MIS Quarterly

RESEARCH ARTICLE

WHEN DOES REPOSITORY KMS USE LIFT PERFORMANCE? THE ROLE OF ALTERNATIVE KNOWLEDGE SOURCES AND TASK ENVIRONMENTS[1]

Seung Hyun Kim
School of Business, Yonsei University, Seoul 120-749 KOREA {seungkim@yonseiac.kr}

Tridas Mukhopadhyay
Tepper School of Business, Carnegie Mellon University, Pittsburgh, PA 15213 U.S.A., and
Carnegie Mellon University in Qatar, Education City, Doha QATAR {tridas@cmu.edu}

Robert E. Kraut
Tepper School of Business, Carnegie Mellon University, Pittsburgh, PA 15213 U.S.A. {robert.kraut@cmu.edu}

Despite a general consensus that use of information technology (IT) is an important link between IT investments and performance, the extant literature provides only a limited explanation as to when the use of IT lifts performance. We posit that the impact of knowledge management systems (KMS) usage is contingent on users' alternative sources of knowledge as well as their specific task environments. We investigate under what conditions repository KMS use leads to higher performance outcomes in a retail grocery context. We use a unique longitudinal dataset composed of objective measures of KMS use and sales performance of 273 managers over 146 weeks collected from a retail grocery chain. We obtain two main results. First, we find a diminishing impact of KMS use for managers who also use other sources of codified knowledge, namely physical or computerized alternative knowledge sources, whereas a complementary relationship seems to exist between KMS use and social sources of knowledge. Second, KMS use produces higher benefits for managers whose task environments require a greater volume of information and knowledge, but smaller benefits for those managers whose task environments demand rapidly changing information and knowledge. Our work contributes to both the IT business value and the KM literature by studying the contingent impact of IT usage while broadening the theoretical scope of the situated knowledge performance framework with a critical empirical test based on fine-grained objective and longitudinal data.

Keywords: Business value of IT, knowledge management systems, IT usage, knowledge channels, contingent impact, retail grocery, complementarity, situated knowledge performance framework, knowledge management

[1]Rajiv Kohli was the accepting senior editor for this paper. Andrew Burton-Jones served as the associate editor.

This paper is based on a dissertation submitted by the first author to Carnegie Mellon University in partial fulfillment of the requirements for the degree of Doctor of Philosophy.

The appendix for this paper is located in the "Online Supplements" section of the *MIS Quarterly*'s website (http://www.misq.org).

Introduction

A majority of the workforce in the United States is viewed as knowledge workers (Zuckerman 1994). Knowledge is often viewed as more important than traditional resources of capital, labor, and land (Hansen et al. 1999). Knowledge is also credited in creating sustainable competitive advantage (Grant 1996; Kogut and Zander 1992; Teece et al. 1997). Many companies have already deployed knowledge management systems (KMS) including knowledge repository to leverage their knowledge assets with the aid of advanced technologies. However, a critical challenge faced by organizations is to evaluate and maximize returns on their investments in KMS.

Assessing the value of information technology (IT) investments has been a fundamental issue in the information systems (IS) discipline (Agarwal and Lucas 2005; Banker and Kauffman 2004; Barua et al. 1995; Kohli and Grover 2008; Melville et al. 2004). A substantial body of research has investigated the issue of IT business value, and has reached a general consensus that IT at large creates positive value for firms (Brynjolfsson and Hitt 1996; Mukhopadhyay and Kekre 2002; Mukhopadhyay et al. 1995; Mukhopadhyay, Rajiv, and Srinivasan 1997). More recently, a stream of literature has examined why IT investments generate differential impacts on performance and offered several explanations. First, the value of IT investments can often be directly traced to process-level performance (Barua and Mukhopahdyay 2000; Davamanirajan et al. 2006). Second, conversion effectiveness (Weill 1992) and intangible assets (Brynjolfsson et al. 2002) may moderate the IT investment–performance relationship. Third, competitive and macro environments may also influence the outcomes of IT investments (Melville et al. 2004). Fourth, the actual IT usage is a key driver of the IT impact (Devaraj and Kohli 2003).

