18	0.00
E	-4905	-2453	371.3	-6.61	0.00
F	-4102	-2051	371.3	-5.52	0.00
G	-3908	-1954	371.3	-5.26	0.00
H	-5956	-2978	371.3	-8.02	0.00

developed a basic hint model that represents creation, sharing, and transformation of knowledge into value. By dividing knowledge flows into fields, we were able to use our model to show that an optimized network assigns agents unique roles as either givers, takers, or loners. Using numerical analysis we showed that system performance in a single field system is balanced between creativity and productivity and has heterogeneous specialists. In a multiple-field network, we further observe that independence between expertise in different fields enhance performance. Finally, we note that heuristics based on partial information about agent capability can be severely suboptimal. Further work is needed to explore the relative effectiveness of local heuristics that lead to emergent knowledge networks.

CHAPTER 4

Dynamics of Collaborative Team Formation

4.1. Introduction

As economies have become increasingly reliant on technology, the role of knowledge creation and distribution has become more critical. Consequently, organizations have begun to systematically focus on improving their knowledge management. In the previous chapter, we discussed knowledge sharing structures from the perspective of a central decision maker with full information on the creativity, productivity, and communication capability of individual agents. In reality, however, centralized decision making based on full information is impossible. Information is always approximate and agents make their own decisions concerning collaborations. In this chapter we examine the problem of how collaborations form and evolve under these conditions and seek managerial insights into policies for improving collaborative performance.

There is an extensive literature on work groups (Radner, 1962; Marschak, 1955; Thompson, 1999; Reagans et al., 2004), embedded social networks (Guimerà et al., 2005; Uzzi, 1996; Singh, 2005; Borgatti and Cross, 2003; Borgatti, 2005), and decentralized matching (Gale and Shapley, 1962; Goyal and Moraga-González, 2001; Bloch and Ryder, 2000). But relatively little attention has been devoted to the mechanics and performance collaboration under conditions of partial information. Consequently, little research has examined the social learning process involved in forming collaborative relationships. In this chapter, we explicitly incorporate the learning process into the collaboration decision process. We hope to answer the following questions: (1) What type of team formation mechanisms lead to high-performance collaborations? (2) Under what circumstances is decentralized decision making efficient? For cases where decentralized decision making is less efficient, what managerial support should be provided to promote effective collaborative behaviors? (3) What role do social networks play in collaboration behaviors, such as, information collection, searching, and cooperation?

In the remainder of this chapter we discuss the model formulation in Section 4.2, present the numerical experiments in Section 4.3 and the results of simulation studies in Section 4.4, and draw conclusion in Section 4.5.

4.2. Model Formulation

Let *agents* represent knowledge workers. A schematic description of the model is as follows. We consider a problem where $2M$ agents in d subunits are to be divided into M teams of size 2. Decisions on collaborations are made over a finite time horizon, which is discretized into T equal time intervals. At the beginning of each period, teams are formed by agents themselves or by the assignment of the manager. Multiple tasks are then performed. Upon team formation, a collaborative tie is established if there is not any or is strengthened if there is one existing due to previous collaborations. While establishing or strengthening a collaborative tie agents still keep other ties preexisting before current collaboration. But the strength of these ties may need to be adjusted depending on each agent's time capacity. During each collaboration, agents can exchange information with their collaborators and other agents with whom they have a tie with. The amount of information exchanged is constrained by the strength of the ties. At the end of the period, team dissolves and both team members observe the outcome of the tasks and update their belief about the productivity of the collaboration. Meanwhile, agents also use the information exchanged during collaboration to modify their beliefs in the pair-wise productivity with those they do not collaborate in this period. Finally, the updated belief is used to determined whether an agent will seek the same or a different collaboration in the next period.

The agents and the ties established mainly through collaborations from a collaboration network, which evolves from period to period and provides a very important platform for information exchange, both directly and indirectly. Since people do rely on information exchange to locate and determine collaborators, incorporation of this collaborative network allows a more realistic model.

Before we dive into detailed description of the model, it is necessary to emphasize Since people's tenure within each organization is finite and the total number of collaborations they can participate in is limited, we consider a short time horizon, i.e., T is small. In the following we discuss some of the key assumptions in our model.

- First, since we only consider a very short time horizon and agents' capability hardly change within such a short period of time, it is reasonable to assume that agents' capability stay constant throughout the time horizon we examine. Moreover, although agents may enter or leave the system in a realistic setting, it rarely happens within a very short period of time. Hence, we assume no agent enter and leave the system within our modeling time horizon.
- Second, we assume tasks must be performed by teams. Joint performance but individual performance is observable by both team members. This assumption is motivated by the fast increasing trend of joint publication in academia (Wuchty et al., 2007) and the dominance of teamwork in business world. This assumption also is made for technical reasons: it forces agents to form collaborations and therefore leads to faster evolution of the collaboration networks; it avoids the complication of individual work and makes the results easier to understand and interpret.

- Third, agents may extend collaboration invitation to any other agent within the organization regardless whether they know each other or not. This assumption is motivated by the fact that in real situation collaboration is not limited among people who already know each other.

4.2.1. Learning Process

Since agents may exchange information regarding themselves and their (current and previous) collaborators, learning may occur both directly (i.e., regarding their collaborators) and indirectly (i.e., regarding other agents through the agent's social ties). The former either strengthens or weakens the agent's belief prior to the collaboration based on the result of the agents' own collaboration experiences. We refer to this type of learning as *reinforced learning*. The indirect learning occurs through the agent's social embedded connections. It relies on information transferred from other agents and does not require direct collaboration. Therefore, we refer to this type of learning as social learning.

4.2.1.1. Reinforced Learning. We assume that in every period $t(\in \{1..T\})$ each team performs multiple ($n \geq 1$) tasks. Each task has a prespecified goal, which is a complex combination of quality, quantity, deadline, and financial target. Upon completion each task is determined to be a *success* if the prespecifiend goal is achieved, otherwise it is determined to be a *failure*. Suppose that there is an unknown true probability of success for team comprised of agents i and j (θ_{ij}), which can be discovered gradually through learning. Then the outcome of each task is a random observation (x_{ij}) of the true probability of team success assuming that task difficulty is uniform across teams and time periods. x_{ij} takes on two values, 1 for success and 0 for failure and follows *Bernoulli* distribution with parameter θ_{ij}. If the unit profit is 1, then the profit generated by the team in each period, π^t, equals the total number of successes the team achieve in that period, i.e., $\pi_{ij} = \sum_{k=1}^{n} x_{ij}^{t,k}$ (n is the total number of tasks performed in each period), which follows

Binomial distribution with parameters n and θ_{ij}. Since each agent has some belief in how likely a particular pair-wise collaboration will succeed, such belief is modeled as the prior information (p_{ij}) for the true probability of success (θ_{ij}) and

$$p_{ij}^t \sim Beta(\alpha_{ij}^t, \beta_{ij}^t).$$

Then by Bayesian rules, the posterior distribution is still Binomial and

$$p_{ij}^{t+1} \sim Beta(\alpha_{ij}^t + \sum_{k=1}^{n} x_{ij}^{t+1,k}, \beta_{ij}^t + n - \sum_{k=1}^{n} x_{ij}^{t+1,k})$$

We assume that each agent has prior information on her collaboration with any other agents. Then the prior information of agent i on the rest of the agents is a vector of dimension $2M$ with the jth element representing agent i's belief in the chance of success when collaborating with agent j. Since agents must work in team to complete tasks, prior p_{ii} is 0 in all periods.

4.2.1.2. Social Learning. One critical feature of our model is that agents may learn through their embedded social ties in the collaboration network. We use a symmetric sociomatrix $A_{2M\times 2M}$ with 0's on the diagonal to represent the collaboration network. The symmetry implies that information can travel in both directions. In each time period, the entry a_{ij} of the sociomatrix represents the strength of connection between agents i and j, with higher value indicating stronger relationship. This relationship can be a result of newly established collaboration or a indication of previous collaborations, for interactions among agents decrease but not cease completely after a collaboration dissolves. If we interpret a_{ij} as the intensity of interactions between agent i and j, and suppose the fraction of capacity an agent allocates to the current collaboration is $\delta(<=1)$, then the value of a_{ij} varies between 0 and δ. We then have

$$a_{ij} \begin{cases} = 0 & \text{never collaborated before} \\ \\ \in (0, \delta\lambda_i] & \text{had collaboration before} \\ \\ = \delta\lambda_i & \text{collaborate in current period.} \end{cases}$$

Then in each given time period, the actual fraction of time agent i spends in ij interaction, q_{ij}, can be calculated as

$$q_{ij} = \frac{a_{ij}}{\lambda_i}(\leq \delta).$$

Since higher frequency of interactions generally leads to higher chance of information transfer, q_{ij} also represents the likelihood that information from agent i is communicated to agent j successfully in a direct manner. Similarly, q_{ijk} then represents the likelihood that information from i gets to k through j and $q_{ijk} = q_{ij} \times q_{jk}$. Since both q_{ij} an q_{jk} are less or equal to $\delta(\leq 1)$, we have $q_{ijk} \leq q_{ij}$ and $q_{ijk} \leq q_{jk}$, which indicates that the probability of successful information transfer decreases as the path length increases (Singh, 2005). Let $Q_{2M\times 2M}$ be the matrix with entry q_{ij}. Then the probability that information from agent i reaches agent k in l steps can be written as

$$Q_{ik}^{(l)} = \sum_{j_1, j_2, \ldots, j_{l-1}} Q_{ij_1}^{(1)} Q_{j_1 j_2}^{(1)} \ldots Q_{j_{l-1}k}^{(1)}.$$

Therefore, the probability of information from i ever reaches j, r_{ij}, can be calculated as

$$r_{ij} = min\{\sum_{l=1}^{2M-1} Q_{ij}^{(l)}, 1\}$$

When information is communicated from one agent to another, the information receiver may not always accept the information. He/she instead first evaluates the credibility of the information source. If the information is from a trusted source, it has a higher chance to be accepted and put into future use. Otherwise, the information is ignored and makes no impact on the receiver's behavior. Therefore, the likelihood of a piece of information from agent i to agent j will be utilized by j, ω_{ij}, depends on both whether the information is successfully transferred and whether it is accepted by the receiver. Let $\gamma_{ij}(\leq 1)$ be the level of trust agent j has in agent i then w_{ij} can be expressed as

$$\omega_{ij} = r_{ij} \times \gamma_{ji}.$$

In literature, trust has been extensively studied from various perspectives (See Kramer (1999) for a review). One important theme of these studies is that trust is not static, it evolves as a consequence of people's experiences. In collaborative relationships, positive outcome reinforces the partners' trust in each other whereas negative outcome damages such trust. In our model, we also take a dynamic view of trust. We consider the level of trust evolves depending on both the agent's previous trust level and most recent experiences. Suppose $\mu(<= 1)$ is the weight that an agent assigns to the trust level in period $t-1$. Then agent i's trust in agent j in period t is as follows:

$$\gamma_{ij}^{t} = \mu\gamma_{ij}^{t-1} + (1-\mu)f(\sum_{k=1}^{n} x_{ij}^{t,k})$$

where $f(\sum_{k=1}^{n} x^{t,k})$ is the experiences agent i gains in ij collaboration, which is a function of the total number of tasks completed successfully.

4.2.1.3. Combined Learning. The total learning is a combination of reinforced learning and social learning:

$$\alpha_{ij}^{t+1} = \alpha_{ij}^{t} + \sum_{k=1}^{n} x_{ij}^{t+1,k} + n\theta_{ij}\omega_{ij}$$

$$\beta_{ij}^{t+1} = \beta_{ij}^{t} + n - \sum_{k=1}^{n} x_{ij}^{t+1,k} + n(1-\theta_{ij})\omega_{ij}$$

4.2.2. Network Evolution

We consider a dynamic environment, in which network evolves as collaboration establishes and dissolves. The network contains all the agents and ties among them. A new tie establishes only if a new collaboration is formed. After a collaboration terminates, the tie does not dissolve consequently. Instead, it remains but the strength of tie may change based on (1) whether the same collaboration is reestablished at the beginning of the next period (2) the total capacity of the agent, and (3) the capacity allocation among the agent's other ties. If the same collaboration is reformed, the tie strength stays the same. Otherwise the tie strength reduces. as a non-decreasing function of the number of periods elapse since last collaboration:

$$a_{ij}^{t} = \begin{cases} \delta\lambda_i & \text{if } i \text{ collaborates with } j \text{ in period } t \\ (1-\delta)\lambda_i \cdot \frac{a_{ik}^{t-1}}{\sum_{k\neq j} a_{ik}^{t-1}} & \text{otherwise} \end{cases}$$

4.2.3. Team Formation

In this section, we consider the formation process of teams of size 2. We study two types of formation process: decentralized process, i.e., team formation is completely determined by agents themselves, and management intrusion, i.e., managers assign teams at certain periods based on their own criterion.

4.2.3.1. Decentralized Process. Decentralized pair formation is a dynamic process, in which agents either extend or accept invitations of collaborations without being intervened by the manager. We assume that agents do not extend their invitations to all the others with equal likelihood. Rather they evaluate the expected benefit of all potential collaborations and preferably first invite those with better chance of higher benefit. Similarly, agents do not always accept an invitation upon its arrival. They always assess the benefit of the collaboration and choose the best available partner to form collaboration. With this said, the pair formation process involves two critical decision makings: whom to extend collaboration invitation to and whose invitation to accept when receives one. We model pair formation as a mutual selection process based on a ranking system. That is, each agent ranks all the other agents based on a certain criterion. Once a rank list is determined, agents will follow the order on the rank list to choose partners as follows: When extending an invitation, an agent first invites the highest ranked agent to collaborate; if the offer is accepted a collaboration is formed; otherwise the agent goes to the next highest ranked agent. When receiving an invitation for the first time, an agent accepts the offer only if the invitation is from the highest ranked agent on his/her list; when receiving an invitation for the second time, an agent accepts the offer if the invitation is from either the first or second highest ranked agent on his/her list; and so on.

We examine two types of ranking criteria: (a) to maximize current pair-wise productivity only and (b) to maximize both current and future pair-wise productivity, with the latter implemented by considering potential social information benefit provided by the collaborator. In Case a, agents make decisions only based on their current belief in productivity, p_{ij}, and the cost of establishing the collaboration, c_{ij}. The rank of all the other agents on agent i's list is the decreasing order of net gain

$$\pi_{ij} = p_{ij} - c_{ij}.$$

In Case b, agents also considers the information benefit in addition to pure productivity. Agents prefer to form collaborations with those who have already had many collaborative ties, i.e., preferential linking. The motivation behind this idea is that people with more collaborative ties tend to have better access to information and connecting to those people improves one's own chance of efficiently identifying one's most compatible collaborative partner. In our model, we calculate the criteria of Case b as

$$\pi_{ij} = \rho(p_{ij} - c_{ij}) + (1 - \rho) I_{\{j \in S_i\}} L_j,$$

where ρ is weight agents assign to productivity, L_j is the number of collaborative ties agent j has, I is an indicator function, and S_i is the set of agents whose number of ties is observable by agent i. It is worth noting that S_i changes over time. We assume that an agent can learn the number of ties his/her partner has. Hence, $|S_i|$ increases by 1 whenever a new collaboration is established.

An important element in calculating the ranking criteria in both cases is the cost. The cost of establishing a collaboration largely involves the overhead cost of mutual understanding. Since previous collaboration improves agents' knowledge of their partners' work style and expertise and therefore greatly reduces the cost of reestablishing a collaboration, we consider the cost as a non-increasing and concave function of the total number of collaborations the two agents have

$$c_{ij} = a y_{ij}^{-b},$$

where a represents the cost of forming a collaboration for the first time, y is the total number of collaborations ij have, and b is the cost decay factor with larger value implying cost declines faster as the number of collaborations increases.

4.2.3.2. Management Intrusion. While in knowledge-intensive work environments, decentralized pairing is the major form of collaboration formation, it can be interrupted by centralized policies. Managers may occasionally make paring decisions in order to improve overall productivity via enhancing the effectiveness of information sharing. In our model, we assume that managers may have a snapshot of the collaborative network in certain time periods. Agents then are ranked based on their *node betweenness* (Wasserman and Faust, 1994) in a decreasing order. Managers ask the highest ranked agent to form a collaboration with the second highest ranked agent, third highest ranked agent to form a collaboration with the fourth highest ranked agent, and so on.

4.3. Numerical Experiments

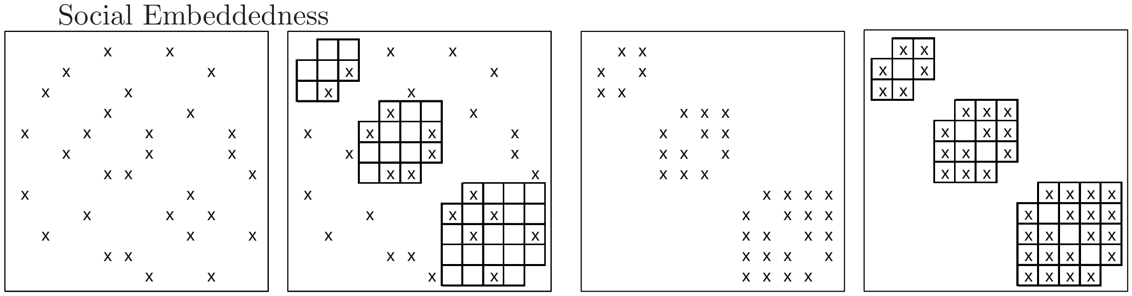
The model we described above represents a complex dynamic system, which we study using simulation method in factorial experiments. Our goal of the numerical experiments are: (1) to compare the efficiency of different management policies, (2) to examine the role of trust in team formation, and (3) to understand the impact of different ranking criteria in team formation decision making.

We examine an organization of 60 agents (i.e., $2M = 60$) forming collaboration teams of size 2 in 20 time periods (i.e., $T = 20$). In each period, teams form, perform 10 independent subtasks (i.e., $n = 10$) and then dissolve. The organization has 4 subunits (i.e., $d = 4$), each with 10, 15, 15, and 20 agents. We study two types of underlying productivity structure: (i) best pairings are within subunits (i.e., within-subunit pairwise productivity is higher than that of cross-subunit paring) and (ii) best pairings can be either within or outside subunits (i.e., within-subunit and cross-subunit pairing are equally likely to be productive). For each productivity structure we examine two configurations of social embeddedness: (i) initially social ties exist only within but not across the subunit and (ii) initially social ties do not exist in the organization. The combination of these two parameters, i.e., productivity type and social embeddedness type, leads to 4 different configurations of the organizational structure, illustrated in Figure 4.1. In organization configuration (a) and (c), no social ties exist in the organization before any team formation. This configuration indicates that workers purely rely on their belief in others' compatibility to determine whom to collaborate with. Although in reality, it is almost impossible to find an organization without existing social ties, such configuration provides modeling advantages. It helps us to have a clear understanding of coevolution process of team and social network formation. In organization configuration (b) and (d), social ties exist among workers within the same subunit but not among workers across subunits. These configurations more closely reflect the reality, which is people tend to know their peers within the subunit better due to closer physical distance, more frequent interactions, etc.. Specifically, we define two types of collaboration network as follows: no ties at time 0 (i.e., $a_{ij} = 0 \ \forall(i,j)$) and only intra-subunit ties exist at time 0 with the strength of ties equally distributed (i.e., $a_{ij} = \frac{\lambda}{\text{size of the subunit}}$ if i, j in the same subunit and $a_{ij} = 0$ otherwise).

We generate different levels of pair-wise true productivity (θ) in two steps. First, we select the percentage (20%) of collaborations which will be assigned higher values. Those collaborations are all intra-subunit for social embeddedness case i and can be either intra- or inter-subunit for social embeddedness case ii. We then generate the actual θ from $U(0.8, 1)$ for collaborations with higher productivity and from $U(0, 0.3)$ for collaborations with lower productivity. We consider agents' prior probability of the true productivity are higher for intra-subunit collaboration and lower for inter-subunit collaboration:

$$(\alpha_{ij}^0, \beta_{ij}^0) = \begin{cases} (2,1) & i,j \text{ from the same subunit} \\ (1,1) & i,j \text{ from different subunits} \end{cases}$$

Figure 4.1. Organization Structure Configuration based on Productivity and Social Embeddedness



"□" indicates social tie; "x" indicates high productivity

(a) (b) (c) (d)

We set the initial trust level for each agent (γ_{ij}^0) to be either 0.2 or 0.8. This initial trust also represents the overall harmony and collaborative environment in the organization. We let weight on the previous trust (μ) be 0.5. We assume each agent's total capacity (λ_i) to be 1 and the percentage of capacity allocated to a collaboration (δ) to be 0.6. δ greater than 0.5 implies that each agent can only has at most one collaboration in each period, i.e., the maximum team size is 2.

We represent the cost of establishing a collaboration for the first time (a) as a percentage of average true productivity ($\bar{\theta}$). We test two levels of a: $0.01\bar{\theta}$ and $0.1\bar{\theta}$. We test two levels of the cost decay factor (b), 0.5 and 1.

We test both decentralized pair formation process and management intrusion with the two decision making criteria: (a) to maximize current pair-wise productivity only and (b) to maximize both productivity and social information benefit. In our experiments, social information benefit refers to the likelihood of accessing more information through socially embedded ties, which implies that in order to have a broader access to information, agents prefer to form teams with those who have many social ties which may predict higher future pair-wise productivity. When Case b is examined, we set the weight on productivity (ρ) to be 0.5. We consider management intrusion occurs at time period $t = 3, 6, 9, 12$.

4.4. Results and Insights

In this section, we discuss the results of simulated factorial experiments. Table 4.1 summarizes the design of the experiments.

Table 4.1. 2^7 Factorial Experimental Design

Factor	Level
Organization Type	Type 1 (Best paring is within the subunits) Type 2 (Best paring can be within or across subunits)
Initial Social Network in the Organization	Type 1 (no ties) Type 2 (ties exist only within but not across subunits)
Decision making criteria	Productivity Productivity and Social Information Benefit
Policy	Decentralized Centralized
Initial Trust Level	Low (0.2) High (0.8)
Initial Cost of Establishing a new tie	Low (0.01) High (0.1)
Cost Decay Factor	Low (0.5) High (1)

4.4.1. Performance

We characterize the performance of the organization by two types of metrics. The first type of metric is performance-oriented measures, which include standardized profit and the total number of corrected pairs. The second type of metric is network-oriented measures, which include average degree centrality and average betweenness centrality.