Despite these recent advances, there is a gap between the IT value literature and the knowledge management (KM) literature. The extant literature on IT value offers only limited explanations as to why and how investments in enterprise-wide applications such as KMS may generate higher or lower performance outcomes. For instance, although the actual usage is seen as an important link between IT investments and performance (Devaraj and Kohli 2003), it is not clear why the same level of KMS use may produce differential impacts for different employees. Without an understanding of these differential impacts, organizational resources can be wasted in developing and promoting enterprise-wide applications even when employees do not benefit from them for fundamental reasons such as their task characteristics. Such differential impacts of IT usage can only be understood by taking into account the types of systems, users, and tasks (Burton-Jones and Straub 2006) in addition to the interactions with other IT applications in a specific organizational context. However, the IT value literature has not yet progressed in guiding a detailed assessment of IT impact at the usage level, which should be of primary concerns to managers who make decisions on specific IT investments.

One possibility would be to rely on the KM literature to better understand the value of KMS usage. However, the extant KM literature does not appear to have reached a consensus on the impact of KMS usage given the empirical evidence of both positive (Ko and Dennis 2011) and negative (Haas and Hansen 2005) effects. Past studies suggest temporal dimensions or experience of a task unit can moderate the KMS impact (Gallivan et al. 2003; Haas and Hansen 2005; Ko and Dennis 2011), which may mislead us to believe that a lapse of time should resolve the problem of low KMS benefit for some employees. In other words, the extant KM literature is incomplete and fails to answer whether the low performance outcome of KMS is inherent to users' task environments and thus likely to persist over time. Methodologically, the KM literature has also not examined the value of repository KMS based on objective measures of usage and performance within a longitudinal framework barring one exception (Ko and Dennis 2011).

In this paper, we study why the use of repository KMS may lead to differential performance outcomes for managers. We use a unique longitudinal dataset with objective measures of KMS usage and performance.[2] We collected data on KMS usage by 273 managers and their performance over 146 weeks from a large retail grocery chain in the northeastern United States. We adopt the situated knowledge performance framework (Haas and Hansen 2005) from the KM literature to explain the differential outcomes of KMS usage. In addition to a substantial positive impact of KMS usage by managers on sales performance, a key finding of our paper is that the impact of KMS usage is contingent on users' alternative sources of knowledge as well as on their specific task environments. Our results show that the impact of KMS use on performance is greater for managers endowed with fewer physical or computerized knowledge sources (e.g., data warehouse usage). In contrast, the impact of KMS use gets amplified in the presence of rich alternative social sources of knowledge. On the task environment side, repository KMS use produces higher benefits for managers whose task environments require a greater volume of information and knowledge; those whose task environments demand rapidly updated information and knowledge benefit less.

[2]Since we examine repository KMS only, we use KMS and repository KMS somewhat interchangeably in this paper.

Our study contributes to the IT business value literature by examining the value of KMS use based on the KM literature. We demonstrate how IT value research can be extended to study the contingent impact of an IT artifact by leveraging the theoretical base on the artifact as well as the specific business context in which the system is used. We also find a negative interaction effect between different IT applications, an issue that gets little attention in the IT business value literature. Our findings imply that firms should make their IT investment decisions more wisely by taking into account their existing IT infrastructure and task environments where IT applications are actually utilized. We also empirically examine such interactions across multiple IT applications by using their actual usage and objective performance data.

We contribute to the KM literature by performing an empirical test of the situated knowledge performance framework (Haas and Hansen 2005) based on fine-grained objective and longitudinal data while extending the scope of this framework by covering the task situations that have not received much attention. Whereas past studies have considered temporal dimensions or experience of a task unit as moderators of the KMS impact (Gallivan et al. 2003; Haas and Hansen 2005; Ko and Dennis 2011), this study examines the impact of KMS usage contingent on external knowledge channels and on task information intensity simultaneously. Our findings take an important step toward discovering how to design an effective KMS initiative by considering its fit with relevant task environments. Thus, we extend previous studies on the fit between knowledge and task environments from non-KMS contexts to KMS usage (Aral et al. 2012; Das 2003; Sorenson 2003).

The balance of this paper is organized as follows. First, research setting is described. Second, we describe our theory development and hypotheses. Next, we explain our research method, after which we present the results. We then discuss in detail the contributions and managerial implications of our study. The last section concludes our paper.

Research Site

Our research site, Ace Grocery (a pseudonym), is a retail grocery chain with about 40,000 employees and more than 200 stores in the northeastern United States. The chain has been in the retail grocery business for over 50 years. A store consists of multiple departments such as meat, seafood, bakery, grocery, produce, and entertainment, each of which has a department manager. To effectively manage knowledge distributed across the organization, Ace Grocery initiated a knowledge management system project and deployed KnowLink (a pseudonym) in 1999.

The main component of KnowLink is a repository of codified documents. It provides a convenient Web-based interface similar to a commercial Web portal site. Users can search for specific knowledge using keywords or navigate through a directory of business areas to find relevant documents. KnowLink is a repository KMS that serves as a place to share codified knowledge documents ranging from corporate policies to best practices, proposed action plans, and employee suggestions. Currently most knowledge documents are created by designated domain experts at the headquarters.

The chain's knowledge management initiative has been led by its knowledge strategy group. Although the company encourages managers to use KnowLink to obtain information and knowledge, its usage has been totally voluntary, which makes the company an ideal research site for an examination of the contingent impact of KMS usage on work performance. In addition to KnowLink, employees in the chain also access information from other computerized sources. In particular, a data warehouse in the company provides useful and rapidly updated operational and financial information. Table 1 summarizes the contextual elements at the research site (gained from the first author's year-long investigation at that company) to help the reader understand the system and its use (Burton-Jones and Gallivan 2007; Burton-Jones and Straub 2006).

Research Model and Hypotheses

An electronic knowledge repository is a common form of KMS that firms implement. We develop a conceptual model to assess the performance impact of prior cumulative KMS usage (Figure 1). We begin with a summary of our research model. While we expect a positive effect of KMS use on performance, this impact is likely to be moderated by several contingent factors. Depending on the alternative knowledge sources and task environments, the impact of KMS usage may decrease or increase. While physical or computerized knowledge sources serve as alternative sources of codified knowledge and may reduce the impact of repository KMS usage, alternative social sources of knowledge function as a channel for tacit knowledge and may complement the repository KMS. The impact of KMS usage may also increase when task environments require a large volume of information and knowledge but may decrease when task environments demand more rapidly updated information and knowledge.

The tasks performed in a retail grocery chain by a store department manager, the unit of analysis in our study, are so highly information and knowledge intensive that KMS usage can be of substantial benefit (refer to the "System" element in

Table 1. Contextual Elements at the Research Site

Contextual Element	Description
User	Users did not seek to misrepresent their work or hinder their peers. (da Cunha 2013). Social interactions helped managers collect relevant information and knowledge for their decision-making. Users did not seem to be intrinsically motivated to use the KMS.
System	The repository KMS largely fit the task it was designed for. The repository KMS and the data warehouse were not designed with their potential interdependencies and substitutability in mind. The repository KMS was designed independently of the distribution of printed knowledge documents.
Task	Managers worked fairly independently from each other (reflecting pooled interdependence only). Performance was rated on sales only, not overall profitability. Some users needed a greater volume of information and knowledge to perform their tasks than others. Some tasks required more frequently updated information and knowledge.
Time	Seasonality for the grocery chain existed at the weekly level. The value of knowledge documents could vary over time. Short life span knowledge documents had contents that did not remain static for more than three months, and thus had to be reviewed frequently.