Standardized profit is chosen because the optimal profit achievable differs for each scenario of generated organization configurations. In order to make fair comparisons among factors, we standardized the profit by dividing the actual profit gained by the optimal profit achievable[1]. The *total number of corrected pair* is a metric that counts the total number of optimal paring occurrence. For each test case, we solve an integer programming problem to find the optimal paring based on the true productivity. We then compare the actual paring with the optimal paring and count the times of agreements as the number of corrected pairs. *Average degree centrality* calculates the average number of direct ties each agent has. Since new ties establish only through collaborations, this metric indicates how many teammates an agent has on average over the entire time horizon. It also reflect an agent's access to diverse information, for having more ties allows more information to flow in through divergent channels. Furthermore, since the number of agents stay the same through out the simulation, average degree centrality essentially is an equivalent measure to network density, which is defined to be $\frac{\sum degree}{2M(2M-1)/2}$ ($2M$=60). *Average betweenness centrality* is defined as $\sum_{i\neq j, i\neq k, k\neq j} \frac{g_{ikj}}{g_{ij}}$, where g_{ij} is the total number of shortest paths between i and j and g_{ikj} is the total number of shortest paths between i and j through k(Wasserman and Faust, 1994). It reflects an agent's capability of accessing information and how closely connected the agents are in the collaboration network. Since the chance of successful information transfer decreases as the number of steps increases, having a high betweenness centrality implies that the agent is more likely to receive information than those with low betweenness centrality.

Table 4.2 shows the linear correlation among those performance measures for different organization configurations. All correlations are non-negative, which suggests that better network connectivity (indicated by degree centrality and betweenness centrality) helps agent search for good collaborators and therefore is more likely to lead to higher productivity. Interestingly, we observe that correlations between profit and other performance

[1]The optimal profit achievable is calculated by the summation of true productivity of optimally assigned teams. The team assignment is solved by an integer program: Max $\sum_{\{i,j\}} \theta_{ij} y_{ij}$, s.t., $\sum_j y_{ij} = 1, \forall i$ and $\sum_i y_{ij} = 1, \forall j$, $y_{i,j}$=0 or 1. The solution for $y_{i,j}$ indicates the optimal team assignment, i.e., when $y_{ij} = 1$, i and j should be assigned to the same team. The optimal profit achievable then is calculated as: $\sum_{\{i,j\}} \theta_{ij} y_{ij}$

measures are significantly higher for organization type a than those for the other organization types. This result implies that the network connection is most beneficial when agents need to seek collaborators both inside and outside their own subunits in order to achieve superior performance. While doing so they cannot rely on preexisting embedded social ties but have to make use of the new ties established through collaborations to help gather information. We also observe that the correlation between the number of corrected pairs and node degree and node betweenness generally are small and some of them are even less than 0.1. This result suggests that benefit of good connection is limited. Being well connected in the collaboration network helps agents search for potential good partners but agents may stop searching for better partners once such a good partner is identified due to the inertia built into the reinforced learning process.

4.4.2. Effect of Management Policy

The most interesting question to ask is whether agents can achieve better performance with the help from the management. To answer this question, we compare the performance of decentralized team formation policy with the management intrusion policy.

4.4.2.1. Effect of Management Policy on Profit. Table 4.3 shows the results of the factorial experiments. In the experiments, decentralized policy is coded as policy 1 and management intrusion is coded as policy 2. The positive main effect of policy suggests that managers may help agents identify good partners and therefore achieve higher productivity by reconfigurating teams sporadically based on the information the manager learns about the collaboration network.

While managers may help boost productivity by the end of the test period, does the management intrusion lead to higher productivity immediately? Figure 4.2 shows the agents' productivity over time when either decentralized or management intrusion policy

Table 4.2. Linear Correlation among Performance Measures

Organization Type (a)

	Corrected Pair	Degree	Betweenness
Profit	0.60	0.68	0.56
CorrectedPair		0.32	0.20
Degree			0.88

Note: All correlation are significant at 0.05 level.

Organization Type (b)

	Corrected Pair	Degree	Betweenness
Profit	0.43	0.46	0.46
CorrectedPair		0.09	0.05
Degree			0.97

Note: All correlations are significant at 0.001 level except for correlations<0.1

Organization Type (c)

	Corrected Pair	Degree	Betweenness
Profit	0.37	0.46	0.30
CorrectedPair		0.12	0.00
Degree			0.85

Note: All correlations are significant at 0.001 level except for correlations<0.15

Organization Type (d)

	Corrected Pair	Degree	Betweenness
Profit	0.31	0.47	0.38
CorrectedPair		0.16	0.22
Degree			0.87

Note: All correlation are significant at 0.05 level.

is applied. We observed that management intrusion leads to a significant higher profit level at period 5, which is two periods after managers shuffle teams for the first time. This suggests that management intrusion at the early stage of the team formation greatly helps agents locate good collaborators. We also observed a big dip between period 5 and 10 for organizations of type b and d and a minor dip for organizations of type a and c. Recall that managers reshuffle the teams at period 6 and 9. Those dips therefore indicate that frequent management intrusion may hurt immediate team productivity, especially

Table 4.3. Profit Analysis

	org(a)	org(b)	org(c)	org(d)
InitTrust	++	++		++
policy	++	++	++	++
decision		- -	+	- -
InitTrust×policy	-	-	- -	- -
InitTrust×decision				
policy×decision		+	++	

"+/-": positive/negative effect signicant at 0.05 level

"++/- -": positive/negative effect signicant at 0.01 level

after agents have gained certain amount of information about others. A possible explanation for this phenomenon is that since the reconfiguration of teams by the managers is aimed at improving the connectivity among agents but the profit, the newly formed teams by the manager may not be as productive as the original teams formed by agents themselves which are established based on maximizing team productivity. Furthermore, we observed the overall productivity increases at a faster speed after the dip, especially for organizations of type a and b, in which an agent's best partner could be inside or outside the agent's subunit. This observation suggests that management intrusion is more useful in organizations where best teams are not limited to within subunit. For example, when interdisciplinary research may produce more high quality publications. Surprisingly, we didn't observe a jump of productivity after managers reshuffle the teams at period 12, which indicates that reassigning teams does little help after agents have had good knowledge of their peers through previous collaborations and reshuffles.

4.4.3. Effect of Trust

Trust has been widely thought to affect information sharing and collaboration formation (Thompson, 1991; Mayer et al., 1995). In our study, we model interpersonal trust as the determinant whether a piece of information to be accepted and put into good use.

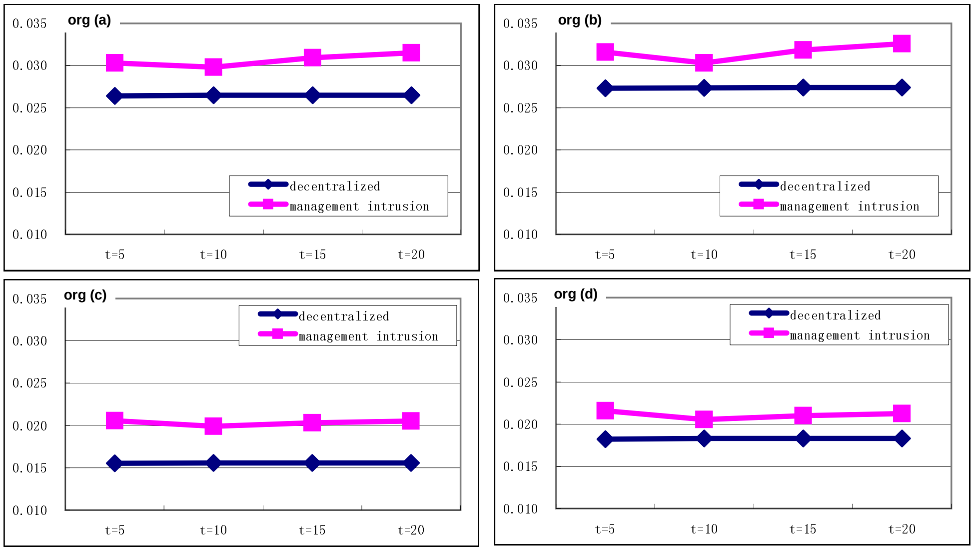


Figure 4.2. Profit vs. Policy over Finite Time Horizon. From left to the right and top to the bottom are organization type a, b, c, and d, respectively.

Table 4.3 shows the effect of overall trust level on organizational productivity. We observed that higher level of interpersonal trust leads to better performance in organizations of type a and b. This result implies that since higher level of trust enhances an agent's willingness to accept and make use of the information from others, an agent may gain larger amount of information and therefore improve his/her chance of identifying and locating good collaborators when the agent has a higher level trust in the source of information. Being trustful is particularly valuable when an agent's good collaborators are not limited to those in the same subunit, such as cases in organization type a and b. Interestingly, we also observed a significant impact of trust in organizations of type d but not c. This suggests that since agents prefer to form collaborations within subunits first due to their belief in higher productivity of intra-subunit teams, it is highly likely for an agent to find a good collaborator within his/her own subunit with very few trials. Once a good collaborator is identified, agents will stick to the collaborator, which prevents them from establishing more social ties through collaboration. Consequently, agents will not be able to take advantage of information accessible through embedded social ties, such as the case in organizations of type *c*. Thus, whether agents trust the information source or not does not have an impact on their productivity, except for the case where social ties exist not only through collaborations, such as the case in organizations of type *d*.

The experimental results in Table 4.3 also show significant interaction among trust level and management polices. The effect is negative for all types of organizations. Since we coded decentralized policy as 1 and management intrusion policy as 2 in our statistical analysis, the negative effect of trust indicates that higher level of trust is more valuable when agents form teams all by their own decisions, i.e., when the decentralized policy is implemented. Figure 4.3 illustrates such effect by the interaction plots of trust and policy. These plots show a steeper upward slope for lower level of trust when decentralized policy is substituted by management intrusion, which implies higher impact of trust on productivity when teams form and dissolve all by agents themselves. The explanation for this observation is that while forcing agents to form teams may improve agents' access to more diverse information in a longer term, it may hurt team productivity in a short term when incompatible agents are assigned to work together. Since trust is dynamic and the mutual trust between team members is strengthened when the team successfully complete a task and weakened when the team fail to do so, the failure caused by forced team formation in early periods greatly reduces the team members' trust in each other. Consequently, having a higher level of initial trust is less effective when management intrusion is applied.

4.4.4. Decision Making Criteria

In our study we considered two types of ranking criteria when agents make team formation decisions. Agents either aim to improve productivity or take social information benefit brought by more connections into account in addition to productivity. While we would expect that valuing benefit of social information is helpful in a long term, surprisingly, we

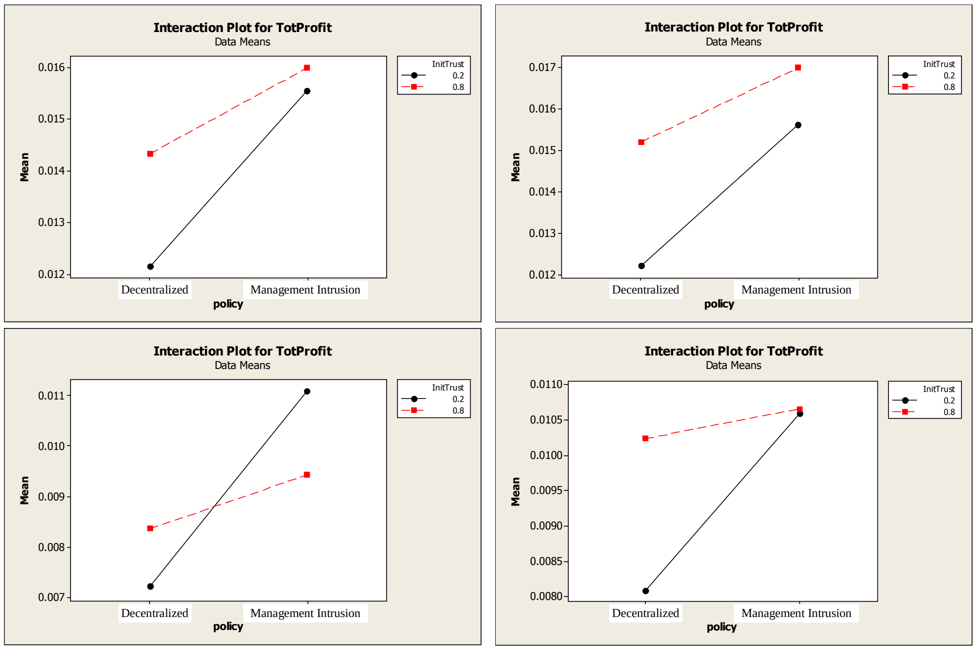


Figure 4.3. Policy and Trust Interaction. From left to the right and top to the bottom are organization type a, b, c, and d, respectively.

did not observe a positive effect of this decision making criterion on agents' productivity. The experimental results show that taking social information benefit into consideration in making team formation decisions affects agents' productivity differently in various types of organizations. The impact is negative in organizations of type b and d and positive in organizations of type c. The reason for the negative effect of productivity and social information benefit combined decision making criterion (i.e., decision making criterion type 2) can be explained as follows. When social ties exist among agents in the same subunit before collaboration starts, agents from a larger subunit is more likely to attract collaborators. Since collaborating with agents from a larger subunit does not necessarily lead to productive teams, using decision making criterion 2 is highly likely to result in lower team productivity. Furthermore, while considering social information benefit may be helpful in a long term, such benefit may not be big enough to cover the loss in productivity when the time horizon is fairly short. In contrast to the negative effect in organizations of type b and d, the effect of decision making criterion 2 is positive in organizations of type c, where no social ties exist before team formation and social ties can be established only through collaborations. In such organizations, it does not matter which decision criterion is used at the beginning of team formation because all agents have no preexisting social ties. Agents therefore are not biased towards collaborating with agents from larger subunit. Consequently, considering social information benefit helps agents quickly gather valuable information in order to form productive teams.

Table 4.3 also indicates significant interaction between decision making criteria and management policy in organizations of type b and c. The left plot in Figure 4.4 suggests that managers may help correct the trend of collaborating with agents from larger subunits by reshuffling teams. Those forced team assignments increase the chance of agents being exposed to new collaborators and gathering information through new channels and therefore predicts better productivity. The right plot in Figure 4.4 implies that when managers pool agents with high betweenness centrality into the same teams, they help improve the connectivity of the collaboration network. Consequently, the likelihood of successful information transfer is greatly enhanced because of shortened path lengthes. Thus, we can expect social information to be better utilized and higher productivity may be achieved.

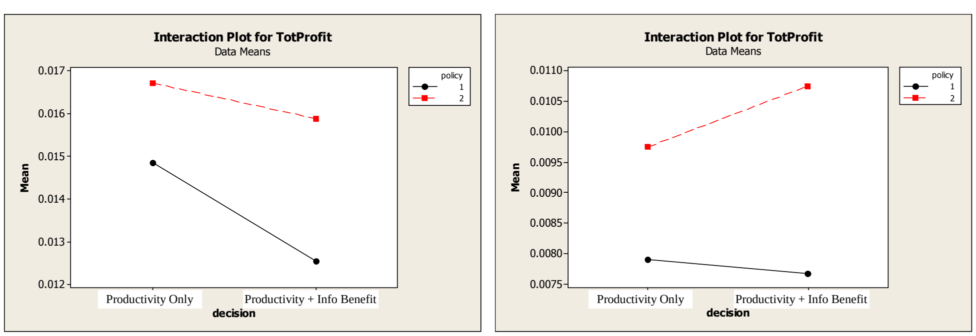


Figure 4.4. Policy and Decision Criterion Interaction. From left to the right are organization type b and c, respectively.

4.5. Conclusion

In this study, we examined dynamic team formation process in different types of organizations. Our primary goal is to understand the role of managers in facilitating effective teams. We modeled each organization as a collection of agents who need to form teams in order to perform knowledge-intensive tasks. Agents may learn the productivity of a particular team through either collaboration or embedded social ties or both. The collection of agents and their social ties established mainly through collaborations comprises the collaboration network, which evolves as teams form and dissolve from time to time. Through simulated factorial experiments, we found consistent positive impact of management intrusion on team productivity across different types of organizations. This result suggests that management policies based on enhancing collaboration network connectivity may help improve information sharing among agents and therefore lead to formation of productive teams.

An important feature of our model is the incorporation of trust. In our model, trust is dynamic and largely determines whether a piece of information will be accepted by the information receiver. We modeled the mutual trust between team members to be strengthened when task processing is a success and weakened when the task processing is a failure. We found that being more trustful is beneficial in general. It is more influential when agents make team formation decision all by themselves, i.e., when decentralized policy is implemented.

In addition to the roles of management policies and trust, we also studied the impact of different criteria in making team formation decisions and its interaction with management policies. We found a mixed main effect of the criterion which takes both productivity and social information benefit into account. We identified the types of organizations where management intrusion is more valuable when this kind of decision making criterion is used.

CHAPTER 5

The Role of Internal Collaboration and Communication on Research Productivity and Impact of an Engineering School

5.1. Introduction

Organizations involved in knowledge-intensive work rely heavily on smart and creative people (Davenport, 2005; Jacobson and Prusak, 2006; Goffee and Jones, 2007). However, organizational success depends on more than the talent and effort of individuals. Goffee and Jones (2007)'s interview with leading organizations (e.g., PricewaterhouseCoopers, Cisco Systems, the British Broadcasting Corporation (BBC)) indicated that it is crucial to foster an environment within which smart people can fully utilize their potential. Since the most important resource in knowledge-intensive environments is intellectual capital, high performance environments are those that support collaboration and knowledge sharing (Perry-Smith and Shalley, 2003; Cross and Cummings, 2004; Uzzi and Dunlap, 2005).

To understand how collaboration influences performance, a number of researchers have made use of social network models (Borgatti and Cross, 2003; Borgatti and Foster, 2003; Hansen, 2002; Hansen et al., 2005; Fleming et al., 2006; Cummings, 2004; Reagans and McEvily, 2003; Tsai, 2001). In addition to providing a mechanism for quantifying collaboration and showing a correlation with performance, network models can help characterize different types of collaboration in order to determine which are most effective. For example, research has shown that positions of high brokerage (which measures the extent to which an individual's communication/collaboration spans different groups) are positively associated with work performance, presumably because a high brokerage position exposes the individual to different types of information (Burt, 1992, 2004; Brass et al., 2004; Brown and Duguid, 2001; Tsai, 2001). Similarly, researchers have found that central (i.e., highly connected) positions promote good performance by enabling quick access to information from the rest of the network (Perry-Smith and Shalley, 2003; Cross and Cummings, 2004).

However, while favorable network positions provide access to information, the ability to transform this into better performance depends on whether an individual has the time to seek out and act on this information. When an individual is highly central, he/she may have to devote considerable time to maintaining existing ties and hence have less time to seek out new connections, which may hinder his/her performance (Perry-Smith and Shalley, 2003). While the fact that people have limited capacity is well known, there has been little attention within the social network literature devoted to empirically investigating the role of capacity on individual performance. In this paper, we address this issue in the context of academic research collaboration.

In addition to network position, the nature of the ties within the network has been found to influence individual performance. For example, weak ties are sometimes more effective than strong ties (Granovetter, 1973; Perry-Smith, 2006) and new ties can sometimes promote more creativity than old ties (Uzzi and Spiro, 2005). In particular, boundary spanning ties (which establish connections between departments/organizations/professions outside one's own) have been shown to benefit individual performance, presumably because integrating disparate types of knowledge promotes creativity (Hargadon and Sutton, 1997; McEvily and Zaheer, 1999; Cross and Cummings, 2004).

However, while having ties to disparate areas may indeed be valuable, it is not clear how valuable such ties are in an environment, such as an academic research institution, that requires a high degree of specialized knowledge. Since time for collaboration is limited, it is important to understand the relative value of ties within one's own department/organization/discipline versus boundary spanning ties. In this paper, we compare the impact on performance of interdisciplinary and intra-disciplinary collaborations.

Modeling the influence of collaborative behavior on performance requires a precise definition of performance. But since knowledge intensive environments are complex, this is a subtle issue. Managers typically use metrics based on immediate past performance, since these metrics are used in setting compensation. Hence, research that uses manager ratings considers only the very recent past (Perry-Smith, 2006; Cross and Cummings, 2004). Researchers have used metrics based on the intermediate past, such as counts of good ideas (Toubia, 2006), or the more distant past, such as citation counts of patents (Fleming and Marx, 2006; Miller et al., 2007). To our knowledge, however, there has been no study that has addressed performance at both the near- and long-term level. By considering both publication rates (near term) and citation rates (long term), we are able to examine differences in the near- and long-term impact of collaboration on performance.

The primary goal of this chapter is to extend our understanding of the impact of collaborative behavior on performance in a complex knowledge-intensive environment. In particular, we seek to characterize the near- and long-term benefits of interdisciplinary communication and collaboration. We do this by studying an engineering school and measuring individual performance in terms of both productivity (quality weighted publication rate) and impact (quality weighted citation rate). In addition to contributing to the literature on knowledge networks, this work offers insights relevant to the current trend of promoting interdisciplinary research within educational institutions and funding agencies.

5.2. Network Position and Work Performance

An advantageous position in an organizational network can provide information and resource benefits for the person who occupies the position. An example of a structurally advantageous position, which can have an important impact on an individual's work performance, is a position of high centrality (Scott, 2000). It is generally believed that a central position promotes an individual's capability to locate, absorb, disperse, and synthesize relevant information into useful resources and therefore eventually enhances individual performance (Tsai, 2001; Cummings, 2004; Borgatti, 2005; Bonacich and Lloyd, 2001).

However, the term "central" may imply very different properties of an individual's position in his/her network depending on what metric is used to characterize centrality (Borgatti, 2005). For example, *flow betweenness centrality* of an individual measures a position's importance by considering the amount of information to which it has access. It is defined as the percentage of all information paths in the network to which that person has access (Wasserman and Faust, 1994)[1]. As such, flow betweenness characterizes an individual's control over information flow. A position with a high betweenness score enables a person to both access a large quantity of information and quickly distribute information among peers. In contrast, *Eigenvector centrality* measures a position's importance as the extent to which it is connected to the most important positions in the network. Eigenvector centrality is defined as the weighted average of the importance of all the neighbors a position is directly connected to (Bonacich, 1972).

Note that flow betweenness implicitly assumes that communications between any pair of people are equally important (e.g., a communication path between two managers is treated the same as that between two new hires) and concentrates only on the quantity of information paths. In many organizational settings, this violates our intuitive sense of the value of communication. Unlike flow betweenness, Eigenvector centrality takes

[1]We chose flow betweenness over node betweenness (defined as the percentage of times a node occupies a position on a shortest path between any other two nodes (Wasserman and Faust, 1994)) because the former considers all the information paths rather than only shortest paths and therefore avoids underestimating the possibility of a piece of information successfully traveling between two nodes.

into account both quantity and quality of the connections (e.g., a professor who collaborates with another professor who has many other collaborations will tend to have higher Eigenvector centrality than if he were to collaborate with a less connected person).