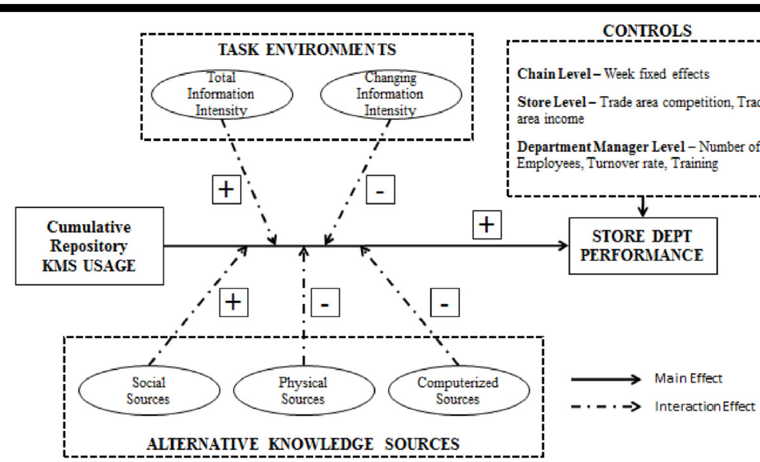

Figure 1. Conceptual Model

Table 1). A department manager makes a multitude of decisions that affect the efficiency and effectiveness of daily operations. These decisions can be made more effectively by accessing codified knowledge from a repository KMS. For instance, managers can use the KMS to learn early of corporate decisions on future advertising and promotion programs, knowledge that makes them aware of the need to clear their slow moving inventories. Managers can ascertain up-to-date market trends and analyses and fine-tune their product portfolios. Department managers can determine how to display better-selling products in easy-to-find spots by referring to detailed product display plans in the KMS. Employee training can be facilitated by the KMS by enabling knowledge transfer from other employees or from subject matter experts. Department managers can also discover best practices that have worked in other stores, and attempt to replicate those innovations in their departments.

We note that the effect of KMS usage is not transient but cumulative and persistent (Ko and Dennis 2011). In a retail grocery context, a substantial amount of knowledge obtained in one period can be applied to subsequent periods. For example, best practices, know-how on displaying products appropriately and market trends learned in the past will continue to influence a manager's performance over time. Because the retail business is characterized by seasonality, knowledge acquired during a previous year remains largely valid in the next season. Furthermore, higher knowledge acquisition in itself changes the way knowledge is exploited and utilized to produce higher order benefits by improving

Table 2. Analysis of Contingent Impact Based on the Situated Knowledge Performance Framework

Contingent Factors (Hypotheses)	Increase/Decrease in Benefit/Cost of KMS use with a higher level of the Contingent Factor			Net KMS Impact = LB – SC – TC
	Learning Benefits (LB)	Search Costs (SC)	Transfer Costs (TC)	
Physical Sources (H2)	↓	↑	Little Impact	↓
Computerized Sources (H3)	↓	↑	Little Impact	↓
Social Sources (H4)	↑	↓	↓	↑
Total Information Intensity of Task (H5)	↑	Little Impact	Little Impact	↑
Changing Information Intensity of Task (H6)	↓	↑	↑	↓

one's cognitive capability in the long term (Gray and Meister 2004). *Thus, the effect of KMS usage hereafter refers to its cumulative effect, and we posit a positive impact of cumulative repository KMS usage on performance*.

> ***Hypothesis 1***: A higher KMS usage by managers leads to higher performance.

To obtain a fine-grained understanding of the contingent impact of KMS usage, we adopt Haas and Hansen's (2005) (henceforth H&H) situated knowledge performance framework. According to H&H, the performance outcomes should be ascertained directly from knowledge utilization as knowledge demonstrates its value through its effects on performance in particular task situations. Thus the effect of utilizing knowledge on task performance is determined by the fit between tasks and utilized knowledge (Aral et al. 2012; Das 2003; Sorenson 2003).

H&H suggest that the net benefit from utilizing knowledge is determined by (1) the learning benefit (LB) from knowledge, (2) the cost of searching (SC) relevant knowledge, and (3) the cost of knowledge transfer (TC) (Huber and Daft 1987; Uzzi 1997). The net impact hinges on the ability of KMS to deliver unique knowledge and its ability to help locate and transfer knowledge efficiently (i.e., Net Benefit = LB – SC – TC). H&H also take the opportunity cost of acquiring codified knowledge from KMS into account. Those managers, who experience deficiency in knowledge required for their tasks, would enjoy higher learning benefit (LB) of reading a suitable knowledge document than those with sufficient knowledge by reading the same document. Similarly, reading a knowledge document would be less beneficial for a manager if the cost of searching useful knowledge for her tasks (SC) and adapting it to her own task environments (TC) is relatively high. Thus, the impact of KMS usage on performance is expected to be moderated by the factors that affect a user's relative deficiency in knowledge and the efforts required for searching and implementing relevant external knowledge. Consider an example from H&H: An experienced task unit has less need for external knowledge and thus gains relatively lower marginal learning benefit (LB) from knowledge in KMS in comparison with a less experienced task unit. Additionally, utilizing codified knowledge from KMS may create a greater opportunity cost for an experienced task unit if searching and transferring knowledge from KMS requires more efforts for this unit than the same action with a more familiar source such as the experienced task unit itself. As a result, an experienced task unit may realize little or no benefit from using codified knowledge from a repository, but the use of such a repository may still improve the performance of an inexperienced task unit.