Another difference between these two centrality measures is related to the number of direct neighbors. Like degree centrality, which is defined as a simple count of direct neighbors, Eigenvector centrality also counts the number of connections, but unlike degree centrality, it weights connection by the centrality scores of the neighbors (Newman, 2007). Hence, both a large number of low quality connections and a small number of high quality connections can lead to a high Eigenvector score. This characteristic of Eigenvector centrality is of particular importance when we consider the fact that each individual has limited capacity. For example, in a collaboration network in which links represent joint work, high Eigenvector centrality indicates that either a person is collaborating with many people or he/she is collaborating with few people but each of them has many collaborators. In either case, high Eigenvector centrality is apt to be correlate with high utilization of an individual capacity, since the individual is either busy working with many collaborators or working to sustain relationships with busy collaborators. Unlike Eigenvector centrality, betweenness centrality has no clear association with the number of direct neighbors. For instance, an individual with few connections but who serves as a mediator between two groups will have a higher betweenness score than an individual with many connections if the less connected individual occupies a greater number of communication paths. Thus, while betweenness reflect an individual's control of information flow, it does not necessarily reveal the utilization level of his/her capacity.

Since there has been little research attention paid to the role of capacity on performance in knowledge-based organizations, incorporating Eigenvector centrality into our analysis is of particular importance. With it, we can introduce the previously neglected issue of individual capacity into social network analysis of organization performance.

Finally, although our objective is to use the above network concepts to understand the impact of collaboration on performance, collaborative behavior can be characterized at different levels. Below, we discuss networks defined in terms of (a) direct collaborative interaction, (b) discussion between individuals, and (c) awareness of the expertise of other individuals.

5.2.1. The Collaboration Network

We define the *collaboration network* by having nodes represent individuals and links indicating explicit collaboration between pairs of individuals. In knowledge intensive environments, joint work enables collaborators to make use of each other's expertise in an efficient manner and therefore facilitates higher work performance without requiring individuals to digest and master new knowledge independently. When an individual holds a relatively central position with access to a large amount of information, he/she can identify, locate and seek collaborators more efficiently and effectively, which may greatly improve his/her work performance. At the same time, such a network position facilitates the spread of one's own work through these same channels, which attracts more attention and potential collaborators. Hence, we conjecture the following:

Hypothesis 1a. *Flow betweenness centrality in the collaboration network has positive impact on individual work performance.*

However, we also speculate that the benefits of such a central position are limited. Joint work requires engagement. With limited time and energy (i.e., capacity), each individual can only sustain a limited number of productive collaborations. Consequently, establishing more collaborations after one has reached his/her capacity results in less engagement in other collaborations and less time for translating ideas and information into useful outputs. Furthermore, since it may take more effort to sustain collaborative relationship with busy (central) individuals (e.g., because they are difficult to see, slow to respond to inquiries, etc.); the knowledge benefits of such collaborations may not improve performance.

In addition to time constraints, a second factor that may mitigate the benefits of direct collaboration is the fact that as one moves to a position with higher Eigenvector centrality, it becomes increasingly likely that one's information sources overlap, which implies that the marginal benefit of information seeking decreases as centrality increases. This reasoning leads us to conjecture that high centrality in the collaboration network may enhance individual performance when one has few collaborators, but may impede individual performance when one has many collaborators.

> Hypothesis 1b. *Eigenvector centrality in the collaboration network has an inverted U-shape impact on individual work performance. That is, performance increases as an individual moves from a peripheral position to a position of increased centrality. But, as the individual becomes increasingly central, his/her performance decreases.*

5.2.2. The Discussion Network

The discussion network is defined on the same set of nodes (i.e., people) as the collaboration network, but has links defined by the occurrence of detailed research discussions between pairs of individuals. We consider discussion links to be directed because the discussants may hold different opinions towards the discussion. For example, while one party may view a discussion as highly informative and relevant to his/her own work, the other party may not regard the discussion as a source of new research ideas. The benefits of discussions are multiple. Like collaboration, discussions help individuals tap into the expertise of others, learn new ways of thinking, and synthesize disparate knowledge into good ideas (Heinze and Bauer, 2007). Discussions help one improve his/her perspective and facilitate communication of his/her ideas to a more diverse audience (Reagans and McEvily, 2003; Cross and Cummings, 2004). The benefits of discussions increase as one has more control over information flows in the discussion network. This is because the more others depend on an individual for information, the more he/she can access useful information, frame and solve new problems, and disperse his/her own ideas. Therefore, we conjecture the following:

Hypothesis 2a. *Greater flow betweenness centrality in the discussion network amplifies individual work performance.*

While establishing and maintaining a discussion tie does not detract as much from other work activities as does a collaboration link, it does require time and energy input. When an individual is in a relatively peripheral position, the benefit of moving toward the center of the discussion network (i.e., via increased access to information and ideas) is greater than the cost of maintaining more ties. However, moving to increasingly central positions in the discussion network (i.e., by having more discussions or having discussions with more central people) will eventually impose a cost in the form of time to maintain ties. Since a queueing-type argument of congestion suggests that overhead cost will increase nonlinearly in the number of ties, we would expect it to eventually overwhelm the benefits. This implies that eigenvector centrality may exhibit a nonlinear effect on work performance (Perry-Smith and Shalley, 2003), as we conjecture in the following:

Hypothesis 2b. *The influence of eigenvector centrality in the discussion network on individual work performance follows an inverted U-shape. That is, performance increases as an individual moves from a peripheral position to a position of increased centrality.But, as the individual becomes increasingly central, his/her individual work performance decreases.*

5.2.3. The Awareness Network

The awareness network is defined on the same set of nodes (people) as the collaboration and discussion networks. Awareness links are directed, indicating detailed knowledge of one individual's expertise by another. Flow betweenness in a directed awareness network indicates the likelihood of an individual's information being distributed to his/her peers. People who occupy peripheral positions in the network are less known by their peers, as is their expertise. However, having one's expertise less known by peers does not necessarily predict poor performance. Indeed, it may actually imply greater potential for creative and influential work. For example, in research environments low visibility may indicate that an individual is working in a less known area (e.g., new or non-mainstream field), that is more likely to yield novel results amenable to quick publications. Since early publications are more likely to set important milestones in a field, they often receive greater attention and have higher impact (i.e., above average citation rates). This reasoning leads us to conjecture the following:

Hypothesis 3a. *Flow betweenness centrality in the awareness network has a negative impact on individual work performance.*

In a directed awareness network, Eigenvector centrality is a weighted average of one's out-going degree, where the weights are the centrality scores of one's direct neighbors. Low Eigenvector centrality implies an individual knows little about others' expertise. This lack of information tends to prevent the individual from locating resources and seeking out advice, help, and collaboration as necessary. As an individual increases his/her knowledge of others' expertise, he/she improves his/her ability to take advantage of the resources within the network and hence should result in better work performance. However, increasing one's awareness of other's expertise is not costless. Gaining knowledge about others requires time and efforts, which are therefore unavailable for other productive activities. Since benefits from awareness are limited, the cost of information gathering will eventually outweigh the benefits. Hence, we posit the following:

Hypothesis 3b. *Eigenvector centrality in the awareness network has an inverted-U shape impact on individual work performance.*

5.3. Interdisciplinary Ties and Work performance

Interdisciplinary ties refer to ties that span disparate sets of knowledge. For example, a collaboration between a statistician and a biochemist in a clinical trials project represents an interdisciplinary tie. Such ties increase the chance of an individual being exposed to alternative ways of thinking and therefore help in synthesizing disparate knowledge into good ideas (Burt, 1992, 2004; Heinze and Bauer, 2007). Moreover, exploration beyond one's field may lead to results with a broader impact than idea exploitation within one's own field. For example, Heinze and Bauer (2007) found that prominent scientists outperform their peers with equivalent capabilities because they communicate with people who are otherwise disconnected and working in a broader range of disciplines. Translating these insights into an understanding of individual performance in a highly creative and knowledge-intensive work environment, we conjecture that having more interdisciplinary ties increases the chance of producing high-impact work. More specifically, working on joint projects and discussing work-related issues with people outside one's own discipline will help an individual draw insights from disparate knowledge pools and therefore promotes more original research. Furthermore, being aware of the expertise of people from other disciplines increases one's chance of locating novel pieces of information and therefore also improves research impact. We state these conjectures as the following hypotheses:

Hypothesis 4a. *Interdisciplinary collaboration has a positive impact on individual work performance. More specifically, having a higher percentage of one's collaboration ties outside one's own discipline promotes higher research productivity and impact.*

Hypothesis 4b. *Interdisciplinary discussion has a positive impact on individual work performance. More specifically, having a higher percentage of one's discussion ties outside one's own discipline promotes higher research productivity and impact.*

Hypothesis 4c. *Interdisciplinary awareness has a positive impact on individual work performance. More specifically, having a higher percentage of one's awareness ties outside one's own discipline promotes higher research productivity and impact.*

5.4. Data and Methods

We tested the above hypotheses using the McCormick School of Engineering at Northwestern University as our environment. The McCormick school consists of nine departments: Biomedical Engineering (BME), Chemical and Biological Engineering (CBE), Civil and Environmental Engineering (CE), Electrical and Computer Engineering (ECE), Computer Science (CS), Engineering Science and Applied Mathematics (ESAM), Indisutrial Engineering and Management Sciences (IEMS), Material Science and Engineering (MSE), and Mechanical Engineering (ME). During the time interval of our study (1988-2006), all of the departments except for CS were located in the same building. This unique feature of the school simplifies the analysis by reducing possible bias due to differences in geographic distance.

5.4.1. Networks

Data for constructing the collaboration/discussion/awareness networks were collected through an online survey. Before we conducted the survey, we spent considerable time understanding the nature of faculty interactions and determining the appropriate personnel to be included in the survey. After consultation with the school administration, we decided to include all faculty members who are tenured or on the tenure track. This gave us a relatively stable set of personnel. Accompanied by an introductory email from the Dean, the survey was conducted via a simple "point and click" website during the summer of 2005. Each faculty member was assured that the data provided be kept anonymous and only used for research purposes. Two weeks later, a reminder was sent by the Dean to each faculty member who had not responded, which included a link to the survey site. A total of 137 out of 184 eligible faculty members completed the entire survey (representing a 74.5% response rate).

In the survey, each faculty member was asked to indicate his/her relationship with all other faculty members in the survey set. We classified relationships into six categories, each of which was described in detail to avoid misinterpretation. A person was instructed to choose the category "have collaborated with", which was coded as a Type 5 interaction, if he/she had worked on a joint paper or proposal with the person listed in the survey. Responses in this category were used to construct the collaboration network. Since collaboration ties are symmetric by nature, we replaced asymmetric ties with symmetric ties if either of the two parties indicated that he/she had done joint work with the other. We did this because, after talking to some faculty members, we found that the most common reason for an asymmetry was that one party forgot about the collaboration due to time lapse or other reasons. Hence, we decides that transforming all ties into symmetric ones gave the most accurate characterization of collaborative relationships we could set from the data.

The Type 4 category was labeled “have had research discussion with”. A person was instructed to choose this category if he/she had not written a joint paper or proposal with an individual but had engaged in detailed research discussion with him/her. Considering the fact that whether a particular discussion is viewed as a detailed research discussion depends strongly on the level and content of discussion, it is not unreasonable for two people to hold different opinions about the same discussion. For example, it is possible that a person who shared his/her domain knowledge with another faculty member does not regard that exchange as a detailed research discussion, while the person who received the information may well think that it is. With this in mind, we allowed asymmetric discussion ties. Since writing a joint paper or proposal implies detailed discussions, we combined the responses to the first two categories, i.e., ties of Type 4 and 5, to create the research discussion network.

Two other possible response categories were “know research area and socially acquainted” (coded as Type 3) and “know research area but not social acquainted” (coded as Type 1). The description of these areas made it very clear that “knowing” someone’s research area indicates that one’s knowledge of the other’s research goes well beyond simply knowing which department that person is from or a short phrase description of the person’s research field. Since one cannot collaborate or have detailed research discussions with someone without being aware of their research area, we combined these responses with those in the previous two categories (i.e., resulting in the set of ties of Type 1, 3, 4 or 5) to construct the awareness network.

If an individual did not choose one of the above categories, they could choose "socially acquainted with but do not know research area" (coded as Type 2) or be defaulted to "do not know" (coded as Type 0).

5.4.2. Performance Measures

One of the benefits of conducting research in an academic environment is that objective performance measures are available. Unlike manager's ratings, which can be highly subjective, performance measures based on publication information are largely objective. Furthermore, using publication data allows us to measure individual performance in terms of both productivity (i.e., based on publications) and impact (i.e., based on citations). Because publications and citations are good indicators of research performance they are frequently used in the tenure and promotion process (Gordon and Purvis, 1991; Park and Gordon, 1996). Data on both of these measures were collected from the Institute for Scientific Information (ISI). For each faculty member included in the survey, we collected detailed information for each of his/her papers published between 1988 and 2006. This information included: number of authors, year of publication, journal of publication, number of citations, and citing journal of each citation.

It is widely agreed that the journal in which a paper is cited and the journals that cite it are indicators of paper quality. Certainly tenure and promotion committees believe this, since many schools have explicit lists that indicate the relative importance of various publications as research outlets. Hence, we also collected journal quality information to use as a weighting factor for publications and citations. In the literature, the most commonly used metric of journal quality is *impact factor* (Newman and Cooper, 1993; Ballas and Theoharakis, 2003), which is the normalized total number of citations a journal receives within certain period of time (generally two years). However, impact factor can be misleading. It counts only the number of citations and ignores the quality of the citing journals. As a result, journals cited by many low-quality journals are inappropriately ranked higher than journals with fewer citations from high-quality journals. To address the shortcomings of impact factor as a measure, some researchers have adopted a metric called *perceptual ranking* (Hull and Wright, 1990; Hull and Ross, 1991), which is calculated based on a subjective rating provided by a selected pool of experts. While this metric partially addresses the problem of not considering citing journal quality, it also has flaws. Experts selected may not be representative and or their opinions may be biased by their own experiences or benefits. For example, perceptual ranking is known to suffer from "self-serving bias", which refers to the fact that people tend to rate journals high if they publish in or serve as reviewer or editor for them (Hull and Ross, 1991).

In our study, we employed a different alternative to impact factor, known as *Journal Pagerank* (Bollen et al., 2006). The idea of Journal Pagerank originated from "Google Pagerank", which is used to rank websites based on two factors: how often a website is linked and the ranks of the sites that link to it. The same idea can be applied in calculating journal pagerank, thereby incorporating both the number and source of citations into the score. To calculate journal pagerank, all journals indexed by ISI as of 2006 were included in a citation network, in which journals are nodes and citation links are directed links. The formula for journal v_i's pagerank score is given by:

$$PR_w(v_i) = \frac{\lambda}{N} + (1-\lambda)\sum_j PR_w(v_j) \times w(v_j, v_i)$$

where N is the total number of journals in the network, PR is the pagerank score, $w(v_j, v_i)$ is the fraction of journal v_j's pagerank it transfers to journal v_i, and λ is an arbitrarily chosen constant between 0 and 1 (We used 0.15)[2]. Note that pagerank is essentially

[2] $\frac{\lambda}{N}$ represents the minimal weight assigned to each journal. When $\lambda = 1$, the pagerank of each journal is equally assigned; when $\lambda = 0$, the pagerank of each journal is fully dependent on the pageranks of its neighbors; a λ value between 0 and 1 indicates that the pagerank is partially dependent on how well connected its neighbors are. We chose $\lambda = 0.15$ in order to emphasize that a journal's pagerank is largely

Eigenvector centrality in a network of journals with links defined by inter-journal citation rates. This metric indicates that when N and λ are fixed, having more citations and linking to journals with higher pagerank indices lead to a higher pagerank score for the journal. The benefits of using pagerank are: (1) it is a objective measure and so avoids the bias introduced by perceptual ranking, and (2) it takes into account both the frequency and quality of citations and is therefore a more convincing metric of journal quality than impact factor. In order to reflect the most up-to-date journal quality, we computed Journal Pagerank using journal information for a two-year time for all journals in the ISI index in 2006.

In our analysis, for each faculty of the engineering school we used the following two performance measures:

Pagerank weighted research productivity ($Prod_{pr}$*)*:

$$Prod_{pr} = \frac{\sum_{year} \sum_{paper} \frac{PR}{Number of Authors}}{Noumber\ of\ Years\ since\ 1st\ publication}$$

Pagerank weighted research impact ($Impact_{pr}$*)*:

$$Impact_{pr} = \frac{\sum_{year} \sum_{paper} \sum_{citation} \frac{PR}{Number of Authors}}{Number\ of\ Years\ since\ 1st\ publication}$$

The first measure tracks research productivity, while the second is a proxy for research impact.

determined by which other journals it is cited. Moreover, since $\frac{\lambda}{N}$ is constant for any given N, varying the value of λ only affects the weight allocation and does not change the relative order of journal pageranks, i.e., relative importance of each journal. Consequently, analysis results based on journal importance pagerank will not be affected.

5.4.3. Independent Variables

To provide insights into the factors that influence performance as measured by the above metrics, we considered the following as independent variables:

% Interdisciplinary Ties. We use the percentage of an individual's ties that are interdisciplinary to measure how likely a person is to be connected to people outside his/her own discipline. Since departments provide a rough classification of research areas, we used department as a proxy for discipline and defined inter-departmental ties to be interdisciplinary. We considered three types of interdisciplinary ties. *% Interdisciplinary collaboration ties* is given by the number of people outside one's own department with whom he/she has collaborated, divided by the total number of people with whom he/she has collaborated. This measure is computed from responses to the first survey question (i.e., Type 5 responses only). Similarly, *% Interdisciplinary discussion ties* is the number of people outside one's own department with whom he/she has had research discussions divided by the total number of people with whom he/she has had research discussions. This is computed using only responses to the first and second questions in the survey (i.e., Type 4 and 5 ties). Finally, *% Interdisciplinary awareness ties* is the number of people outside a faculty member's own department about whom he/she has detailed knowledge of their research areas, divided by the total number of people about whom he/she has detailed knowledge of their research areas. This is calculated from responses to the first, third, fourth and fifth questions in the survey (i.e., Type 1, 3, 4 and 5 ties). Using these networks, we generated the following network metrics for use as independent variables.

Betweenness Centrality. We calculated betweenness for the collaboration, discussion, and awareness networks, respectively. We included this variable to measure an individual's access to large amounts of information.

Eigenvector Centrality. We computed eigenvector centrality for the collaboration, discussion, and awareness networks respectively. In addition to using this directly as an independent variable, we also included the second-order term for Eigenvector centrality as an independent variable. This was calculated as:

$$\text{Eigenvector Centrality}^2 = (\text{Eigenvector centrality} - \text{mean(Eigenvector centrality)})^2.$$

The "mean(Eigenvector centrality)" is calculated as the summation of all the Eigenvector centrality of each individual divided by the total number of individuals.

By using the squared difference, instead of the simple square of the eigenvector centrality, we reduced the likelihood of multicollinearity problems. A negative coefficient in this second order term would indicate diminishing returns in the Eigenvector centrality score. That is, when a person is on the periphery of the network, moving towards the center promotes his/her creative work, but when a person is already at a relatively central position, moving towards an even more central position jeopardizes his/her creativity (Perry-Smith and Shalley, 2003)

5.4.4. Control Variables

Since research productivity and impact are influenced by more than collaboration and communication behaviors, we included several control variables in our model.

Tenure. Tenure counts the years of employment at the university.

Rank. Rank of professors is represented by a pair of indicator variables, *asso* and *full*. The pair "$asso = 0$, $full = 0$" indicates an assistant professor, "$asso = 1$, $full = 0$" indicates an associate professor, and "$asso = 0$, $full = 1$" indicates a full professor.

Department. Indicator variables were created for departments to control for the differing publication and citation rates across disciplines, as well as for the size and quality of the departments.

5.5. Analysis and Results

Table 5.1 shows the Pearson's correlations among all variables. This indicates that *% interdisciplinary ties* and *Eigenvector centrality* have significant correlation with the two dependent variables. While some correlations exist among the other network related variables, they are sufficiently small to allow joint inclusion of variables without serious multicollinearity problems.

We used ordinary least squares (OLS) regression to test our hypotheses. For all the models tested, we checked both the distribution and variance of residuals and did not find serious violation of the normality or constant variance assumptions. We also checked the variation of inflation (VIF) and did not find evidence of multicollinearity (i.e., VIF>10). Finally, we used the Durbin-Watson test to check for autocorrelation and found no evidence of interdependence among residuals. Table 5.2 and Table 5.3 summarizes the results of the ordinary least squares (OLS) regression analysis on pagerank weighted performance measures.

Prior to testing the effect of the independent variables, we examined the impact of the control variables. Models 1a, 1b, 2a and 2b regress the control variables on both the research productivity and impact metrics. Note that these did not indicate a significant effect of *tenure* or *rank*. However, when other independent variables are included, we observed a significant negative effect of tenure on productivity in models 2a, 3a, 4a, and 5a, which suggests that as the number of years of service increases, an individual's productivity decreases. We also observed a significant impact of rank on research impact in models 2b and 3b, which suggests that having a rank above assistant professor is associated with higher citation rates. The apparent interpretation is that as an individual becomes more experienced, he/she becomes more likely to produce high-impact work. Finally, the high R^2 value for model 2a for research productivity (50.9%) and model 2b for research impact (55.8%) indicate that there exist large differences in publication and citation rates across disciplines and that these differences have been largely captured by the *department* indicator variables.

5.5.1. Network Position and Performance: Hypotheses 1, 2, and 3

To test the effect of central positions on individual work performance, we first examined the main effect of *flow betweenness* in collaboration, discussion, and awareness networks. Hypotheses 1a and 2a conjectured that greater flow betweenness is associated with higher research productivity and impact. Indeed, models 3a and 3b showed that flow betweenness in the discussion network is positively associated with work performance ($p < 0.01$ for research productivity and $p < 0.05$ for research impact). However, flow betweenness in the collaboration and awareness networks has no impact on work performance. Thus, Hypothesis 1a is not supported but Hypothesis 2b is supported. However, when *Eigenvector centrality* is included as shown in models 5a, 5b, 7a and 7b, the effect of flow betweenness in the discussion network becomes insignificant, which indicates that *Eigenvector centrality* is a stronger factor than *flow betweenness*. Although we did not observe a significant impact of the *flow betweenness* in the awareness network when *flow betweenness* was tested independently, we did find significant negative impact when *Eigenvector centrality* is also included (i.e., $p < 0.05$ in models 5a, 5b, 7a and 7b). Thus, Hypothesis 3a,which conjectured that peripheral positions in the awareness network (i.e., working in less known areas) promote individual work performance, is supported.

According to Hypotheses 1b, 2b, and 3b, *Eigenvector centrality* in the collaboration, discussion, and awareness networks has inverted-U shaped relationship with individual work performance. We tested these hypotheses in models 4a, 4b, 5a, 5b, 7a, and 7b. The results showed that the second order term of Eigenvector centrality in the discussion network is negative and significant (i.e., $p < 0.01$ for both research productivity and research impact). This is consistent with our conjecture that moderate centrality in the discussion network leads to the highest performance because both highly central and highly peripheral positions hinder good performance, the former due to the negative influence of high overhead associated with centrality and the latter due to lack of access to vital information. This result provides full support for Hypothesis 2b. However, we did not observe a similar effect of Eigenvector centrality in either the collaboration network or the awareness network. Therefore, Hypotheses 1b and 3b are not supported.

5.5.2. Percentage of Interdisciplinary Ties and Performance: Hypotheses 4

Recall that Hypotheses 4a, 4b, and 4c conjecture that interdisciplinary ties promote individual work performance. Models 6a and 6b reveal that the *percentage of interdisciplinary discussions* has a positive influence on both individual research productivity and impact (i.e., $p < 0.05$ for research productivity and $p < 0.01$ for research impact). This result supports Hypothesis 4b that interdisciplinary discussion improves work performance. However, the impact of interdisciplinary discussions on research productivity becomes insignificant ($p > 0.05$) while that on research impact remains significant ($p < 0.05$) when network position measures (flow betweenness and Eigenvector centrality) are considered simultaneously in models 7a and 7b. This result suggests that the network position metrics for the discussion network capture the positive benefits of research discussions on productivity than does the percentage of interdisciplinary ties. However, the fact that the second order terms for Eigenvector centrality in the discussion network has a significant negative coefficient suggests that, while exposure to disparate thinking and expertise helps one to synthesize divergent perspective and knowledge threads into new ideas, it may also require time and energy to sustain. Consequently, centrality in the discussion network exhibits diminishing returns. The fact that both Eigenvector centrality and percentage of interdisciplinary ties are significant in the research impact model (Model 7b) implies that percent of interdisciplinary ties has a strong impact on research impact than on research productivity. We speculate that the reason for this is that while talking to interdisciplinary colleagues about research may be too time-consuming to yield a net benefit in research output, the fact that they stimulate novel ideas which have broad appeal makes the papers that are published more likely to be cited. However, we did not find a significant impact of interdisciplinary ties in either the collaboration or the awareness network. Hence, Hypotheses 4a and 4c are not supported. These results imply that interdisciplinary interactions are primarily valuable at the discussion level. Being aware of other people's expertise is not valuable unless it is translated into action in the form of detailed discussions. But, once the discussions are held, it is not essential that one actually write papers with someone from another discipline. Evidently, simply holding interdisciplinary conversations is the crucial step.

Table 5.1: Correlations

		1	2	3	4	5	6	7	8
1	$\ln(prod_pr)$								
2	$\ln(impact_pr)$	.873**							
3	tenure	-0.02	0.135						
4	Asso	0.112	.27**	.521**					
5	Full	0.12	.242**	.605**	.637**				
6	Department 1	.232**	.245**	0.021	0.062	-0.014			
7	Department 2	-0.128	-0.093	.305**	0.101	0.06	-0.131		
8	Department 3	-.258**	-.373**	-.26**	-0.082	-0.067	-0.123	-0.141	
9	Department 4	-.171*	-.175*	-0.011	-.174*	-0.125	-0.155	-.179*	-0.168
10	Department 5	0.07	.175*	0.098	0.057	0.08	-0.084	-0.097	-0.091
11	Department 6	-.227**	-.206*	-0.037	0.004	-0.063	-0.114	-0.131	-0.123
12	Department 7	.506**	.438**	0.061	0.092	.178*	-0.127	-0.146	-0.137
13	Department 8	0.008	0.082	-0.093	0.11	0.033	-0.135	-0.156	-0.146
14	% Interdisciplinary collaboration	.181*	.23**	0.073	0.145	0.048	.2*	0.008	-.317**
15	% Interdisciplinary discussion	.382**	.418**	0.028	0.167	0.137	0.124	0.062	-.269**
16	% Interdisciplinary awareness	.328**	.387**	0.139	.227**	.264**	.177*	.189*	-.311**
17	Flowbetweenness collaboration	-0.095	-0.114	0.008	0.113	.169*	-0.065	0.075	0.126
18	Flowbetweenness discussion	0.071	0.032	-0.052	0.088	0.111	0.07	-0.008	0.104
19	Flowbetweenness awareness	-0.094	-0.111	0.006	0.089	0.102	-0.039	-0.098	0.105
20	Eigen-cent collaboration network	.407**	.442**	0.131	.219*	.35**	-0.028	-0.003	-.262**
21	Eigen-cent discussion network	.517**	.552**	0.151	.28**	.333**	0.095	0.073	-.276**
22	Eigen-cent awareness network	.296**	.349**	.209*	.283**	.319**	.173*	0.154	-.344**
23	Eigen-cent collaboration network square	.229**	.232**	0.12	0.149	.217*	-0.084	-0.039	-0.077
24	Eigen-cent discussion network square	.287**	.26**	0.083	0.113	.227**	0.028	-0.043	-0.082
25	Eigen-cent awareness network square	-0.018	0.009	0.109	0.135	.209*	0.104	-0.012	0.039

		9	10	11	12	13	14	15	16
10	Department 5	-0.115							
11	Department 6	-0.155	-0.084						
12	Department 7	-.173*	-0.094	-0.127					
13	Department 8	-.185*	-0.1	-0.135	-0.151				
14	% Interdisciplinary collaboration	-.235**	0.018	0.096	-0.063	.196*			
15	% Interdisciplinary discussion	-.307**	0.135	-0.101	0.091	.201*	.712**		
16	% Interdisciplinary awareness	-.375**	.211*	-0.111	0.116	0.071	.448**	.703**	
17	Flowbetweenness collaboration	-0.027	0.04	0.002	-0.088	0.031	0.158	.23**	.279**
18	Flowbetweenness discussion	-0.034	0.026	0.057	-0.078	-0.064	.277**	.374**	.398**
19	Flowbetweenness awareness	0.125	0.057	0.036	-0.078	-0.137	.197*	.249**	.411**
20	Eigen-cent collaboration network	-0.065	-0.036	-.208*	.478**	.205*	.283**	.469**	.398**
21	Eigen-cent discussion network	-.257**	-0.004	-.23**	.569**	0.157	.293**	.57**	.497**
22	Eigen-cent awareness network	-0.107	0.018	-0.159	.216*	0.088	.285**	.509**	.765**
23	Eigen-cent collaboration network square	-0.15	-0.076	-0.053	.335**	0.153	0.114	.245**	0.157
24	Eigen-cent discussion network square	-0.15	-0.096	-0.081	.479**	-0.03	0.073	.308**	.194*
25	Eigen-cent awareness network square	-0.085	0.047	0.004	-0.052	-0.117	0.077	0.085	.211*

		17	18	19	20	21	22	23	24
18	Flowbetweenness discussion	.662**							
19	Flowbetweenness awareness	.481**	.611**						
20	Eigen-cent collaboration network	.321**	.335**	.208*					
21	Eigen-cent discussion network	0.149	.314**	0.128	.818**				
22	Eigen-cent awareness network	.314**	.393**	.513**	.52**	.59**			
23	Eigen-cent collaboration network square	0.128	.175*	0.095	.645**	.537**	.255**		
24	Eigen-cent discussion network square	-0.015	.191*	0.071	.55**	.749**	.312**	.676**	
25	Eigen-cent awareness network square	0.128	0.156	.402**	0.031	0.052	.495**	0.142	.18*

*$p < 0.5$, ** $p < 0.01$

5.6. Conclusion

This research study is an attempt to extend our understanding of the impact of network positions and interdisciplinary ties on individual work performance in a knowledge intensive environment. Specifically, we studied the impact of network positions and ties in collaboration, discussion, and awareness networks in a research-oriented engineering school. Our results suggest that central positions and interdisciplinary collaborations in the discussion network, but not those in collaboration and awareness networks, have the most significant impact on the research performance of individual faculty members.

A distinguishing feature of this study is the use of multiple dimensions of performance. Unlike previous research exploring the impact of network position on work performance, which have relied on a single performance measure, we have characterized work performance using both the near-term metric of research productivity (measured via publication rate) and the long-term metric of research impact (measured via citation rate). Our results suggest that having more interdisciplinary research discussions increases one's chance of producing high impact work, even though it may not increase the volume of work.

This research also contributes to the literature by examining the influence of individual capacity on the benefits of network ties. Specifically, we found that performance in terms of both productivity and impact increases as individuals move from peripheral positions to positions of increasing centrality. However, this advantage diminishes, and may even become negative as individuals become increasingly central. We interpret this as a consequence of the overhead associated with maintaining so many relationships, which hinders the ability of an individual researcher to translate the insights from them into tangible outputs.

Finally, our full model indicated a negative correlation between flow betweenness centrality in the awareness network and individual work performance. One possible explanation for this counter intuitive result could be that people with low awareness centrality

Table 5.2. OLS Analysis of Individual Research Productivity

	$\log(Prod_pr)$						
Variable	Model 1a	Model 2a	Model 3a	Model 4a	Model 5a	Model 6a	Model 7a
Tenure	-0.015384	-.019123*	-.01717*	-.01592*	-.014893*	-0.013444	-0.012115
Asso	0.2227	0.2003	0.2141	0.0607	0.0896	0.1304	0.0481
Full	0.3329	0.1815	0.1676	0.1819	0.1453	0.1145	0.1316
Department 1		.6827*	0.5412	0.3611	0.2135	.838*	0.5471
Department 2		-0.2525	-0.3298	-.6374*	-.7467*	-0.1478	-0.4512
Department 3		-.8332**	-.8595**	-.841**	-.7232*	-0.5421	-0.4214
Department 4		-0.3656	-0.3693	-0.3781	-0.3829	-0.1038	0.0507
Department 5		0.2092	0.1747	-0.1606	-0.165	0.2502	-0.0526
Department 6		-.6964*	-.7709*	-.7112*	-.7164*	-0.4612	-0.4033
Department 7		1.2474**	1.1816**	0.6507	0.5434	1.3483**	.9774*
Department 8		-0.1397	-0.1886	-0.594	-.6989*	-0.044	-0.3644
% Interdisciplinary collaboration						-0.388	-0.4084
% Interdisciplinary discussion						1.4436*	1.0422
% Interdisciplinary awareness						-0.2165	0.5628
Flowbetweenness collaboration			-0.152		-0.1466		-0.1511
Flowbetweenness discussion			.5036**		0.2832		0.2595
Flowbetweenness awareness			-0.3178		-.4317*		-.4413*
Eigen-cent collaboration network				-3.794	-2.353		-2.368
Eigen-cent discussion network				12.052**	10.449**		9.291*
Eigen-cent awareness network				-2.287	0.666		-2.961
Eigen-cent collaboration network^2				26.19	24.97		26.47
Eigen-cent discussion network^2				-64.54**	-65.59**		-68.31**
Eigen-cent awareness network^2				0.13	3.1		30.68
R-Sq	4%	50.9%	53.9%	57%	59.1%	54.6%	61.2%
R-Sq(adj)	1.9%	46.5%	48.5%	50.8%	52%	49.1%	52.8%
F	1.84	11.58**	10.01**	9.12**	8.25**	9.88**	7.27**
n	135	135	135	135	135	130	130

$^*p < 0.5$, $^{**}\ p < 0.01$

Table 5.3. OLS Analysis of Individual Research Impact

	log($Impact_pr$)						
Variable	Model 1b	Model 2b	Model 3b	Model 4b	Model 5b	Model 6b	Model 7b
Tenure	-0.01315	-0.02507	-0.0234	-0.01806	-0.01709	-0.00952	-0.00625
Asso	0.9027	.7823*	.8176*	0.4803	0.5342	0.6676	0.4709
Full	0.6191	0.4258	0.4504	0.4187	0.3483	0.1941	0.1912
Department 1		1.5771**	1.3613*	0.9244	0.5869	2.41**	1.8041*
Department 2		-0.2797	-0.3674	-1.0517	-1.3347*	0.3969	-0.24
Department 3		-1.8328**	-1.8251**	-1.8742**	-1.5077**	-0.7408	-0.2956
Department 4		-0.4489	-0.4192	-0.4315	-0.4507	0.5897	1.0432
Department 5		1.2419	1.2253	0.4444	0.4138	1.809*	1.1231
Department 6		-1.0217	-1.1118	-1.0236	-0.96	-0.0362	0.2603
Department 7		2.2231**	2.1076**	0.9913	0.5458	2.9203**	2.0092*
Department 8		0.2356	0.1685	-0.6976	-1.0353	0.9157	0.2081
% Interdisciplinary collaboration						-0.8583	-0.9391
% Interdisciplinary discussion						3.165**	2.311*
% Interdisciplinary awareness						-0.6066	1.377
Flowbetweenness collaboration			-0.3402		-0.3347		-0.3675
Flowbetweenness discussion			.8093*		0.2742		0.277
Flowbetweenness awareness			-0.5811		-.8457*		-.8924*
Eigen-cent collaboration network				-7.703	-4.029		-3.88
Eigen-cent discussion network				27.365**	25.252**		22.667**
Eigen-cent awareness network				-7.643	-0.339		-8.144
Eigen-cent collaboration network^2				51.96	50.15		52.21
Eigen-cent discussion network^2				-148.67**	-155.09**		-163.1**
Eigen-cent awareness network^2				36.61	35.83		101.48
R-Sq	9.5%	55.8%	58.4%	63.7%	66.6%	60.3%	69.8%
R-Sq(adj)	7.5%	51.9%	53.5%	58.5%	60.8%	55.5%	63.2%
F	4.6**	14.13**	12.03**	12.1**	11.38**	12.49**	10.65**
n	135	135	135	135	135	130	130

$^*p < 0.5$, ** $p < 0.01$

are involved in less familiar, and more innovative area, which enables them to generate publications and citations more easily than people in more established areas.

Much remains to be done to understand the influence of collaborative and interdisciplinary activities on individual performance in knowledge-intensive work systems. One direction that this research could be extended is a longitudinal study of how network positions evolve over time. For instance, it may be the case that peripheral positions in the awareness network are initially indicators of strong performance, but that individuals become more central as they succeed. Beyond this, extending the analysis to include multiple institutions would provide a more rigorous test of the robustness of our results. Finally, expanding the analysis to other knowledge-intensive work environments would allow us to examine the extent to which these insights for academic research are transferrable.

CHAPTER 6

The Increasing Importance of Interdisciplinary Collaboration in Academic Research

6.1. Introduction

Collaboration is a decisive principal of scientific research. The increasing dominance of teams (Wuchty et al., 2007) and the widely observed collaboration networks (Newman, 2001) in scientific research suggest that collaboration is critical in searching for innovative ideas and promoting work efficiency. Recently, a special form of collaboration, interdisciplinary research, has gained vast attention. Many key topics are interdisciplinary in nature, e.g., natotechnology, bioinformatics, and neurosciences. Many significant accomplishments are products of interdisciplinary inquiry and collaboration, e.g., the discovery of the structure of DNA. Many newly established research and education programs are also interdisciplinary, e.g. NIH. While interdisciplinary collaboration is observed to increase dramatically, it remains unclear whether interdisciplinary collaboration is beneficial and whether its benefits exceeds that of intradisciplineary collaborations.

"Interdisciplinary research is a mode of research by teams or individuals that integrates information, data, techniques, tools, perspectives, concepts, and/or theories from two or more disciplines or bodies of specialized knowledge to advance fundamental understanding or to solve problems whose solutions are beyond the scope of a single discipline or area of research practice (National Academy of Sciences, 2004)." Interdisciplinary research can be beneficial because it synthesizes the strengths of two or more often disparate scientific disciplines and therefore is more innovative and likely to produce high-impact outcome. However, interdisciplinary research is more costly than intradisciplinary research due to coordination losses and greater outcome uncertainty (Cummings and Kiesler, 2005). Hence, it is not clear whether interdisciplinary research is a superior form of collaboration.

Many studies in collaboration has been focused on understanding the impact of boundary spanning ties (i.e., ties across departmental or organizational boundaries) (Bouty, 2000; Perry-Smith, 2006). The prevailing result of those studies is that people who span boundaries of two or more business units or organizations tend to outperform their peers because they are more aware of disparate knowledge pools, have access to a broader range of knowledge sources, and are able to better synthesize disparate knowledge streams into innovative ideas. While those studies reveal the benefits of collaborating with people from outside one's own functional units, they generally are carried out in business but scientific research environment. Those studies examine ties either between subunits within the same organization or among different organizations. Those subunits and organizations do not necessarily specialize in different areas. Thus, those results may not apply to interdisciplinary collaborations. Studies closely examine interdisciplinary collaboration are very sparse. Cummings and Kiesler (2005) examined the impact of interdisciplinary research on research performance statistically. They studied 62 scientific collaborations supported by the National Science Foundation (NSF) and concluded that the number of PI disciplines do not have a significant impact on research performance. Hopp et al. (2008) in their study of an engineering school showed that professors who have higher percentage of interdisciplinary ties (defined as the ratio of the number of interdisciplinary ties to the total number of ties for each individual) are more likely to produce papers with higher impact. While their result shows a significant correlation between interdisciplinary research discussion and research impact, it is based on a single-period model and not sufficient to establish the cause-and-effect relationship between interdisciplinary collaboration and research performance. Different from those previous studies, our work concentrates on scientific research and is aimed to reveal the cause-and-effect relationship between interdisciplinary collaboration and research output. We use a two-period linear model to examine whether more interdisciplinary collaborators predicts better research performance.

6.2. Model and Results

We study the impact of interdisciplinary collaboration in academic research environment. We examine research collaborations in the top 25 engineering schools[1] in the United States from year 2000 to 2005. We capture collaboration by the research articles published in the Institute for Scientific Information (ISI) Web of Science database by faculty members from those 25 schools. In defining interdisciplinary, researchers have used different metrics. Some researchers follow the field classification in ISI (Wuchty et al., 2007). Some use departments as an approximate for disciplines (Cummings and Kiesler, 2005). Considering departments generally are organized based on disciplines, we also use departments as a proxy for disciplines. Interdisciplinary collaboration then is defined as a joint paper by authors from two or more departments. Consequently, two professors have an interdisciplinary tie between them if they are from different departments and have published a joint paper. For papers with more than two coauthors, interdisciplinary ties exist between any two coauthors who are from different departments.

The 25 schools we study vary greatly regarding the type of departments. Some departments only appear in very few schools and represent non-core engineering disciplines, e.g., Architectural Engineering. Since including such departments may bias our analysis due to very limited presence, we exclude departments with no more than three presence

[1]Based on 2006 ranking from www.usnews.com. Those schools are: Harvard, Massachusetts Institute of Technology, Princeton, Columbia, Cornell, Carnegie Mellon, Pennsylvania State, Maryland, Georgia Technology, Florida, Purdue, Michigan, Wisconsin, Northwestern, U of Illinois Urban Champaign, Taxes A&M, Taxes Austin, South California, UC Los Angles, California Tech, UC San Diego, UC Santa Barbara, Stanford, Berkeley, Washington.

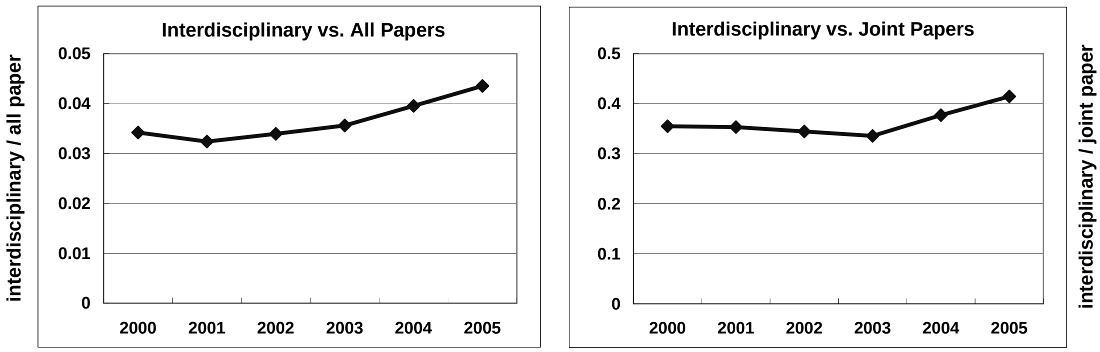
from our study. Some departments which carry out essentially same type of research are called different names in different schools, e.g., engineering science and mechanics vs. theoretical and applied mechanics. We treat those departments as the same discipline. Furthermore, division of some departments differ in different schools. For instance, computer science and electrical engineering are two different departments in some schools but are combined into one department in some other schools. Considering there is considerable research overlap in computer science and electrical engineering, we follow the classification of single department. After excluding non-core departments[2] and consolidating similar departments, we keep the 10 most common departments or combined departments[3] in our analysis.

Exploratory analysis shows an increasing trend of interdisciplinary research in the science and engineering fields as indicated in Figure 6.1. During the year 2000 to 2005, the fraction of papers written by authors from two or more disciplines to the total number of papers published during this period has been increasing consistently. Previous research has shown a significant lift of fraction of paper written by teams (Wuchty et al., 2007), which suggests that we may not observe a lift in the ratio of the number of interdisciplinary publications to the total number of joint publications. However, when compared to joint papers, interdisciplinary paper presents a even stronger increasing trend starting from year 2003, which is indicated by roughly 10% lift of the fraction of interdisciplinary papers to the total number of joint papers.

---

[2]Those departments are: Engineering and Public policy, Biological and Environmental, Fire Protection Engineering, Polymer, Textile and Fiber Engineering, Agricultural and Biological, Potroleum and Geosystems, Technical Communication, Architectural Engineering, Naval, Atmospheric, and Oceanic and Space Sciences

[3]Aeronautics and Astronautics, Bioengineering/Biomedical, Chemical, Civil and Environmental (including Civil, Earth and Environmental, and Structuring), Electrical Engineering/Computer Science, Industrial, Material, Mechanical, Nuclear, Applied Physics and Applied Mathematics (including Applied Physics, Applied Mathematics, Engineering Science and Mechanics, and Theoretical and Applied Mechanics).