Notably, the learning benefit of knowledge (LB) and the cost of knowledge transfer (TC) continue to have their effects on performance after a knowledge document is viewed; these effects support our focus on cumulative repository KMS usage. Table 2 summarizes the effect of utilizing knowledge from repository KMS contingent on five factors studied in this paper. Next, we explain this table in detail.

Alternative Physical Sources. Organizations typically publish and distribute policies, best practices, standard operating procedures, training materials, internal reports, and manuals as physical documents. Those who use such alternate physical sources of knowledge heavily have a lower need than others to learn from codified electronic knowledge documents. For instance, a department manager who already uses hard-copy training manuals on a regular basis may not find comparable electronic training manuals in KMS more valuable, thus reducing her learning benefit (LB) from using KMS. This overlapping nature of knowledge from KMS and knowledge from printed physical sources stems from their inherent limitation of only providing codified knowledge.

The relative cost of searching (SC) knowledge documents from KMS is higher for a user who is highly comfortable with corresponding physical sources. This can be contrasted with social sources in which an expert can advise a manager, based on her specific needs, on what knowledge in a repository would be useful and where to find it. Thus, searching codified knowledge in the repository KMS imposes a penalty if one already has at hand an excellent physical source of knowledge.

The costs of transferring knowledge (TC) from physical or electronic documents would not be much different. Additionally, a heavy use of physical sources does not make it easier to transfer needed knowledge from KMS. Any supplementary knowledge to help transfer codified knowledge from KMS is more likely to be found in the KMS than in physical printed documents. We speculate that the cost of transferring codified knowledge from KMS is hardly affected by any physical sources.

In sum, for a manager who uses a higher level of alternate physical knowledge sources, the marginal learning benefit from using KMS is lower, the cost of searching knowledge in KMS is significant, and the cost of transferring knowledge from KMS is not lower in comparison to another manager who hardly uses physical knowledge sources. Or, phrased differently, the net impact of KMS usage is negatively moderated by superior access to alternate physical knowledge sources.

> ***Hypothesis 2***: The impact of KMS usage on performance decreases in magnitude when a manager uses a greater level of alternate physical knowledge sources.

Computerized Sources. Employees can also access information through various computer application systems from accounting and inventory control to payroll systems. Often, a data warehouse combines such information over a long period of time and serves as a potential source of business intelligence. The data warehouse in a retail grocery chain can provide information on product sales trends to help department managers determine both the quantity and variety of products to carry. A consideration of computerized sources as distinct from traditional social or physical sources allows us to study multiple IT systems and their interactions, which has received little attention with a few exceptions (Aral et al. 2006). Considering computerized sources also enables us to avoid a biased conclusion based only on a simple aggregation across multiple knowledge sources.

Similar to what occurs with physical knowledge sources, if a department manager uses information from the data warehouse a lot, the knowledge from KMS yields a lower learning benefit (LB) as a source of unique knowledge. The information and knowledge from KMS and the contents of the data warehouse may sometimes overlap. For example, the corporate headquarters often analyzes sales patterns throughout the chain and presents it as market knowledge in the KMS. A user of the data warehouse can gain similar insights by viewing sales patterns over time (refer to the "System" element in Table 1). As with physical knowledge sources, this overlapping nature of knowledge from KMS and knowledge from computerized sources such as a data warehouse is rooted in its inherent limitation of the inability to provide tacit knowledge.

The search cost (SC) for KMS also is not lower for a manager who uses the data warehouse a lot. In fact, the opportunity cost of searching for knowledge in KMS is higher for a manager who frequently uses data the warehouse. Similarly, the use of a data warehouse does not necessarily facilitate knowledge transfer from a repository KMS. Overall, the reduced learning benefit and the non-zero search cost for employees using the data warehouse point to the possibility that prior KMS usage will reduce its performance impact.