(a) (b)

Figure 6.1. The Growth of Interdisciplinary Research. These plots present the changes over time in the percentage of interdisciplinary publication (a) of all publications, including both joint- and single-author paper (b) of joint publications.

6.2.1. The Linear Regression Model

To answer the question whether having more interdisciplinary collaborators predicts better research performance, we study the impact of interdisciplinary collaboration on research performance using linear regression models. We examine the cause-and-effect relationship at individual, department, and school three levels. A two-period regression model is constructed, which predict research performance in the second period based on the collaborative behaviors in the first period. A positive relationship indicates that interdisciplinary collaboration promotes research performance. A schematic illustration of the model is as follows:

$$\begin{aligned}
\text{research performance(period 2)} &= \beta_0 + \beta \times \text{control variables} \\
&\quad + \gamma_1 \times \text{research performance(period 1)} \\
&\quad + \gamma_2 \times \text{intradisciplinary collaboration (period 1)} \\
&\quad + \gamma_3 \times \text{interdisciplinary collaboration (period 1)}
\end{aligned}$$

We define the first period to be between year 2000 and 2004 and the second period to be year 2005. Research performance in the second period is the dependent variable and research performance in the first period is the control for individual (or departmental or school) differences in research capability. Research performance in both periods are measured in two dimensions: productivity (i.e., based on publications) and impact (i.e., based on citations). Both productivity and impact are good indicators of research performance (Aksnes, 2006) and widely used in tenure and promotion process in academics institutions (Gordon and Purvis, 1991; Park and Gordon, 1996). Previous research often use publication counts and citation counts as productivity and impact measures, respectively. While these measures provide a way of measuring performance, they have two major drawbacks. The first drawback lies in the fact that single-author paper and multiple-author paper are treated equally, which underestimates (or overestimates) the contribution of the single (or multiple) authors. Moreover, using publication and citation counts as performance measures implicitly assumes that all publications are of equal qualities, which fails to recognize that paper published or receiving citations from higher-ranked journals are generally more valuable. As a matter of fact, academic institutions generally weigh single-author more than multiple-author paper. They also give higher credits to publication and citation in higher-ranked journal than to lower-ranked journals. Following the same convention, we take the number of coauthors and the journal quality (measured by impact factor, the normalized total number of citations a journal receives within two years (Newman and Cooper, 1993; Ballas and Theoharakis, 2003) into consideration and define research performance as journal impact factor weighted publication ($Prod_{IF}$) or citation parts ($Cite_{IF}$).

6.2.2. Individual Level Analysis and Results

At individual level analysis, research performance in period 1, i.e., the control for research capability, are calculated as follows:

$$Prod_{IF}^{1} = \frac{\sum_{y_i}^{2004} \sum_{paper} \frac{Publication\ Journal\ IF}{No.Authors}}{2004 + 1 - y_i}$$

$$Cite_{IF}^{1} = \frac{\sum_{y_i}^{2004} \sum_{paper} \sum_{citation} \frac{Citation\ Journal\ IF}{No.Authors}}{2004 + 1 - y_i}$$

where $y_i = \max\{2000, \text{1st year of publication}\}$ measures the total number of years individual i has been publishing since 2000. Research performance in period 2 are calculated similarly,

$$Prod_{IF}^{2} = \sum_{2005}^{2005} \sum_{paper} \frac{Publication\ Journal\ IF}{No.Authors}$$

$$Cite_{IF}^{2} = \sum_{2005}^{2005} \sum_{paper} \sum_{citation} \frac{Citation\ Journal\ IF}{No.Authors}$$

Since research performance is highly right skewed, we use natural logarithm transformation of these variables in the analysis in order to satisfy the modeling assumptions of linear regression models (i.e., normality of the errors and constant variance). To measure intradisciplinary and interdisciplinary collaborations, we first creat a collaboration network for each school based on coauthorship in period 1 (Newman, 2001). In this collaboration network, nodes represent individual professors and links represent joint publication. A symmetric link exists between two individuals if they have published at least one joint paper between year 2000 and 2004. Hence, the degree of each node equals the number of collaborators an individual has in period 1.

Based on whether the two end nodes are from the same department, links were classified into intradisciplinary (i.e., the two nodes are from the same department) and interdisciplinary (i.e., the two nodes are from the different departments). The number of intradisciplinary (interdisciplinary) collaborators for each individual can be calculated by counting the number of intradisciplinary (interdisciplinary) links a node has in the collaboration network. Since the sizes of departments and schools vary greatly and direct application of the number of intradisciplinary and interdisciplinary collaborators to the model may confound the collaboration effects with the sizes, we normalize the number of intradisciplinary (interdisciplinary) ties by dividing the theoretical maximum to obtain the normalized number of intradisciplinary ($IntraNor$) and interdisicplinary ($InterNor$) collaborators as as follows:

$$IntraNor = \frac{\textit{Total No. Intradisciplinary Links}}{\textit{Dept Size} - 1}$$

$$InterNor = \frac{\textit{Total No. Interdisciplinary Links}}{\textit{School Size - Dept Size}}.$$

We create indicator variables for departments to control for the differing publication and citation rates across disciplines and schools, as well as the size and quality of the department and the school. Finally we construct a pair of indicator variables, asso and full, to represent the rank of professors. The pair ”asso=0, full=0” indicates an assistant professor, ”asso=1, full=0” indicates an associate professor, and ”asso=1, full=1” indicates a full professor.

The results of ordinary least square analysis is shown in Table 6.1. We find a significant positive effect of normalized number of interdisciplinary collaborators in period 1 (i.e., $interNor$) on both research productivity and impact in period 2 (p-value=0.03). This result suggests that having more collaborators outside one's own discipline promotes an individual's research performance.

Table 6.1: OLS Analysis at Individual Level

Predictor	$log(Cite^2_{IF})$			$log(Prod^2_{IF})$		
	coefficient	T	P	coefficient	T	P
Constant	0.06	0.55	0.58	0.22	3.55	0.00
school1	0.37	2.82	0.01	0.26	3.57	0.00
school2	0.17	2.09	0.04	0.03	0.57	0.57
school3	0.20	1.93	0.05	0.06	1.05	0.30
school4	0.02	0.17	0.87	0.04	0.65	0.52
school5	0.14	1.55	0.12	0.08	1.64	0.10
school6	0.09	0.84	0.40	0.13	2.34	0.02
school7	0.07	0.81	0.42	0.01	0.11	0.92
school8	-0.03	-0.33	0.74	0.01	0.18	0.86
school9	0.16	1.92	0.06	0.12	2.60	0.01
school10	0.10	1.06	0.29	0.05	0.91	0.36
school11	0.09	1.06	0.29	0.08	1.64	0.10
school12	0.03	0.38	0.70	0.07	1.54	0.13
school13	-0.02	-0.21	0.84	0.00	0.06	0.95
school14	0.11	1.16	0.25	0.04	0.75	0.45
school15	0.07	0.87	0.39	0.07	1.43	0.15
school16	0.02	0.23	0.82	0.02	0.33	0.74
school17	0.15	1.66	0.10	0.06	1.11	0.27
school18	0.05	0.55	0.59	0.10	1.90	0.06
school19	0.03	0.32	0.75	0.09	1.72	0.09
school20	0.35	3.16	0.00	0.14	2.22	0.03
school21	0.24	2.48	0.01	0.06	1.15	0.25
school22	0.26	2.52	0.01	0.16	2.81	0.01
school23	0.17	1.87	0.06	0.09	1.82	0.07
school24	0.16	1.84	0.07	0.13	2.75	0.01
dept1	-0.05	-0.53	0.60	-0.05	-0.83	0.41
dept2	0.02	0.20	0.84	-0.01	-0.11	0.91
dept3	0.21	2.34	0.02	0.12	2.56	0.01
dept4	-0.17	-2.00	0.05	-0.11	-2.41	0.02
dept5	-0.15	-1.89	0.06	-0.08	-1.80	0.07
dept6	-0.22	-2.25	0.02	-0.13	-2.43	0.02
dept7	0.18	1.96	0.05	0.08	1.67	0.10
dept8	-0.11	-1.33	0.18	-0.05	-1.15	0.25
dept9	-0.08	-0.62	0.53	-0.10	-1.37	0.17
asso prof	-0.22	-4.56	0.00	-0.08	-2.91	0.00
full prof	-0.09	-2.76	0.01	-0.05	-2.92	0.00
P1 performance	0.49	46.46	0.00	0.62	51.57	0.00
IntraNor	2.78	0.80	0.43	0.00	0.00	1.00
InterNor	10.78	2.23	0.03	5.75	2.16	0.03
n	3258			3258		

R^2	55.3%	58.5%
F	104.68	
$p-value$	0.00	0.00

6.2.3. Department Level Analysis and Results

At department level, we measure research performance in period 1 and 2 by the departmental average research productivity and average research impact in period 1 and 2, respectively, i.e.,

$$Prod^t_{IF} = \frac{\sum_{i=1}^{Dept\ Size} Prod^t_{IF_i}}{Dept\ Size} \quad t = 1, 2$$

$$Cite^t_{IF} = \frac{\sum_{i=1}^{Dept\ Size} Cite^t_{IF_i}}{Dept\ Size} \quad t = 1, 2.$$

We use the square root of these measures (i.e., $sqrt(avgProd)$ abd $sqrt(avgCite)$) in the analysis in order to satisfy the linear regression model assumptions. In measuring intradisciplinary and interdisciplinary collaborations we followed the same idea as for individual level analysis and used the normalized number of intradisciplinary and interdisciplinary links. The calculation essentially is the same as calculating network density (Wasserman and Faust, 1994), which measures the ratio of the number of actual links to the maximum number of links possible:

$$IntraNor = \frac{Total\ No.\ Intradisciplinary\ Links \times 2}{Dept\ Size \times (Dept\ Size - 1)}$$

$$InterNor = \frac{Total\ No.\ Interdisciplinary\ Links}{(School\ size\ \text{-}\ Dept\ Size) \times Dept\ Size}.$$

We also create indicator variables for department to control for the variation of publication and citation rates across disciplines. However, our pilot study does not find

Table 6.2. OLS Analysis at Department Level

Predictor	sqrt(Cite05)			sqrt(Prod05)		
	coefficient	T	F	coefficient	T	F
Constant	0.12	1.59	0.11	0.20	4.62	0.00
P1 performance	0.35	22.74	0.00	0.63	21.59	0.00
IntraNor	0.10	0.32	0.75	0.10	0.79	0.43
InterNor	10.14	2.12	0.04	7.09	3.59	0.00
n	173			173		
R^2	83.5%			82.9%		
F	285.21			273.54		
$p - value$	0.00			0.00		

significant impact of disciplines and we therefore excluded those indicator variables from our final model.

Table 6.2 shows the result of department level analysis. The small p-values (0.04 for research impact and 0.00 for research productivity) suggest that while controlling for difference in research capabilities, departments with more interdisciplinary collaborators are likely to generate more high-quality and high-impact publications. The graphical presentation of this result is shown in Figure6.2.

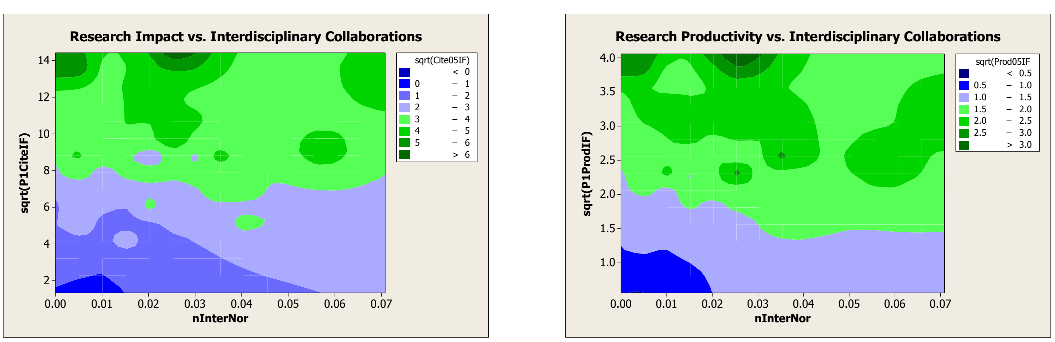


Figure 6.2. Impact of Interdisciplinary Collaboration on Departmental Research Performance. Left: impact. Right: productivity

6.2.4. School Level Analysis and Results

At school level, we measure research performance by the school average research productivity and average research impact:

$$Prod^t_{IF} = \frac{\sum_{i=1}^{School\ Size} Prod^t_{IF_i}}{School\ Size} \quad t = 1, 2$$

$$Cite^t_{IF} = \frac{\sum_{i=1}^{School\ Size} Cite^t_{IF_i}}{School\ Size} \quad t = 1, 2.$$

Square root of these variables are used in the statistical analysis in order to satisfy the linear regression model assumptions. Intra- and interdisciplinary collaborations are measured by the average number of intra- and interdisciplinary links within the school, respectively, i.e., $avgIntra$ and $avgInter$:

$$avgIntra = \frac{\sum_{SchoolSize} Total\ No.\ Intradisciplinary\ Links}{School\ Size}$$

$$avgInter = \frac{\sum_{SchoolSize} Total\ No.\ Interdisciplinary\ Links}{School\ Size}.$$

The results in Table 6.3 show a significant impact of interdisciplinary collaboration on research impact (p-value=0.09). But similar effect is not observed for research productivity. This result suggests that schools may improve its overall research impact by promoting more interdisciplinary collaborations. The graphical presentation of the effect of interdisciplinary collaboration on research impact is shown in Figure6.3.

6.3. Conclusion

In this study we examined the impact of interdisciplinary collaboration on research performance at individual, department, and school levels. We used a two-period model

Table 6.3. OLS Analysis at School Level

Predictor	sqrt(avgCite05)			sqrt(avgProd05)		
	coefficient	T	F	coefficient	T	F
Constant	0.33	2.35	0.03	0.21	1.87	0.08
P1 Performance	0.33	15.26	0.00	0.68	10.37	0.00
avgIntra	-0.05	-0.77	0.45	-0.02	-0.44	0.67
avgInter	0.15	1.81	0.09	0.04	0.84	0.41
n	25			25		
R^2	92.9%			85.9%		
F	92.25			42.57		
$p - value$	0.00			0.00		

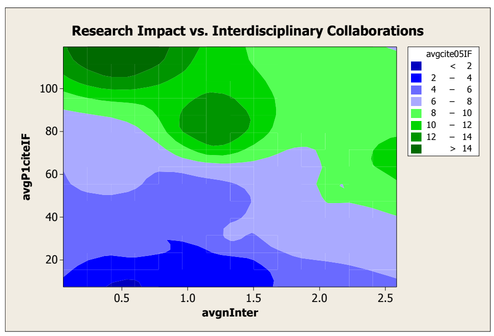


Figure 6.3. Impact of Interdisciplinary Collaboration on School Research Impact.

to establish the cause-and-effect relationship between collaboration behaviors in the first period and the research performance in the second period. Using department as a proxy for discipline, our analysis consistently showed a significant positive effect of interdisciplinary collaborations on research impact at individual, department, and school levels. This result suggests that having more collaborators outside one's own discipline help people identify important research stream and synthesize disparate knowledge into innovative ideas which may have a broader impact. We also found a significant positive impact of interdisciplinary collaboration on research productivity at individual and department level but not school level, which implies that both individual and department may improve their productivity by making use of specialties in other disciplines through interdisciplinary collaborations.

However, collaboration across disciplines also incur coordination cost. As higher level, i.e., school level, the benefits of interdisciplinary collaboration may not overcome the hurdle of increased coordination cost.

References

Adler, P. S., A. Mandelbaum, V. Nguyen, E. Schwerer. 1995. From project to process management: An empirically-based framework for analyzing product development time. *Management Science* **41**(3) 435–461.

Almeida, P., B. Kogut. 1999. Localization of knowledge and the mobility of engineers in regional networks. *Management Science* **45**(7) 905–917.

Amabile, T. M. 1983a. *The Social Psychology of Creativity*. New Yori: Springer-Verlag.

Amabile, T. M. 1983b. The social psychology of creativity - a componental conceptualization. *Journal of Personality and Social Psychology* **45**(2) 357–376.

Amabile, T. M. 1996. *Creativity in Context*. Westview Press. Boulder, CO.

Amabile, T. M., R. Conti, H. Coon, J. Lazenby, M. Herron. 1996. Assessing the work environment for creativity. *Academy of Management Journal* **39**(5) 1154–1184.

Argote, L., S. Beckman, D. Epple. 1990. The persistence and transfer of learning in industrial settings. *Management Science* **36** 140–154.

Argote, L., P. Ingram. 2000. Knowledge transfer: A basis for competitive advantage in firms. *Organizational Behavior and Human Decision Processes* **82** 150–169.

Arthur, W. B. 1991. Designing economic agents that act like human agents - A behavioral-approach to bounded rationality. *American Economic Review* **81**(2) 353–359.

Askin, R. G., J. B. Goldberg. 2002. *Design and Analysis of Lean Production Systems*. New York: Wiley.

Baiman, S., M. V. Rajan. 1995. The information advantages of discretionary bonus schemes. *Accounting Review* **70**(4) 557–579.

Baker, G. 1992. Incentive contracts and performance measurement. *Journal of Political Economy* **C** 598–614.

Baker, G., R. Gibbons, K. J. Murphy. 1994. Subjective performance-measures in optimal incentive contracts. *Quarterly Journal of Economics* **109**(4) 1125–1156.

Bala, V., S. Goyal. 2000a. A noncooperative model of network formation. *Econometrica* **68**(5) 1181–1229.

Baldwin, C. Y., K. B. Clark. 2000. *Design Rules: The Power of Modularity*. Cambridge, MA: MIT Press.

Barley, S. R., G. Kunda. 2001. Bringing work back in. *Organization Science* **12**(1) 76–95.

Barron, F., D. M. Harrington. 1981. Creativity, ingelligence, and personality. *Annual Reivew of Psychology* **32** 439–476.

Bass, L., D. McMurrer. 2007. Maximizing your return on people. *Harvard Business Review* **85**(3) 115+.

Bellman, R. 1961. *Adaptive Control Process: A Guide Tour*. Princeton University Press. Prince, NJ.

Berger, P. D. 1972. On setting optimal sales commissions. *Operational Research Quarterly* **23** 213.

Berger, P. D. 1991. The impact of risk attitude on the optimal compensation plan in a multiproduct situation. *Journal of the Operational Research Society* **42** 323.

Bettenhausen, K. L. 1991. Five years of groups research - what have learned and what needs to be addressed. *Journal of Management* **17**(2) 345–381.

Bommer, W. H., J. L. Johnson, G. A. Rich, P. M. Podsakoff, S. B. Machenzie. 1995. On the interchangebility of objective and subjective measures of employee performance - a metaanalysis. *Personnel Psychology* **48**(3) 587–605.

Borgatti, S. P., R. Cross. 2003. A relational view of information seeking and learning in social networks. *Management Scence* **49**(4) 432–446.

Borgatti, S. P., P. C. Foster. 2003. The network paradigm in organizational research: A review and typology. *Journal of Management* **29**(6) 991–1013.

Boss, W. J. 1978. Trust and managerial problem sovling revisited. *Group and Organizational Management* **3**(3) 331–342.

Bosworth, D. L. 1978. Rate of obsolescence of technical knowledge - note. *Journal of Industrial Economics* **26** 273.

Boudreau, J., W. J. Hopp, J. O. McClain, L. J. Thomas. 2003. On the interface between operations and human resources management. *Manufacturing and Service Operations Management* **5**(3) 179–202.

Brass, D. J., J. Galaskiewicz, H. R. Greve, W. P. Tsai. 2004. Taking stock of networks and organizations: A multilevel perspective. *Academy of Management Journal* **47**(6) 795–817.

Brown, J. S., P. Duguid. 2001. Knowledge and organization: A social-practice perspective. *Organization Science* **12**(2) 198–213.

Burt, R. S. 1992. *Structural Holes: the Social Structure of Comptetion*. Harvard University Press. Cambridge, MA.

Burt, R. S. 2004. Structural holes and good ideas. *The American Journal of Sociology* **110**(2) 349–399.

Buzacott, J. A., J. G. Shanthikumar. 1993. *Stochastic Models of Manufacturing Systems*. Prentice Hall.

Cameron, J., W. D. Pierce. 1994. Reinforcement, reward, and intrinsic motivation - a metaanalysis. *Review of Educational Research* **64**(3) 363–423.

Campion, M. A., G. J. Medsker, A. C. Higgs. 1993. Relations between work group characteristics and effectiveness - impalicatoins for designing effective work groups. *Personnel Psychology* **46**(4) 823–850.

Carrillo, J. E., C. Gaimon. 2000. Improving manufacturing performance through process change and knowledge creation. *Management Science* **46**(2) 265–288.

Carrillo, J. E., C. Gaimon. 2004. Managing knowledge-based resource capabilities under uncertainty. *Management Science* **50**(11) 1504–1518.

Castelfranchi, C., R. Falcone, G. Pezzulo. 2003. Trust in information sources as a source for trust: a fuzzy approach. *In: AAMAS03* 89–96.

Che, Y. K., S. W. Yoo. 2001. Optimal incentives for teams. *American Economic Review* **91**(3) 525–541.

Cheng, J. L. C. 1983. Interdependence and coordiantion in organizations - a role-system analysis. *Academy of Management Journal* **26**(1) 156–162.

Chesbrough, W. H. 2003. A better way to innovate. *Harvard Business Review* **81**(7) 12–13.

Coates, J. E. 1986. Three models for white collar productivity improvement. *Industrial Management* **28**(2) 7–13.

Cohen, W. N., D. A. Levinthal. 1990. Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly* **35** 128–152.

Crosby, L. A., K. R. Evans, D. Cowles. 1990. Relationship quality in services selling - an interpersonal influence perspective. *Journal of Marketing* **54**(3) 68–81.

Cross, J. G. 1983. *A Thoery of Adaptive Economic Behavior*. Cambridge University Press. New York/London.

Cross, R., S. P. Borgatti. 2006. *The Ties That Share: Relational Characteristics that Facilitate Information Seeking in M.H. Huysman and V. Wulf (Eds) Social Capital and IT*. MIT Press: Cambridge. Forthcoming.

Cross, R., J. N. Cummings. 2004. Tie and network correlates of individual performance in knowledge-intensive work. *Academy of Management Journal* **47**(6) 928–937.

Cummings, J. N. 2004. Work groups, structural diversity, and knowledge sharing in a global organization. *Management Science* **50**(3) 352–364.

Datar, S., S. C. Kulp, R. A. Lambert. 2001. Balancing performance measures. *Journal of Accounting Research* **39**(1) 75–92.