> ***Hypothesis 3***: The impact of KMS usage on performance decreases in magnitude when a manager has a greater level of data warehouse usage.

Alternative Social Sources. Employees learn from either their own experiences or the experiences of others (Levitt and March 1988). The traditional sources of external knowledge before the advent of KMS had been other employees or published documents (Gray and Meister 2004). Interactions with other employees such as supervisors and colleagues within an organization enable a worker to obtain and accumulate appropriate knowledge (Pee et al. 2010; Sykes et al. 2014). Thus, we also consider social sources as an alternative for managers in this study.

There are a number of ways the marginal value of utilizing knowledge from KMS (LB) may be enhanced because of superior social sources of knowledge. Alternative social sources can offer a user unparalleled opportunities to acquire higher-order tacit knowledge through social interactions (Nonaka 1994) (refer to the "User" element in Table 1). The value of codified knowledge documents in a repository may be augmented through the assistance and personal advice from other people (Haas and Hansen 2007). For instance, a department manager may call another department manager or a field support group that acts as a bridge between store department managers and headquarters to gain a better understanding of the retrieved knowledge. Although the KMS documents are abstracted through codification, a manager may further learn through social interactions how to contextualize and fine-tune codified knowledge for application to local and specific environments, which leads to the creation of new knowledge.

The search cost (SC) for KMS can also be lowered through the assistance of other users in identifying relevant information. Thus, rich social sources of knowledge may facilitate the discovery of new knowledge in an electronic repository. Similarly, knowledge transfer can be facilitated with the help of rich social sources. In the context of a retail grocery chain, a great deal of knowledge is complex and not easily codifiable. A recipient's lack of capability to assimilate knowledge is a major barrier to knowledge transfer (Alavi and Leidner 2001; Gupta and Govindarajan 2000; Szulanski 1996). By utilizing social links with more knowledgeable individuals on various topics, knowledge transfer from KMS can become easier, thus reducing the transfer cost (TC). Therefore, identifying and applying new knowledge from KMS is less costly when a user possesses superior knowledge networks.

It is noteworthy that the integration of repository KMS and social sources of knowledge help employees overcome the inherent limitations of both sources. Any nuances and details lost during the codification of knowledge can be supplemented by social interactions while the cost of acquiring knowledge from KMS can be lowered. On the other hand, social sources of knowledge are limited by an individual's network; KMS offers an opportunity to access others' knowledge that is otherwise unreachable. In consideration of the increased benefit and reduced cost of obtaining knowledge from KMS because of social sources of knowledge, we expect a complementary relationship between the two sources, which is congruent with the recent view in knowledge management (Haas and Hansen 2007; Kim et al. 2013).

> ***Hypothesis 4***: The impact of KMS usage on performance increases in magnitude when a manager has a greater level of alternate social knowledge sources.

The role of information intensity has been studied at various levels (Glazer 1993; Mithas and Whitaker 2007; Mudambi 2008; Sung 2008). It has been posited that the level of information intensity in processes and products determines the value of information technology (Porter and Millar 1985). It is natural that the demand for information and knowledge by knowledge workers depends on the nature of tasks. We define task information intensity as the degree to which an individual's tasks involve the acquisition, processing, and distribution of information and knowledge. We conceptualize (1) the volume of information and knowledge needed and (2) the rate of change in needed information and knowledge as two subdimensions of task information intensity. We refer to the two dimensions, respectively, as *total* and *changing* information intensity of task. A portfolio of tasks performed by some managers may simply require more information and knowledge than those performed by others, indicating a higher *total information intensity of tasks* (TIIT). On the other hand, the tasks performed by other managers may require rapidly changing information and knowledge, signaling a higher *changing information intensity of tasks* (CIIT). The performance impact of repository KMS is determined by the extent to which it can satisfy the volume and change requirements of information intensity at each task unit.