Davenport, T. H. 2005. *Thinking for a Living: How to Get Better Performances And Results from Knowledge Workers*. Boston, MA.

Davenport, T. H., L. Prusak. 2002. *Working Knowledge: How Organization Manage What They Know*. Boston, MA.

Davenport, T. H., L. Prusak, J. H. Wilson. 2007. Who's bringing you hot ideas (and how are you responding)? *Harvard Business Review* **85**(3) 24–30.

Davenport, T. H., R. J. Thomas, S. Cantrell. 2002. The mysterious art and science of knowledge-worker performance. *MIT Sloan Management Review* **44**(1) 23–30.

de Holan, P. M., N. Phillips. 2004. Remembrance of things past? the dynamics of organizational forgetting. *Management Science* **50**(11) 1603–1613.

Debo, L. G., L. B. Toktay, L. N. Van Wassenhove. 2004. Queueing for expert services. *INSEAD Working Paper* **46**(TM). Fontainebleau, France.

DeMatteo, J. S., L. T. Eby, E. Sundstrom. 1998. Team-based rewards: Current empirical evidence and directions for future research. *Group Dynamics - Theory Research and Practice* **20** 141–183.

Dewatripont, M., J. Tirole. 2005. Modes of communication. *Journal of Political Economy* **113**(6) 1217–1238.

Dewett, T., G. R. Jones. 2001. The role of information technology in the organization: a review, model, and assessment. *Journal of Management* **27**(3) 313–346.

Dietz, G., D. N. Den Hartog. 2006. Measuring trust inside organisations. *Personnel Review* **35**(5) 557–588.

Dirks, K. T. 1999. The effects of interpersonal trust on work group performance. *Journal of Applied Psychology* **84**(3) 445–455.

Doney, P. M., J. P. Cannon. 1997. An examination of the nature of trust in buyer-seller relationships. *Journal of Marketing* **61**(April) 307–319.

Drucker, P. F. 1999. Knowledge-worker productivity: The biggest challenge. *California Management Review* **41**(2) 79.

Dupouet, O., M. Yildizoglu. 2006. Organizational performance in hierarchies and communities of practice. *Journal of Economic Behavior & Organization* **61**(4) 668–690.

Dvorak, R. E., E. Holen, D. Mark, W. F. Meehan. 1997. Six principles of higher performance it. *McKinsey Quarterly* **3** 164–177.

Ebel, K. H., E. Ulrich. 1987. Some workplace effects of cad and cam. *International Labor Review* **126**(3) 351–370.

Egelhoff, W. G. 1991. Information-processing theory and the multinational enterprise. *Journal of International Business Studies* **22**(3) 341–368.

Eisenberger, J., S. K. Hui, Zhang J. Z. 2007. From storyline to box office: A new approach for green-lighting movie scripts. *Management Science* Forthcoming.

Eisenberger, R., S. Armeli. 1997. Can salient reward increase creative performance without reducing intrinsic creative interest? *Journal of Personality and Social Phychology* **72** 652–663.

Eisenberger, R., L. Rhoades. 2001. Incremental effects of reward on creativity. *Journal of Personality and Social Phychology* **81**(4) 728–741.

Eisenberger, R., L. Shanock. 2003. Rewards, intrinsic motivation, and creativity: A case study of conceptual and methodological isolation. *Creativity Research Journal* **15**(2-3) 121–130.

Feltham, G. A., J. Xie. 1994. Performance-measure congruity and diversity in multitask principal-agent relations. *Accouting Review* **69**(3) 429–453.

Ferrin, D. L., K. T. Dirks. 2003. The use of rewards to increase and decrease trust: Mediating processes and differential effects. *Organization Science* **14**(1) 18–31.

Fleming, L. 2001. Recombinant uncertainty in technological search. *Management Science* **47**(1) 117–132.

Fleming, L., M. Marx. 2006. Managing creativity in small worlds. *California Management Review* **48**(4) 6–27.

Fleming, L., O. Sorenson. 2001. The dangers of modularity. *Harvard Business Review* **79**(8) 20–21.

Fornell, C. 2005. *The American Customer Satisfaction Index at Ten Years*. Stephen M. Ross School of Business, University of Michigan. Ann Arbor, MI.

Friedlander, F. 1970. Primacy of trut as a facilitator of further group accomplishment. *Journal of Applied Behavioral Science* **6**(4) 387.

Gaimon, C. 1997. Planning information technology-knowledge worker systems. *Management Science* **43**(9) 1308–1328.

Garicano, L. 2000. Hierarchies and the organization of knowledge in production. *The Journal of Political Economy* **108**(5) 874–904.

Garicano, L., E. Rossi-Hansberg. 2006. Organization and inequality in a knowledge economy. *Quarterly Journal of Economics* Forthcoming.

Gerwin, D. 1993. Manufacturing flexibility: a strategic perspective. *Management Science* **39**(4) 395–410.

Gibbs, M., K. A. Merchant, W. A. Van der Stede, M. E. Vargus. 2004. Determinants and effects of subjectivity in incentives. *Accounting Review* **79**(2) 409–436.

Gillson, L. L., J. E. Mathieu, C. E. Shalley, T. M. Ruddy. 2005. Creativity and standardization: Complementray or conflicting drivers of team effectiveness. *Academy of Management Journal* **48**(3) 521–531.

Goffee, R., G. Jones. 2007. Leading clever people. *Harvard Business Review* **85**(3) 72+.

Gottschalg, O., M. Zollo. 2007. Interest alignment and competitive advantage. *Academy of Management Review* **32**(2) 418–437.

Gough, H. G. 1979. Creative personality scale for the adjective check list. *Journal of Personality and Social Psychology* **37**(8) 1398–1405.

Granovetter, M. 1985. Economic action and social structure: The problem of embeddedness. *American Journal of Sociology* **91** 481–510.

Granovetter, M. S. 1973. The strength of weak ties. *American Journal of Sociology* **78** 1360–1380.

Granovetter, M. S. 1978. Threshold modelds of diffusion and collective behavior. *Journal of Mathematical Sociology* **9** 165–179.

Granovetter, M. S. 1983. The strength of weak ties: A network theory revisited. *Sociological Theory* **1** 201–233.

Grant, R. M. 1996. Toward a knowledge-based theory of the firm. *Strategic Management Journal* **17** 109–122.

Guimerà, R., A. Arenas, A. Diaz-Guilera, F. Giralt. 2002a. Dynamical properties of model communication networks. *Physical Reveiw E* **66**(2) Art. No. 026704 Part 2.

Guimerà, R., A. Diaz-Guilera, F. et al. Vega-Redondo. 2002b. Optimal network topologies for local search with congestion. *Physical Reveiw Letters* **89**(24) Art. No. 248701.

Guimerà, R., B. Uzzi, J. Spiro, L.A.N. Amaral. 2005. Team assembly mechanisms determine collaboration network structure and team performance. *Science* 698–702.

Guzzo, R. A., M. W. Dickson. 1996. Teams in organizations: Recent research on performance and effectiveness. *Annual Review of Psychology* **47** 307–338.

Haas, MR. 2006. Knowledge gathering, team capabilities, and project performance in challenging work environments. *Management Science* **52**(8) 1170–1184.

Hansen, M. T. 1999. The search-transfer problem: The role of weak ties in sharing knowledge across organization subunits. *Administrative Science Quarterly* **44** 82–111.

Hansen, M. T. 2002. Knowledge networks: Explaining effective knowledge sharing in multiunit companies. *Organization Science* **13**(3) 232–248.

Hansen, M. T., M. L. Mors, B. Lovas. 2005. Knowledge sharing in organizations: Multiple networks, multiple phases. *Academy of Management Journal* **48**(5) 776–793.

Hansen, M. T., N. Nohria, T. Tierney. 1999. What's your strategy for managing knowledge? *Harvard Business Review* **77**(2) 106.

Hoegl, M., H. Ernst, L. Proserpio. 2007. How teamwork matters more as team member dispersion increases. *Journal of Product Innovation Management* **24**(2) 156–165.

Hoegl, M., L. Proserpio. 2004. Team member proximity and teamwork in innovative projects. *Research Policy* **33**(8) 1153–1165.

Holmstrom, B., P. Milgrom. 1987. Aggregation and linearity in the provision of intertemporal incentives. *Econometrica* **55**(2) 303–328.

Holmstrom, B., P. Milgrom. 1991. Multitask principal agent analyses - incentive contracts, asset ownership, and job design. *Journal of Law Economics and Organization* **7**(Sp. Iss.) 24–52.

Hopp, W. J., S. M. R. Iravani, G. Yuen. 2007a. Discretionary task completion: A key difference between white-collar and blue-collar work systems. *Management Science* **53**(1) 61–77.

Hopp, W. J., S. M. R. Iravani, G. Yuen. 2007b. Trust and information sharing in supply chains Working paper, Northwestern University.

Hopp, W. J., M. L. Spearman. 2000. *Factory Physics: Foundations of Manufacturing Management*. 2nd ed. Irwin/McGraw-Hill. Burr Ridge, IL.

Hopp, W. J., M. P. Van Oyen. 2004. Agile workforce evaluation: a framework for cross-training and coordination. *IIE Transactions* **36**(10) 919–940.

Huberman, B. A., T. Hogg. 1995. Communities of practice: Performance and evolution. *Comuputational and Mathematical Organization Theory* **1** 73–92.

Huston, L., N. Sakkab. 2006. Connect and develop: Inside procter & gamble's new model for innovation. *Harvard Business Review* **84**(3) 58–66.

Hwang, P., W. P. Burgers. 1997. Properties of trust: An analytical view. *Organizational Behavior and Human Decisoin Processes* **69**(1) 67–73.

Ibarra, H., S. B. Andrew. 1993. Power, social influence, and sense making: Effects of network centrality and proximity on employee perceptions. *Administratie Science Quarterly* **38** 277–303.

Ishida, J. 2006. Team incentives under relative performance evaluation. *Journal of Economics and Management Strategy* **15**(1) 187–206.

Jackson, M. O. 2003. A survey of models of network formation: Stability and efficiency. *Working Paper* Economic Working Paper Archive at WUSTL.

Jaffe, A. B., M. Trajtenberg, R. Henderson. 1993. Geographic localization of knowledge spillovers as evidenced by patent citations. *Quarterly Journal of Economics* **108**(3) 577–598.

Janz, B. D., J. A. Colquitt, R. A. Noe. 1997. Knowledge worker team effectiveness: The role of autonomy, interdependence, team development, and contextual support variables. *Personnel Psychology* **50**(4) 877–904.

Kanawattanachai, P., Y. Yoo. 2002. Dynamic nature of trust in virtual teams. *Journal of Strategic Information Systems* **11**(3-4) 187–213.

Kim, P. H. 2003. When private beliefs shape collective reality: The effects of beliefs about coworkers on group discussion and performance. *Management Science* **49**(6) 801–815.

Kozlowski, S. W. J., D. R. Ilgen. 2006. Enhancing the effectiveness of work groups and teams. *Psychological Science* **Suppl. S** 77–124.

Krackhardt, D. 1992. The strength of strong ties: The importance of philo in organizations. in N. Nohria & R. C. Ecclas (Eds.). *Networks and Organizations: Structure, Form, and Actions* 216–239Cambridge, MA: Harvard University Press.

Lal, R., V. Srinivasan. 1993. Compensation plans for single-product and multiproduct salesforces - an application of the holmstrom-milgrom model. *Management Science* **39**(7) 777–793.

Langfred, C. W. 2004. Too much of a good thing? negative effects of high trust and individual autonomy in self-managing teams. *Academy of Management Journal* **47**(3) 385–399.

Lapre, M. A., N. Tsikriktsis. 2006. Organizational learning curves for customer dissatisfaction: Heterogeneity across airlines. *Management Science* **52**(3) 352–366.

Laudel, G. 2001. Collaboration, creativity and rewards: Why and how scientists collaborate. *International Journal of Technology Management* **22**(7-8) 762–781.

Lee, D. J., J. H. Ahn. 2005. Reward systems for intra-organizational knowledge sharing. *European Journal of Operational Research* **180**(2) 938–956.

Leonard-Barton, D., K. Bowen, K. B. Clark, C. A. Holloway, S. C. Wheelwright. 1994. How to integrate work and deepen expertise. *Harvard Business Review* **72** 121–131.

Levinthal, D. A., J. G. March. 1993. The myopia of learning. *Strategic Management Journal* **14**(Sp. Iss. SI, WIN) 95–112.

Lewicki, R. J., D. J. McAllister, R. J. Bies. 1998. Trust and distrust: New relationships and realities. *Academy of Management Review* **23**(3) 438–458.

Lewicki, R. J., E. C. Tomlinson, N. Gillespie. 2006. Models of interpersonal trust development: Theoretical approaches, empirical evidence, and future directions. *Journal of Management* **32**(6) 991–1022.

Lieberman, J. K. 1981. *The Litigious Society*. New York: Basic Books. New York, NY.

Locke, E. A., G. P. Latham. 1990. *A Theory of Goal Setting and Task Performance*.

Locke, E. A., G. P. Latham. 2004. What should we do about motivation theory? six recommendations for the twenty-first century. *Academy of Management Review* **29**(3) 388–403.

Locke, E. A., M. D. Plummer. 2002. Building a practically useful theory of goal setting and task motivation - a 35-year odyssey. *American Psychologist* **57**(9) 705–717.

MacCrimmon, K. R., C. Wagner. 1994. Stimulationg ideas through creativity software. *Management Science* **40**(11) 1514–1532.

MacLeod, W. B. 2003. Optimal contracting with subjective evaluation. *American Economic Review* **93**(1) 216–240.

Mantrala, M. K., P. S. Murali, A. A. Zoltners. 1994. Structuring a multiproduct sales quota-bonus plan for a heterogeneous sales force: a practical model-based approach. *Marketing Science* **13**(2) 121–144.

Marsden, P. V. 1990. Network data and measurement. *Annual Review of Sociology* **16** 435–463.

Martins, L. L., L. L. Gilson, M. T. Maynard. 2004. Virtual teams: What do we know and where do we go from here? *Journal of Management* **30**(6) 805–835.

Mayer, G. W. 1994. Social information processing and social networks: A test of social influence mechanisms. *Human Relations* **47** 1013–1048.

Mayer, R., J. Davis, F. Schoorman. 1995. An integrative model of organizational trust. *Academy of Mangagement Review* **20**(3) 709–734.

McAllister, D. J. 1995. Affect- and cognition-based trust as foundations for interpersonal cooperation in organizations. *Academy of Management Journal* **38** 24–59.

McNamar, T. 1973. White collar job enrichment - pay board experience. *Public Administrative Review* **33**(6) 563–368.

Melaye, D., Y. Demazeau. 2005. Bayesian dynamic trust model. *Multi-Agent Systems and Applications IV, Proceedings Lecture Notes in Artificial Intelligence* **3690** 480–489.

Mellinger, G. D. 1956. Interpersonal trust as a factor in communication. *Journal of Abnormal Social Psychology* **52** 304–309.

Morgan, P. 1995. A model of search, coordination, and market segmentation Revised mimeo, SUNY Buffalo.

Morgan, R. M., S. D. Hunt. 1994. The commitment-trust theory of relationship marketing. *Journal of Marketing* **58**(3) 20–38.

Morrman, C. 1993. Factors affecting trust in market-research relationships. *Journal of Marketing* **57**(1) 81–101.

Morten, T. H., L. M. Mors, B. Lovas. 2005. Knowledge sharing in organizations: Multiple networks, multiple phases. *Academy of Management Journal* **48**(5) 776–793.

Napoleon, K., C. Gaimon. 2004. The creation of output and quality in services: A framework to analyze information technology-worker systems. *Production and Operations Management* **13**(3) 245–259.

Nasrallah, W. F., R. E. Levitt. 2001. An interaction value perspective on firms of differing size. *Computational and Mathematical Organization Theory* **7** 113–144.

Nasrallah, W. F., R. E. Levitt, P. Glynn. 2003. Interaction value analysis: When structured communication benefits organizations. *Organization Science* **14**(5) 541–557.

Nidumolu, S. R., M. R. Subramani. 2003. The matrix of control: Combining process and structure approaches to managing software development. *Journal of Management Information Systems* **20**(3) 159–196.

Nonaka, I. 1994. A dynamic theory of organizational knowledge creation. *Organization Science* **5**(1) 14–37.

Nooteboom, B., H. Berger, N. G. Noorderhaven. 1997. Effects of trust and governance on relational risk. *Academy of Management Journal* **40**(2) 308–338.

Oldham, G. R., A. Cummings. 1996. Employee creativity: Personal and contextual factors at work. *Academy of Management Journal* **39**(3) 607–634.

Park, G., J. Shin, Y. Park. 2006. Measurement of depreciation rate of technological knowledge: Technology cycle time approach. *Journal of Scientific & Industrial Research* **65**(2) 121–127.

Perry-Smith, J. E., C. E. Shalley. 2003. The social side of creativity: A static and dynamic social network. *Academy of Management Review* **28**(1) 89–106.

Pil, F. K., S. K. Cohen. 2006. Modularity: Implications for imitation, innovation, and sustained advantage. *Academy of Management Review* **31**(4) 995–1011.

Pisano, G. P. 1994. Knowledge, integration, and the locus of learning - an empirical analysis of process-development. *Strategic Management Journal* **15**(Sp. Iss. SI) 85–100.

Pisano, G. P. 1996. Learning-before-doing in the development of new process technology. *Research Policy* **25**(7) 1097–1119.

Porter, T., B. Lilly. 1996. The effects of conflict, trust, and task commitment on project team performance. *International Journal of Conflict Management* **7**(4) 361–376.

Prandy, K., A. Stewart, R. M. Blackburn. 1982. *White-Collar Work*. Macmillan Press. London.

Quercia, D., S. Hailes, L. Capra. 2006. B-trust: Bayesian trust framework for pervasive computing. *Lecture Notes in Computer Science* **3986** 298–312.

Radner, R. 1993. The organization of decentralized information processing. *Econometrica* **61**(5) 1109–1146.

Rajan, M. V., S. Reichelstein. 2006. Subjective performance indicators and discretionary bonus pools. *Journal of Accounting Research* **44**(3) 585–618.

Ramirez, Y. W., D. A. Nembhard. 2004. Measuring knowledge worker productivity. *Journal of Intellectual Capital* **5**(4) 602–628.

Reagans, R., B. McEvily. 2003. Network structure and knowledge transfer: The effects of cohesion and range. *Administrative Sciences Quarterly* **48**(2) 240–267.

Roth, A. E., I. Erev. 1995. Learning in extensive-form games: Experimental data and simple dynamic models in the intermediate term. *Games and Economic Behavior* **Special Issue: Nobel Symposium**(8) 164–212.

Rousseau, V., H. J. Jeppesen. 2006. Teamwork and associated psychological factors: A review. *Work and Stress* **20**(2) 105–128.

Ryu, C., Y. J. Kim, A. Chaudhury, H. R. Rao. 2005. Knowledge acquisition via three learning processes in enterprise information portals: Learning-by-investment, learning-by-doing,and learning-from-others. *MIS Quarterly* **29**(2) 245–278.

Sanchez, R., J. T. Mahoney. 1996. Modularity, flexibility, and knowledge management in product and organization design. *Strategic Management Journal* **17**(63-76 Sp. Iss. SI, WIN).

Schilling, M. A., P. Vidal, R. E. Polyhart, A. Marangoni. 2003. Learning by doing something else: Variation, relatedness, and the learning curve. *Management Science* **49**(1) 39C56.

Seijts, G. H., G. P. Latham, K. Tasa, B. W. Latham. 2004. Goal setting and goal orientation: An integration of two different yet related literatures. *Academy of Management Journal* **47**(2) 227–239.

Sethi, A. K., S. P. Sethi. 1990. Flexibility in manufacturing: a survey. *International Journal of Flexible Manufacturing Systems* **2**(4) 289–328.

Shalley, C. E. 1991. Effects of productivity goals, creativity goals, and personal discretion on individual creativity. *Journal of Applied Psychology* **76**(2) 179–185.

Shalley, C. E. 1995. Effects of coaction, expceted evaluation, and goal-setting on creativity and productivity. *Academy of Management Journal* **38**(2) 483–503.

Shalley, C. E., L. L. Gilson. 2004. What leaders need to know: A review of social and contextual factors that can foster or hinder creativity. *Leadership Quarterly* **15**(1) 33–53.

Shalley, C. E., L. L. Gilson, T. C. Blum. 2000. Matching creativity requirements and the work environment: Effects on satisfaction and intentions to leave. *Academy of Management Journal* **43**(2) 215–223.

Shim, J. K., J. G. Siegel. 1999. *Operations Managment*. Barron's Educational Series.

Shirai, T. 1983. A theory of enterprise unionism. *In: Shirai, T. (Ed.) Contemporary Industrial Relations in Japan* 117–143University of Wisconsin Press, Madison, WI.

Singh, J., D. Sirdeshmukh. 2000. Agency and trust mechanisms in consumer satisfaction and loyalty judgments. *Journal of the Academy of Marketing Science* **28**(1) 150–167.

Sirdeshmukh, D., J. Singh, B. Sabol. 2002. Consumer-trust, value, and loyalty in relational exchanges. *Journal of Marketing* **66**(1) 15–37.

Slikker, M., A. van den Nouweland. 2001. *Social and Economic Networks in Cooperative Game Theory*. Kluwer Academic Publishers.

Sosa, M. E., S. D. Eppinger, C. M. Rowles. 2003. The misalignment of product architecture and organizational structure in complex product development. *Management Science* **50**(12) 1674–1689.

Stamp, D. 1995. *The Invisible Assembly Line: Boosting White Collar Productivity in The New Economy*. Amacom Books. New York.

Straub, D., M. Limayem, E. Karahannaevaristo. 1995. Measuring syetem usage-implication for is theory testing. *Management Science* **41**(8) 1328–1342.

Sutton, R. S., A. G. Barto. 1998. *Reinforcement Learning: An Introduction*. MIT Press, Cambridge, MA.

Szulanski, G. 1996. Exploring internal stickiness: Impediments to the transfer of best practice within the firm. *Strategic Management Journal* **17** 27–43.

Thomke, S., D. Reinertsen. 1998. Agile product development: Managing development flexibility in uncertain environments. *California Management Review* **41**(1) 8.

Thompson, M., P. Heron. 2005. The difference a manager can make: organizational justice and knowledge worker commitment. *International Journal of Human Resource Management* **16**(3) 383–404.

Toubia, O. 2006. Idea generation, creativity, and incentives. *Marketing Science* **25**(5) 411–425.