Total Information Intensity of Tasks. At the task level, some tasks may require more information and knowledge than others. Such variations may result from different levels of job responsibilities and the variety of tasks to be performed. A higher level of complexity, interdependency, and non-routineness of tasks would demand a larger volume of knowledge as well (Gray and Meister 2004). The marginal learning benefit (LB) of repository KMS usage becomes greater under a task environment that requires a greater volume of information and knowledge. For instance, when the tasks require a diverse set of knowledge, access to a broader spectrum of knowledge enabled by KMS would be more beneficial (cf. Aral et al. 2012). In contrast, when the task environment requires the acquisition and application of a narrow set of new knowledge, a user can learn less from viewing documents in KMS and there is little learning benefit. For example, a department manager in the grocery chain who deals with a greater number of unique items would need more information and knowledge for ordering, stocking, producing, and displaying these items than a manager who replenishes a small shelf area in a store. We note that the costs of searching and transferring specific knowledge (SC and TC) from KMS (e.g., sales trends or new promotion programs) are not directly affected by total information intensity of tasks. Given the increased learning benefit under a high level of total information intensity of yasks, we expect

> ***Hypothesis 5***: The impact of KMS usage on performance increases in magnitude when a manager faces a higher degree of total information intensity of tasks.

Changing Information Intensity of Tasks. Environmental dynamism refers to the extent to which one's environment is predictable (Baum and Wally 2003). In an unstable environment, the need for quicker response increases (Nayyar and Bantel 1994). Increased dynamics demand the creation of rapidly changing and situation-specific knowledge (Eisenhardt and Martin 2000). Unfortunately, KMS as a source of generalized and simplified knowledge makes it harder to provide context-specific and customized solutions (Haas and Hansen 2007). In rapidly changing business environments, knowledge becomes obsolete and its value degrades quickly as well (Birkinshaw and Sheehan 2002; Gilmour 2003; Sorenson 2003). Although a codified knowledge document in the repository can be revised by its author, it is difficult to keep all codified documents up-to-date when the volume of codified documents is significant in a large enterprise. Therefore, the marginal learning benefit (LB) of KMS decreases as the task environment mandates fast changing information and knowledge because of the increased mismatch between the knowledge available through KMS and the requirements of the task environments.

We speculate that the costs of searching and transferring knowledge (SC and TC) from KMS also increase as the information and knowledge required for tasks are unstable and change quickly over time. It becomes more challenging and difficult to identify the information and knowledge that best match any given problem situation if environmental dynamism increases (Dennis and Vessey 2005). Likewise, transferring knowledge in a way that knowledge acquired from the KMS suits specific dynamic task environments requires more customization and fine-tuning and consequently increases the transfer cost (Haas and Hansen 2005). In the grocery chain context, the degree of change in information and knowledge required for tasks varies considerably across different departments. For example, a department manager's performance depends heavily on her timely acquisition of rapidly updated information and knowledge if her department deals with perishable items.[3] In such a case, her cumulative KMS usage in the past would be less helpful in performing her tasks compared with another manager whose task environment is more stable and whose cumulative KMS usage remains relevant longer. In sum, the decreased learning benefit and increased costs under a higher degree of changing information intensity of tasks lead to a reduced impact of repository KMS usage.

> ***Hypothesis 6***: The impact of KMS usage on performance decreases in magnitude when a manager faces a higher degree of changing information intensity of tasks.

It is notable that the five moderating factors studied in this paper are new to the literature. Although a few studies have examined the contingent effects of repository KMS usage, they have focused on the experience level of user groups, competition level, and elapse of time (Gallivan et al. 2003; Haas and Hansen 2005; Ko and Dennis 2011). The evaluation of KMS impact contingent on various knowledge channels has not received adequate attention yet. Moreover, despite the possible moderation of KMS impact by such characteristics as competition level, it is unclear what specific aspect of competition may lead to the effect (Haas and Hansen 2005). Our study suggests that the contingent effect may be due to the changing information intensity of tasks.

Despite these merits, our model may not fully open up the "black box" in that it does not differentiate the types of knowledge utilized but captures the aggregate level effects only. Two pertinent questions still remain unanswered. Does a certain type of knowledge result in a better performance outcome? Will the contingent effect be affected if different types of knowledge are utilized? These challenges lead to our supplementary analysis in which we examine the utilization of different types of knowledge, short life span and long life span knowledge, later in this paper.