Tsai, W. P. 2001. Knowledge transfer in intraorganizational networks: Effects of network position and absorptive capacity on business unit innovation and performance. *Academy of Management Journal* **44**(5) 996–1004.

Turner, K. L., M. V. Makhija. 2006. The role of organizational controls in managing knowledge. *Academy of Management Review* **31**(1) 197–217.

Urban, G. L., F. Sultan, W. J. Qualls. 2000. Placing trust as the center of your internet strategy. *Sloan Management Review* **42**(Fall) 39–49.

Uzzi, B. 1996. The sources and consequences of embeddedness for the economic performance of organizations: The network effect. *American Sociological Review* **61**(4) 674–698.

Uzzi, B., S. Dunlap. 2005. How to build your network. *Harvard Business Review* **83**(12) 53–62.

Uzzi, B., R. Lancaster. 2003. Relational embeddedness and learning: The case of bank loan managers and their clients. *Management Science* **49**(4) 383–399.

Uzzi, B., J. Spiro. 2005. Collaboration and creativity: The small world problem. *American Sociological Review* **111**(2) 447–504.

Van der Vegt, G. S., O. Janssen. 2003. Joint impact of interdependence and group diversity on innovation. *Journal of Management* **29**(5) 729–751.

Van der Vegt, G. S., E. Van de Vliert. 2005. Effects of perceived skill dissimilarity and task interdependence on helping in work teams. *Journal of Management* **31**(1) 73–89.

Vayanos, D. 2003. The decentralization of information processing in the presence of interactions. *Review of Economic Studies* **70**(3) 667–695.

Wageman, R. 1995. Interdependence and group effectiveness. *Administrative Science Quarterly* **40**(1) 145–180.

Wageman, R., G. Baker. 1997. Incentives and cooperation: The joint effects of task and reward interdependence on group performance. *Journal of Organizational Behavior* **18**(2) 139–158.

Watts, D. J. 2004. The new science of networks. *Annual Review of Sociology* **30** 243–270.

Watts, D. J., S. H. Strogatz. 1998. Collective dynamics of 'small-world' networks. *Nature* **393** 440–442.

Weldon, E., L. R. Weingart. 1993. Group goals and group performance. *British Journal of Social Psychology* **32** 302–334.

Wolinsky, A. 1993. Competition in a market for informed experts services. *Rand Journal of Economics* **24**(3) 380–388.

Woodman, R. W., L. F. Schoenfeldt. 1989. Individual differences in creativity: An interactionist perspective. *Handbook of Creativity*. J. G. Glover, R. R. Ronning, C. R. Reynolds, 77–92. New York: Plenum.

Zack, M. H., J. L. McKenney. 1995. Social-context and interaction in ongoing computer-supported management groups. *Organization Science* **6**(4) 394–422.

Zand, D. 1972. Trust and managerial problem solving. *Administrative Science Quarterly* **17** 229–239.

Zander, U., B. Kogut. 1995. Knowledge and the speed of transfer and imitation of organizational capabilities: An empirical test. *Organization Science* **6**(1) 76–92.

Zellmer-Bruhn, M. E. 2003. Interruptive events and team knowledge acquisition. *Management Science* **49**(4) 514–528.

Zuboff, S. 1988. *In the Age of the Smart Machine: The Future of Work and Power*.

Ballas, A., V. Theoharakis. 2003. Exploring diversity in accounting through faculty journal perception. *Contempory Accounting Research* **20**(4) 619–644.

Bollen, J., M. A. Rodriguez, H. Van De Sompel. 2006. Journal status. *Scientometrics* **69**(3) 669–687.

Bonacich, P. 1972. Factoring and weighting approaches to status scores and clique identification. *Journal of Mathematical Sociology* **2**(1) 113–120.

Bonacich, P., P. Lloyd. 2001. Eigenvector-like measures of centrality for asymmetric relations. *Social Networks* **23**(3) 191–201.

Borgatti, S. P. 2005. Centrality and network flow. *Social Networks* **27**(1) 55–71.

Borgatti, S. P., R. Cross. 2003. A relational view of information seeking and learning in social networks. *Management Scence* **49**(4) 432–446.

Borgatti, S. P., P. C. Foster. 2003. The network paradigm in organizational research: A review and typology. *Journal of Management* **29**(6) 991–1013.

Brass, D. J., J. Galaskiewicz, H. R. Greve, W. P. Tsai. 2004. Taking stock of networks and organizations: A multilevel perspective. *Academy of Management Journal* **47**(6) 795–817.

Brown, J. S., P. Duguid. 2001. Knowledge and organization: A social-practice perspective. *Organization Science* **12**(2) 198–213.

Burt, R. S. 1992. *Structural Holes: the Social Structure of Comptetion*. Harvard University Press. Cambridge, MA.

Burt, R. S. 2004. Structural holes and good ideas. *The American Journal of Sociology* **110**(2) 349–399.

Cross, R., J. N. Cummings. 2004. Tie and network correlates of individual performance in knowledge-intensive work. *Academy of Management Journal* **47**(6) 928–937.

Cummings, J. N. 2004. Work groups, structural diversity, and knowledge sharing in a global organization. *Management Science* **50**(3) 352–364.

Davenport, T. H. 2005. *Thinking for a Living: How to Get Better Performances And Results from Knowledge Workers*. Boston, MA.

Fleming, L., M. Marx. 2006. Managing creativity in small worlds. *California Management Review* **48**(4) 6–27.

Fleming, L., S. Mingo, D. Chen. 2006. Brokerage and collaborative creativity Working paper.

Goffee, R., G. Jones. 2007. Leading clever people. *Harvard Business Review* **85**(3) 72+.

Gordon, M. E., J. E. Purvis. 1991. Journal publication records as a measure of research performance in industrial-relations. *Industrial & Labor Relations Review* **45**(1) 194–201.

Granovetter, M. S. 1973. The strength of weak ties. *American Journal of Sociology* **78** 1360–1380.

Hansen, M. T. 2002. Knowledge networks: Explaining effective knowledge sharing in multiunit companies. *Organization Science* **13**(3) 232–248.

Hansen, M. T., M. L. Mors, B. Lovas. 2005. Knowledge sharing in organizations: Multiple networks, multiple phases. *Academy of Management Journal* **48**(5) 776–793.

Hargadon, A., R. I. Sutton. 1997. Technology brokering and innovation in a product development firm. *Administrative Science Quarterly* **42**(4) 716–749.

Heinze, T., G. Bauer. 2007. Characterizing creative scientists in nano-s&t: Productivity, multidisciplinarity, and network brokerage in a longitudinal perspective. *Scientometrics* **70**(3) 811–830.

Hull, R. P., G. B. Wright. 1990. Faculty perceptions of journal quality: an update. *Account Horizons* 77–98.

Hull, T. W., W. R. Ross. 1991. Contextual effect in measureing accounting faculty perceptions of accounting journals: an empirical test and updated journal rankings. *Advanced in Accounting* 161–182.

Jacobson, A., L. Prusak. 2006. The cost of knowledge. *Harvard Business Review* **84**(11) 34+.

McEvily, B., A. Zaheer. 1999. Bridging ties: A source of firm heterogeneity in competitive capabilities. *Strategic Management Journal* **20** 1133–1156.

Miller, D. J., M. J. Fern, L. B. Cardinal. 2007. The use of knowledge for technological innovation within diversified firms. *Academy of Management Journal* **50**(2) 308–326.

Newman, J. M., E. Cooper. 1993. Determinants of academic recognition: the case of the journal of applied psychology. *Journal of Applied Psychology* **78**(3) 518–526.

Newman, M. E. J. 2007. *Mathematics of networks in The New Palgrave Encyclopedia of Economics*, vol. 2th ed. in press. L. E. Blume and S. N. Durlauf(eds). Palgrave Macmillan, Basingstoke.

Park, S. H., M. E. Gordon. 1996. Publication records and tenure decisions in the field of strategic management. *Strategic Management Journal* **17**(2) 109–128.

Perry-Smith, J. E. 2006. Social yet creative: The role of social relationships in facilitating individual creativity. *Academy of Management Journal* **49**(1) 85–101.

Perry-Smith, J. E., C. E. Shalley. 2003. The social side of creativity: A static and dynamic social network. *Academy of Management Review* **28**(1) 89–106.

Reagans, R., B. McEvily. 2003. Network structure and knowledge transfer: The effects of cohesion and range. *Administrative Sciences Quarterly* **48**(2) 240–267.

Scott, J. 2000. *Social Network Analysis: A Handbook (2nd ed.)*. Thousand Oaks. CA: Sage.

Simonton, D. K. 2004. Group artistic creativity: Creative clusters and cinematic success in feature films. *Journal of Applied Social Psychology* **34**(7) 1494–1520.

Toubia, O. 2006. Idea generation, creativity, and incentives. *Marketing Science* **25**(5) 411–425.

Tsai, W. P. 2001. Knowledge transfer in intraorganizational networks: Effects of network position and absorptive capacity on business unit innovation and performance. *Academy of Management Journal* **44**(5) 996–1004.

Uzzi, B., S. Dunlap. 2005. How to build your network. *Harvard Business Review* **83**(12) 53–62.

Uzzi, B., J. Spiro. 2005. Collaboration and creativity: The small world problem. *American Sociological Review* **111**(2) 447–504.

Wasserman, S., K. Faust. 1994. *Social Network Analysis; Methods and Applications*. Cambridge, UK, Cambridge University Press.

Ahuja, G. 2000. Collaboration networks, structural holes, and innovation: A longitudinal study. *Administrative Science Quarterly* **45**(3) 425–455.

Albert, R., H. Jeong, A.-L. Barabasi. 1999. Diameter of the world-wide web. *Nature* **401** 130–131.

Albrecht, T. L., V. A. Ropp. 1984. Communicating about innovation in networks of three u.s. organizations. *Journal of Communication* **34** 78–91.

Altiok, T. 1997. *Performance Analysis of Manufacturing Systems*. Springer.

Bala, V., S. Goyal. 2000a. A noncooperative model of network formation. *Econometrica* **68**(5) 1181–1229.

Borgatti, S. P. 2005. Centrality and network flow. *Social Networks* **27**(1) 55–71.

Borgatti, S. P., R. Cross. 2003. A relational view of information seeking and learning in social networks. *Management Scence* **49**(4) 432–446.

Borgatti, S. P., P. C. Foster. 2003. The network paradigm in organizational research: A review and typology. *Journal of Management* **29**(6) 991–1013.

Brass, D. J. 1995. A social network perspective on human resources management. *Research in Personnel and Human Resources Management* **13** 39–79.

Burt, R. S. 1992. *Structural Holes: the Social Structure of Comptetion*. Harvard University Press. Cambridge, MA.

Burt, R. S. 2004. Structural holes and good ideas. *The American Journal of Sociology* **110**(2) 349–399.

Buzacott, J. A., J. G. Shanthikumar. 1993. *Stochastic Models of Manufacturing Systems*. Prentice Hall.

Campbell, D. T. 1969. Reforms as experiments. *American Psycologist* **24** 409–429.

Chesbrough, W. H. 2003. A better way to innovate. *Harvard Business Review* **81**(7) 12–13.

Cross, R., J. N. Cummings. 2004. Tie and network correlates of individual performance in knowledge-intensive work. *Academy of Management Journal* **47**(6) 928–937.

Erdös, P., A. Rényi. 1959. On random graphs. *Publicationes Mathematica* **6** 290–297.

Erdös, P., A. Rényi. 1960. On the evolution of random graphs. *Hungarian Academy of Sciences* **5** 17–61.

Erdös, P., A. Rényi. 1961. On the strength of connectedness of random graph. *Acta Mathematica Scientia* **12** 261–267.

Faraj, S., L. Sproull. 2000. Coordinating expertise in software development teams. *Management Science* **46**(12) 1554–1568.

Follett, M. P. 1924. *Creative Experience*. Longmans. New York.

Fombrun, C. J. 1986. Structural dynamics with and between organizations. *Administrative Science Quarterly* **31** 403–421.

Galeotti, A., S. Goyal. 2007. The law of the few. *Working Paper* University of Essex.

Galeotti, A., S. Goyal, J. Kamphorst. 2006. Network formation with heterogeneous players. *Games and Economic Behavior* **54**(2) 353–372.

Goyal, S. 2007. *Connections: An Introduction to the Economics of Networks*. Princeton University Press.

Granovetter, M. S. 1978. Threshold modelds of diffusion and collective behavior. *Journal of Mathematical Sociology* **9** 165–179.

Hopp, W. J., M. L. Spearman. 2000. *Factory Physics: Foundations of Manufacturing Management*. 2nd ed. Irwin/McGraw-Hill. Burr Ridge, IL.

Huberman, B. A., T. Hogg. 1995. Communities of practice: Performance and evolution. *Comuputational and Mathematical Organization Theory* **1** 73–92.

Jackson, J. R. 1957. Networks of waiting lines. *Operations Research* **5** 518–521.

Jackson, M. O. 2003. A survey of models of network formation: Stability and efficiency. *Working Paper* Economic Working Paper Archive at WUSTL.

Jackson, M. O. 2008. Social networks in economics. *Handbook of Social Economics*. Elsevier. Forthcoming.

Jackson, M. O., A. Watts. 2002. On the formation of interaction networks in social coordination games. *Economic Behavior* **41**(2) 265–291.

Jackson, M. O., A. Wolinsky. 1996. A strategic model of social and economic networks. *Journal of Economic Theory* **71** 44–74.

Kogut, B., U. Zander. 1992. Knowledge of the firm, combinative capabilites and the replication of technology. *organization Science* **3**(3) 383–397.

Laesser, E. L., J. Storck. 2001. Communities of practice and organizational performance. *IBM Systems Journal. Knowledge Management* **40**(4).

Newman, M. E. J. 2000. Models of the small world. *Journal of Statistical Physics* **101**(3-4) 819–841.

Pelled, L. H. 1996. Demographic diversity, conflict, and work group outcomes: An intervening process theory. *Organization Science* **7**(6) 615–631.

Perry-Smith, J. E., C. E. Shalley. 2003. The social side of creativity: A static and dynamic social network. *Academy of Management Review* **28**(1) 89–106.

Powell, W. W. 1990. Neither market nor hierachy: Network forms of organization. *Barry Staw and L. L. Cummings (eds.), Research in Organizational Behavior* **12** 295–336. Greenwich, CT: JAI Press.

Reagans, R., E.W. Zuckerman. 2001. Networks, diversity, and productivity: the social capital of corporate r&d teams. *Organization Science* **12**(4) 502–517.

Stevenson, W. B., M. C. Gilly. 1991. Information processing and problem solving: the migration of problems through formal positions and networks of ties. *Academy of Management Journal* **34** 918–928.

Uzzi, B., L. An Amaral, F. Reed-Tsochas. 2007. Small-world networld networks and managment science research: a review. *European Management Review* **4** 77–91.

Uzzi, B., S. Dunlap. 2005. How to build your network. *Harvard Business Review* **83**(12) 53–62.

Uzzi, B., R. Lancaster. 2003. Relational embeddedness and learning: The case of bank loan managers and their clients. *Management Science* **49**(4) 383–399.

Uzzi, B., J. Spiro. 2005. Collaboration and creativity: The small world problem. *American Sociological Review* **111**(2) 447–504.

Vega-Redondo, F. 2007. *Complex Social Networks*. Cambridge: Cambridge University Press. Econometric Society Monograph Series.

Watts, A. 2001. A dynamic model of network formation. *Games and Economic Behavior* **34** 331–341.

Watts, A. 2002. Non-myopic formation of circle networks. *Economics Letters* **74** 227–282.

Aksnes, D. W. 2006. Citation rates and perceptions of scientific contribution. *Journal of the American Society for Information Science and Technology* **57**(2) 169–185.

Ballas, A., V. Theoharakis. 2003. Exploring diversity in accounting through faculty journal perception. *Contempory Accounting Research* **20**(4) 619–644.

Bouty, I. 2000. Interpersonal and interaction influences on informal resource exchanges between r&d researchers across organizational boundaries. *Academy of Management Journal* **43**(1) 50–65.

Cummings, J. N., S. Kiesler. 2005. Collaborative research across disciplinary and organizational boundaries. *Social Studies of Science* **35**(5) 703–722.

Gordon, M. E., J. E. Purvis. 1991. Journal publication records as a measure of research performance in industrial-relations. *Industrial & Labor Relations Review* **45**(1) 194–201.

Hopp, W. J., S. M. R. Iravani, F. Liu. 2008. The role of internal collaboration and communication on research productivity and impact of an engineering school. *Wroking Paper* Northwestern University.

National Academy of Sciences, Institute of Medicine, National Academy of Engineering. 2004. *Facilitating Interdisciplinary Research (Paperback)*.

Newman, J. M., E. Cooper. 1993. Determinants of academic recognition: the case of the journal of applied psychology. *Journal of Applied Psychology* **78**(3) 518–526.

Newman, M. E. J. 2001. The structure of scientific collaboration networks. *Proceedings of the National Academy of Sciences* **98** 404–409.

Park, S. H., M. E. Gordon. 1996. Publication records and tenure decisions in the field of strategic management. *Strategic Management Journal* **17**(2) 109–128.

Perry-Smith, J. E. 2006. Social yet creative: The role of social relationships in facilitating individual creativity. *Academy of Management Journal* **49**(1) 85–101.

Uzzi, B., S. Dunlap. 2005. How to build your network. *Harvard Business Review* **83**(12) 53–62.

Wasserman, S., K. Faust. 1994. *Social Network Analysis; Methods and Applications*. Cambridge, UK, Cambridge University Press.

Bloch, F., H. Ryder. 2000. Two-sided search, marriages, and matchmakers. *International Economic Review* **41**(1) 93–117.

Borgatti, S. P. 2005. Centrality and network flow. *Social Networks* **27**(1) 55–71.

Borgatti, S. P., R. Cross. 2003. A relational view of information seeking and learning in social networks. *Management Scence* **49**(4) 432–446.

Gale, D., L. S. Shapley. 1962. College admissions and the stability of marriage. *American Mathematical Monthly* **69** 9–15.

Goyal, S., J. L. Moraga-González. 2001. R&d networks. *Rand Journal of Economics* **32**(4) 686–707.

Guimerà, R., U. Brian, S. Jarrett, A.L. Amaral. 2005. Team assembly mechanisms determine collaboration network structure and team performance. *Science* **308**(29) 697–702.

Kramer, R. M. 1999. Trust and distrust in organizations: Emerging perspectives, enduring questions. *Annual Review of Psychology* **50** 569–598.

Marschak, J. 1955. Elements for a theory of teams. *Management Science* **1** 127–137.

Mayer, R., J. Davis, F. Schoorman. 1995. An integrative model of organizational trust. *Academy of Mangagement Review* **20**(3) 709–734.

Radner, R. 1962. Team decision problems. *The Annals of Mathmatical Statistics* **33**(3) 857–881.

Reagans, R., E.W. Zuckerman, B. McEvily. 2004. How to make the team: social networks versus demography as criteria for designing effective teams. *Administrative Sciences Quarterly* **49**(1) 101–33.

Singh, J. 2005. Collaborative networks as determinants of knowledge diffusion patterns. *Management Science* **51**(5) 756–770.

Thompson, L. L. 1991. Information exchange in negotiation. *Journal of Experimental Psychology* **27** 61–179.

Thompson, L. L. 1999. *Making the Team: A Guide for Managers*. Prentice Hall.

Uzzi, B. 1996. The sources and consequences of embeddedness for the economic performance of organizations: The network effect. *American Sociological Review* **61**(4) 674–698.

Wasserman, S., K. Faust. 1994. *Social Network Analysis; Methods and Applications*. Cambridge, UK, Cambridge University Press.

Wuchty, S., B. Jones, B. Uzzi. 2007. The increasing dminance of teams in the production of knowledge. *Science* Forthcoming.

APPENDIX A

Proofs of Chapter 3

Proof of Lemma 1: We will show that for any feasible solution of our LP model that allows idling, there exists another feasible solution (in which idling is replaced by self-work) that achieves a higher value of the objective function.

Without loss of generality suppose that agent n in the network idles for some time $\tau_n(>0)$ and makes profit Π_n^{idle}. Recall that $T_n^g + T_n^p$ is the total time needed to generate and process a hint into value when agent n works independently. As such, when idling is replaced by self-work, $\frac{\tau_n}{T_n^g+T_n^p}$ hints can be generated and processed into value. Let V denote the average value of each successfully processed hint. Then, the profit that agent n can make without idling, Π_n, is:

$$\Pi_n = \Pi_n^{idle} + \frac{\tau_n V}{T_n^g + T_n^p} > \Pi_n^{idle},$$

which implies that idling cannot be optimal. ■

Proof of Lemma 2: Recall that S_{nm} is the percentage of acceptance of hints sent from agent n to m. We will first show that for any two arbitrarily chosen agents n and m $(n, m \in \{1, \ldots, N\})$, increasing S_{nm} enables the two agents to generate same profit while enjoy idling. Then we argue that by Lemma 1 replacing the idling with self-work leads to a higher network profit.

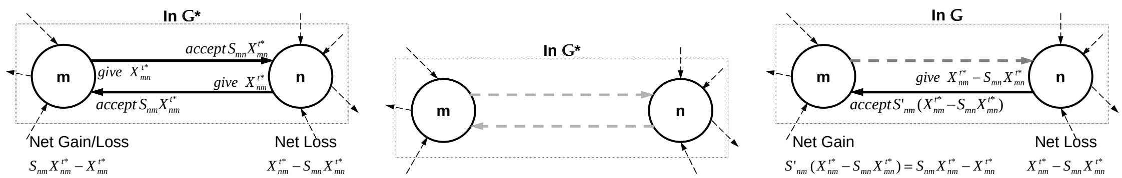
Suppose that under optimal policy agents m and n collaborate, either unidirectionally or bidirectionally. We prove the lemma only for unidirectional hint sharing, since it can be easily used to prove the case for bidirectional hint sharing. Without loss of generality suppose in the optimal solution n sends X_{nm}^{t*} hints to m and only $S_{nm}X_{nm}^{t*}$ of these hints are accepted by m. Then the time involved in transferring X^{t*}_{nm} hints from n to m for both agents is $X^{t*}_{nm}T^{*}_{nm}$. If S_{nm} is increased to βS_{nm}, where $\beta > 1$, then for agent m to accept same number of hints, n only needs to send out X^{t*}_{nm}/β hints. As a result, m and n both save $(1-\frac{1}{\beta})X^{t*}_{nm}T^{t}_{nm}$ units of time in communication if S_{nm} is increased to βS_{nm}. Define $\tau_m = (1-\frac{1}{\beta})X^{t*}_{nm}T^{t}_{nm}$ and let it be the idle time for agent m. Also define $\Pi_{m(S)}$ to be the profit generated by agent m when percentage of hint acceptance from n to m is S. Then we have $\Pi^{*}_{m(S_{nm})} = \Pi^{idle}_{m(\beta S_{nm})}$, i.e., profit made by agent m with idling (for τ_m units of time) and higher percentage of hint acceptance βS_{nm} equals to that in the optimal solution without idling and lower percentage of hint acceptance S_{nm}.

When the number of hints sent from n to m is reduced from X^{t*}_{nm} to X^{t*}_{nm}/β, then $(1-1/\beta)X^{t*}_{nm}$ extra hints become available to n. Let n ignore (i.e., neither transfer or process) those extra hints and idle for $\tau_n = \tau_m$ units of time, then similarly $\Pi^{*}_{n(S_{nm})} = \Pi^{idle}_{n(\beta S_{nm})}$. Replacing idling with self-work for both agents n and m we have by Lemma 1 that:

$$\begin{aligned}\Pi_{m(\beta S_{nm})} + \Pi_{n(\beta S_{nm})} &= \Pi^{idle}_{m(\beta S_{nm})} + \frac{\tau_m V}{T^g_m + T^p_m} + \Pi^{idle}_{n(\beta S_{nm})} + \frac{\tau_n V}{T^g_n + T^p_n} \\ &> \Pi^{idle}_{m(\beta S_{nm})} + \Pi^{idle}_{n(\beta S_{nm})} = \Pi^{*}_{m(S_{nm})} + \Pi^{*}_{n(S_{nm})}\end{aligned}$$

The above inequality shows that in a network in which agent n and m has a higher percentage of hint acceptance, there exists a feasible solution that results in higher joint performance for agent n and m. Therefore the optimal solution results in higher joint performance of agent n and m as percentage of hint acceptance between those two agents increases. ■

Proof of Lemma 3: We use contradiction. Assume that bidirectional sharing exists in the optimal solution. We show that replacing bidirectional sharing with no or unidirectional sharing enables the network to achieve the same objective value while some agents idle for some fraction of their time. We then show that replacing idling with self-work leads to a higher objective value.



(a) (b) (c)

Figure A.1. From Bidirectional to No or Unidirectional Sharing

Suppose in the optimal solution $\mathbb{X}^*$, there exists bidirectional sharing between agents m and n, i.e., $X^{t*}_{mn}X^{t*}_{nm} > 0$. As shown in Figure A.1(a) the number of hints n accepts from m is $S_{mn}X^{t*}_{mn}$ and that m accepts from n is $S_{nm}X^{t*}_{nm}$. Without loss of generality, assume that $S_{nm}X^{t*}_{nm} \geq S_{mn}X^{t*}_{mn}$ (which implies $X^{t*}_{nm} \geq S_{mn}X^{t*}_{mn}$, since $S_{nm} \in (0, 1]$), then $X^{t*}_{nm} - S_{mn}X^{t*}_{mn} \geq 0$ indicates that agent n gives more (or same number of) hints than (or as) that he/she receives. However, whether agent m gives more hints than he/she accepts or vice verse depends on the relation between X^{t*}_{mn} and $S_{nm}X^{t*}_{nm}$. Therefore we consider two possibilities:

$$\text{Case 1}: \quad X^{t*}_{mn} \geq S_{nm}X^{t*}_{nm} \geq S_{mn}X^{t*}_{mn}, \text{ and}$$

$$\text{Case 2}: \quad S_{nm}X^{t*}_{nm} \geq X^{t*}_{mn} \geq S_{mn}X^{t*}_{mn}$$

<u>*Case 1:*</u> In this case, we propose a new solution $\mathbb{X}_I$ where $X^t_{mn} = X^t_{nm} = 0$, that is, to replace bidirectional sharing between m and n by no sharing while holding the rest of the network fixed. We show that with the new solution the network can achieve the same value of objective while agents m and n enjoy idling. Then by Lemma 1 we argue that higher value of objective function can be achieved when agents m and n use idle time to do self-work.

When m and n stop sharing hint with each other, two changes are resulted. One is that both agents save $X^{t*}_{mn}T^{t}_{mn} + X^{t*}_{nm}T^{t}_{nm}$ units of time in communication. The other is that the number of hints available to agent m is increased by $X^{t*}_{mn} - S_{nm}X^{t*}_{nm}$ and that for agent n is increased by $X^{t*}_{nm} - S_{mn}X^{t*}_{mn}$. This is because reducing total number of hints transferred between m and n may result in less number of hints being discarded by the receivers because communication often incurs loss (recall $S \in (0, 1]$) . Let agents m and n ignore those hints available because of reduced sharing between themselves and idle for the time saved in communication, where idle times are $\tau_m = \tau_n = X^{t*}_{mn}T^{t}_{mn} + X^{t*}_{nm}T^{t}_{nm}$. Under these conditions, both agents will process the same number of hints as those in the optimal solution $\mathbb{X}^*$. Therefore the total profit generated by the network with the new solution ($\mathbb{X}_I$) when agents m and n idle equals to that with the optimal solution $\mathbb{X}^*$ when agents m and n do not idle, which can be expressed as:

$$\Pi(\mathbb{X}_I) = \sum_{l \neq m,n} \Pi^*_l + \Pi^{idle}_m + \Pi^{idle}_n = \sum_{l \neq m,n} \Pi^*_l + \Pi^*_m + \Pi^*_n = \Pi(\mathbb{X}^*)$$

where Π^*_l ($l \in \{1, \ldots, N\}$) is the profit generated by agent i in the optimal solution.

Now consider policy $\mathbb{X}'_I$, in which idling of agents m and n is replaced by self-work. Then the total profit of the network becomes:

$$\begin{aligned}
\Pi(\mathbb{X}'_I) = \sum_{l \neq m,n} \Pi^*_l + \Pi_m + \Pi_n \quad &= \sum_{l \neq m,n} \Pi^*_l + \Pi^{idle}_m + \frac{\tau_m V}{T^g_m + T^p_m} + \Pi^{idle}_n + \frac{\tau_n V}{T^g_n + T^p_n} \\
&> \sum_{l \neq m,n} \Pi^*_l + \Pi^{idle}_m + \Pi^{idle}_n = \sum_{l \neq m,n} \Pi^*_l + \Pi^*_m + \Pi^*_n = \Pi(\mathbb{X}^*)
\end{aligned}$$

Which proves that bidirectional sharing is not optimal.

Case 2: In case 2, we compare the optimized network ($\mathbb{G}^*$) and a second network ($\mathbb{G}$) that is exactly the same as the former except for: (i) In network $\mathbb{G}$ agents m and n shares hints unidirectionally, $X^t_{mn} = 0$ and $X^t_{nm} = X^{t*}_{nm} - S_{mn}X^{t*}_{mn}$, and (ii) In network $\mathbb{G}$ the percentage of hint acceptance of m from n is $S'_{nm} = S_{nm} \cdot \frac{X^{t*}_{nm} - X^{t*}_{mn}/S_{nm}}{X^{t*}_{nm} - S_{mn}X^{t*}_{mn}}$. Note that since $S_{mn} \in (0, 1]$ we have $\frac{X^{t*}_{nm} - X^{t*}_{mn}/S_{nm}}{X^{t*}_{nm} - S_{mn}X^{t*}_{mn}} \leq 1$. Therefore:

$$S'_{nm} = S_{nm} \cdot \frac{X^{t*}_{nm} - X^{t*}_{mn}/S_{nm}}{X^{t*}_{nm} - S_{mn}X^{t*}_{mn}} \leq S_{nm}$$

We will show that network $\mathbb{G}$ can achieve the same value of the objective function as $\mathbb{G}^*$ does, while allowing m and n to idle. Then by Lemma 1 we show that $\mathbb{G}$ will have a higher objective value when idling is replaced by self-work. Finally, when S'_{nm} is replaced with S_{nm}, the agents in the network $\mathbb{G}$ will be exactly the same as those in the optimized network $\mathbb{G}^*$; however, it attains higher objective value than $\mathbb{G}^*$ (by Lemma 2). This implies that network $\mathbb{G}^*$ in which agents n and m perform bidirectional sharing cannot be optimal.

Let $\mathbb{X}_{II}$ denote the solution in $\mathbb{G}$, in which agent m does not give hints to agent n, i.e., $X^t_{mn} = 0$, and the number of hints agent n gives to m equals to the difference in the number of hints agents n gives to and accepts from m in $\mathbb{G}^*$, i.e., $X^t_{nm} = X^{t*}_{nm} - S_{mn}X^{t*}_{mn}$. As a result, the number of hints agent m accepts from n in $\mathbb{G}$ equals to the difference in the number of hints m accepted from and gives to n in $\mathbb{G}^*$, which is $S'_{nm}(X^{t*}_{nm} - S_{mn}X^{t*}_{mn}) = S_{nm}X^{t*}_{nm} - X^{t*}_{mn}$ (see Figure A.1(c)). However, since the total number of hints transferred between the two agents is decreased by $X^{t*}_{mn} + S_{nm}X^{t*}_{nm}$ the time agents m and n spend in communication is both reduced by $X^{t*}_{mn}T_{mn} + S_{mn}X^{t*}_{mn}T_{nm}$. Let the time saved be the idle time for m and n (τ_m and τ_n). Then the total profit generated by $\mathbb{G}$ equals to that by $\mathbb{G}^*$. By Lemma 1, replacing the idling with self-work, $\mathbb{G}$ achieves higher objective value, that is,

$$\begin{aligned}\Pi(\mathbb{X}_{II}) &= \sum_{l\neq m,n}\Pi_l^* + \Pi_m^* + \frac{\tau_m V}{T_m^g + T_m^p} + \Pi_n^* + \frac{\tau_n V}{T_n^g + T_n^p}\\ &> \sum_{l\neq m,n}\Pi_l^* + \Pi_m^* + \Pi_m^* = \Pi(\mathbb{X}^*)\end{aligned}$$

Now consider a new solution $\mathbb{X}'_{II}$ when S'_{nm} is replaced with S_{nm}. Since $S'_{nm} \leq S_{nm}$, by Lemma 2 we have:

$$\Pi(\mathbb{X}'_{II}) \geq \Pi(\mathbb{X}_{II}) > \Pi(\mathbb{X}^*)$$

which proves that bidirectional sharing is not optimal. ■

Proof of Lemma 4: Assume that transmitter n ($\sum_{m\neq n} X_{mn}^{t*} > 0$ and $\sum_{l\neq n} X_{nl}^{t*} > 0$) exists in the optimal solution. We will show that there always exists another solution in which $(\sum_{m\neq n} X_{mn}^{t})(\sum_{l\neq n} X_{nl}^{t}) = 0$ and leads to a higher value for the objective function.

Suppose in the optimal solution, M ($M \leq N$) agents (without loss of generality numbered 1 to M) are linked by a chain, i.e., $\prod_{n=1}^{M-1} X_{n,n+1}^{t*} > 0$, $X_{M1}^{t*} = 0$. Therefore, by Lemma 3 we have $\prod_{n=1}^{M-1} X_{n+1,n}^{t*} = 0$. Without loss of generality assume that $\min\{X_{n,n+1}^{t*}, n = 1, \ldots, M-1\} = X_{12}^{t*} = \underline{X}^*$. We propose a new solution $\mathbb{X}_f$, in which the rest of the network is held fixed and the hint flows X_{1M}^{t*} is increased by $\underline{X}^*$ and $X_{n,n+1}^{t*}$ reduced by $\underline{X}^*$ for $n = 1, \ldots, M-1$, i.e.,

$$\mathbb{X}_f = [\mathbf{X_1}, \ldots, \mathbf{X_M}, \mathbf{X^*_{M+1}}, \ldots, \mathbf{X^*_N}]$$

in which

$$X_{1M}^t = X_{1M}^{t*} + \underline{X}^* \text{ and } X_{n,n+1}^t = X_{n,n+1}^{t*} - \underline{X}^* \ \forall\ n = 1, \ldots, M-1$$

Note that with X_{12}^{t*} being redirected to agent M, the total number of hints given out by agent 1 does not change and so is the total number of hints accepted by M given that the percentage of hint acceptance is the same for all pairs of agents, i.e., $S_{12} = S_{1M} = S$ which implies that $S_{12}\underline{X}^* = S\underline{X}^* = S_{1M}\underline{X}^*$. However, for each of agents $2, \ldots, M-1$ reducing both the total numbers of hints he/she gives out and receives by $\underline{X}^*$ results in a net increase in the total number of hints available to him/her by $(1-S)\underline{X}^*$. Moreover, $2\underline{X}^*T$ units of time are saved for each of these agents due to reduced communication. Let agents $2, \ldots, M-1$ ignore the extra hints available to them and idle for $\tau_n = 2\underline{X}^*T$ units of time. Then the network profits with idling equals to that without idling. Furthermore, by Lemma 1 the network profits may be improved when idling is replaced by self work.

Successively applying this argument to eliminate transmitters we can find a new solution without transmitters that outperforms the original solution. Therefore, transmitter cannot exist in the optimal solution.

Furthermore, if the network contains cycle (i.e., $X_{M1}^{t*} \neq 0$), the same argument can be used by taking nodes $1, \ldots, M-1$ as the chain. Then following the same argument, when the chain is broken into 2 pieces the cycle breaks into chains. As a result same steps can be followed to prove that transmitters do not exist in the optimal solution. ■

Proof of Proposition 1: Suppose in an N-agent($N \geq 2$) single-field network $T_n^p/T_n^g = r, \forall\ n$. We consider both cases of when transmitter is and is not present in the network.

Case 1: In this case we consider hint transfer between two agents, neither of whom is transmitter. Without loss of generality, suppose that agent n gives hint to agent m. Let $\tau_{m(m)}$ and $\tau_{n(n)}$ denote the time agents m and n spend in generating and processing self-hints. Let $\tau_{n(m)}$ denote the time that agent n spends in generating and transferring the hints that are received and processed by agent m, and $\tau_{m(n)}$ the time that agent m spends in receiving and processing those hints, where $\tau_{m(m)} + \tau_{m(n)} = 1 - \sum_{i \neq m,n} \tau_{m(i)}$ and $\tau_{n(n)} + \tau_{n(m)} = 1 - \sum_{i \neq m,n} \tau_{n(i)}$. Since only S_{nm} of all transferred hints are accepted, the average time agent m spends in obtaining a hint which later is processed into value by m is T^t_{nm}/S_{nm}. Therefore, the total profit produced by $m, n's$ self-work and hint sharing between them, denoted by $\Pi_{m,n}$, can be expressed as:

$$\Pi_{m,n} = V \cdot \{\frac{\tau_{n(n)}}{T^g_n + T^p_n} + \frac{S_{nm}\tau_{n(m)}}{T^g_n + T^t_{nm}} + \frac{\tau_{m(m)}}{T^g_m + T^p_m}\}$$

where

$$\text{(A.1)} \qquad \frac{S_{nm}\tau_{n(m)}}{T^g_n + T^t_{nm}} = \frac{\tau_{m(n)}}{T^p_m + T^t_{nm}/S_{nm}}$$

Then by elementary calculus we have

$$\frac{d\Pi_{m,n}}{d\tau_{m(n)}} = -V \cdot \{\frac{1}{T^g_n + T^p_m} + \frac{S_{nm}T^p_m + T^t_{nm}}{(T^g_n + T^t_{nm})(T^g_m + T^p_m)} + \frac{S_{nm}}{T^g_n + T^g_m}\}$$

When $T^p_m/T^g_m = T^p_n/T^g_n = r$,

$$\frac{d\Pi_{m,n}}{d\tau_{m(n)}} = -V \cdot \frac{(1 - S_{nm})T^g_n T^g_m + (T^g_n + T^g_m)T^t_{nm}}{(1 + r)(T^g_n + T_{nm})T^g_n T^g_m} < 0$$

which implies

$$p_{m(n)} = 0$$

and by (A.1)

$$p_{n(m)} = 0$$

This proves that communicating is not optimal.

Case 2: In this case we consider transmitters exist in the network. Since the proof can be easily generalized we will focus on the case with three agents. Without loss of generality, assume that agent n gives hints to m and m passes n's hints and gives his/her own hints to agent l. Recall that $\tau_{n(m)}$ denotes the time that agent n uses to generate and transfer hints to agent m, which will be processed into value by agent m and $\tau_{m(n)}$ denotes the time agent m spends receiving and processing those hints. Similarly, we define $\tau_{m(l)}$ to be the time that agent m spends in generating and transferring hints to agent l, which will be processed into value by agent l and $\tau_{l(m)}$ the time agent l spends receiving and processing those hints. Let $\tau_{n(m)l}$ denote the time that agent n uses to generate and transfer hints to agent m, which later on are passed on to agent l. Let $\tau_{l(m)n}$ be the time that agent l spends in processing and receiving hints that are originally generated by agent n but passed by agent m. Let $\tau_{(n)m(l)}$ denote the time agent m spends in passing those n generated and l processed hints. Finally, let $\Pi_{l,m,n}$ be the profit generate by the three agents' independent work and hint sharing among themselves. Then:

$$\Pi_{n,m,l} = V \cdot \{ \frac{\tau_{n(n)}}{T_n^g + T_n^p} + \frac{\tau_{m(m)}}{T_m^g + T_m^p} + \frac{\tau_{l(l)}}{T_l^g + T_l^p} + \frac{\tau_{m(n)}}{T_n^p + T_{nm}^t/S_{nm}} + \frac{S_{ml}\tau_{m(l)}}{T_m^g + T_{ml}^t} + \frac{S_{ml}\tau_{(n)m(l)}}{T_{nm}^t/S_{nm} + T_{ml}^t} \}$$

where

$$\text{(A.2)} \qquad \frac{\tau_{m(n)}}{T_m^p + T_{nm}^t/S_{nm}} = \frac{S_{nm}\tau_{n(m)}}{T_n^g + T_{nm}^t}$$

$$\text{(A.3)} \qquad \frac{S_{ml}\tau_{m(l)}}{T_n^g + T_{ml}^t} = \frac{\tau_{l(m)}}{T_l^p + T_{ml}^t/S_{ml}}$$

$$\text{(A.4)} \qquad \frac{S_{ml}\tau_{(n)m(l)}}{T_{nm}^t/S_{nm} + T_{ml}^t} = \frac{\tau_{l(m)n}}{T_l^p + T_{ml}^t/S_{ml}} = \frac{S_{nm}S_{ml}\tau_{n(m)l}}{T_n^g + T_{nm}^t}$$

Then we have

$$\begin{aligned}
\frac{\partial \Pi_{l,m,n}}{\partial \tau_{m(n)}} &= -V \cdot \frac{(1-S_{nm})T_n^g T_m^g + (T_n^g + T_m^g)T_{nm}^t}{(1+r)(S_{nm}T_m^g r + T_{nm}^t)T_n^g T_m^g} < 0 \\
\frac{\partial \Pi_{l,m,n}}{\partial \tau_{m(l)}} &= -V \cdot \frac{(1-S_{ml})T_m^g T_l^g + (T_m^g + T_l^g)T_{ml}^t}{(1+r)(T_m^g + T_{ml}^t)T_m^g T_l^g} < 0 \\
\frac{\partial \Pi_{l,m,n}}{\partial \tau_{(n)m(l)}} &= -V \cdot \frac{(1-S_{nm}S_{ml})T_n^g T_m^g T_l^g + T_m^l T_{nm}^t (T_n^g + T_m^g) + S_{nm}T_n^g T_{ml}^t (T_m^g + T_l^g)}{(1+r)(T_{nm}^t + S_{nm}T_{ml}^t)T_n^g T_m^g T_l^g} < 0
\end{aligned}$$

Therefore, in the optimal solution the following conditions must be satisfied:

$$\tau_{m(n)} = \tau_{m(l)} = \tau_{(n)m(l)} = 0$$

And by (A.2), (A.3), and (A.4),

$$\tau_{n(m)} = \tau_{l(m)} = \tau_{n(m)l} = \tau_{l(m)n} = 0$$

which proves that hint transferring is not optimal.

Successively applying same process to other pairs of agents rules out the possibility of hint sharing in the rest of the network in the optimal solution. This completes the proof. ■

APPENDIX B

Academic Research Collaboration Survey Form for Chapter 5

McCormick Collaboration Network Survey

In the questionnaire that follows department names are listed by schools. Faculty names are listed alphabetically in each department. For each name please choose one answer that best describes your relationship with that person. There are six categories to choose from, which are defined below:

- **Have had successful collaboration with:** choose this option if you have ever (i) written a joint paper (or book) with this person and the paper (or book) has turned into a publication or (ii) written a funded grant proposal and you had research discussion with this person. You should not select this choice if you had written a grant proposal but have never had research discussion with this person.

- **Have had research discussion with:** choose this option if you have (i) had a substantive discussion about research with this person via face-to-face conversation, email correspondence, or through other means, or (ii) had collaborated on a grant proposal but the project was not funded. You should not select this choice if you had a talk with this person and exchanged only basic information about the area and sub-areas you work in.

- **Know research area and socially acquainted:** choose this option if you both know the research area of the person and are socially acquainted with him/her. "Knowing" the research area of the person requires more detailed information than what department the person works in (e.g., that he/she works on the application of chaos theory to turbulent mixing processes). "Socially acquainted" means that you know the person on a first name basis (e.g., through joint committee work, teaching collaborations or social interactions).

- **Don't know research area but socially acquainted:** choose this option if you know this person on a first name basis but do not know his/her research area in any detail (e.g., you have worked with him/her on a committee or teaching effort but have never studied his/her research).

- **Know research area but not socially acquainted:** choose this option if you know the research area of the person (in detail) but are not socially acquainted with him/her (e.g., you may have seen a presentation, read a paper or heard about him/her from someone else, but you have never had an extended conversation with him/her).

- **Neither know research area nor socially acquainted:** choose this option if you neither know this person on a first name basis nor have detailed information about his/her research.

McCormick Collaboration Network Survey

- Please check the one choice that best describes your relation with each and every McCormick faculty member.
- The expected time to fill out the survey is approximately 20 minutes.
- If you have any questions, please contact xxx, xxx@northwestern.edu,

Faculty Name	**Have had successful collaboration with**	**Have had research discussion with**	**Know research area and socially acquainted**	**Don't know research area but socially acquainted**	**Know research area but not socially acquainted**	**Neither know research area nor socially acquainted**
Professor 1	☐	☐	☐	☐	☐	☐
Professor 2	☐	☐	☐	☐	☐	☐
Professor 3	☐	☐	☐	☐	☐	☐

Please click on the submit button below to submit your survey. Thanks you for your participation.

Notes: At the top of each new page add “You’ve completed xx% of the survey. The rest of the survey will take about xx more minutes to finish”.