Research Method

Data Collection

As stated earlier, our research site is a retail grocery chain. The data for our study come from four sources: (1) systems usage per designation from the IT department;[4] (2) database systems containing historical data on store department performance and departmental labor inputs; (3) classification of retail area income and competition from the strategic planning department; and (4) a survey designed to complement the archived data. Our survey of the selected department managers measures four research variables: (1) alternative social knowledge sources, (2) alternative physical knowledge sources, (3) total information intensity of task, and (4) changing information intensity of task. The grocery chain allowed us to send a survey to about one third of the department managers. Accordingly, 638 store departments were randomly selected for our survey, and 273 managers returned complete responses (response rate = 43 percent) at the end of year 2006. They represent about 15 percent of all store departments.[5] The survey items are presented in Table 3. The repository KMS usage and performance of respondents over 146 weeks ending in year 2006 were retrieved from the system logs and store performance database.

[3]This is because the task environment is less certain in departments dealing with such perishable product categories as meats, produce, fish, or bakery items with short shelf lives that fluctuate in terms of the variability of lead times and the impact of such environmental factors as humidity, temperature, and handling (Nahmias 1977).

[4]For example, a user ID is assigned to a specific managerial role in store departments. According to the chain's policy, a user ID is not shared with other employees, which ensures the validity of our measurement.

[5]Given the relatively high response rate (43%), we expect that nonresponse bias is not a major issue. We checked that the "response" group and the "nonresponse" group were not significantly different from each other in terms of their cumulative KMS usage. We also compared between early responses and late responses (Armstrong and Overton 1977). We found no significant difference between the first third and the last third of responses.

Table 3. Survey Items
Traditional Alternative Sources of Information and Knowledge
Alternative Social Sources of Information & Knowledge (alpha = 0.754) • My supervisor often provides useful information and advice that I need to do my work. • My colleagues are accessible for information and advice that I need to do my work. • I know many employees outside my own department from whom I can get information and advice for doing my work. • The people whom I work with provide me with useful information and advice. Alternative Physical Sources of Information & Knowledge (alpha = 0.879) • I get a lot of the information that I need to do my work in printed reports and documents. • The printed reports and documents I get are useful for my work.
Information Intensity of Task
Total Information Intensity of Task (alpha = 0.854) • I need to keep up with a lot of information to do my work. • It is important for me to bring together information from many sources in my job. • I have to compare many alternatives to make work-related decisions. • My job requires me to stay on top of a variety of information. Changing Information Intensity of Task (alpha = 0.733) • The information I need to do my work changes a lot week to week. • I have to pay attention to changes in information related to my work. • If I can respond quickly to changes in information, I can do my job better. • I have to make new decisions each week, because the environment changes quickly.

Model Specification

The unit of analysis in our paper is the individual department manager within a store. Department sales is an excellent and highly relevant measure of a department manager's performance because department sales is the key criterion in evaluating department managers' overall performance at the research site. One reason why sales data are considered critical in this context is that other performance data such as profit or value-added are not calculated at the individual department level in contrast with sales that are immediately available from POS (point of sales) data (refer to the "Task" element in Table 1). The calculation of profit at the department level is also difficult because various other factors such as damaged products, book value of products, discounts, promotions, and store theft should all be considered. Since it is not computed at the individual department level, profit is not useful for managers as a benchmark for daily operations. Some of the cost-related factors mentioned above are also not under the control of store department managers. Therefore, the management at our research site views that department managers are responsible for sales, which encourages them to maximize their sales from an operational point of view. Some prior studies have examined the performance of sales representatives based on percent of sales quota achieved (Ahearne et al. 2008; Ko and Dennis 2011). In our context, department managers are not given any well-defined quotas, thus making the raw sales number suitable for our analysis. In summary, we believe that sales can be used as the best measure of performance in our study.

We formulate that the weekly performance measured by sales ($SALE_{iT}$) at the department of manager i (i = 1, 2, …, 273), at week T (T = 1, 2, …, 146), is determined by its labor inputs ($LEMP_{iT}$) and cumulative knowledge usage from KMS ($KMSU_{iT}$) as well as other store and department manager level characteristics. We select the cumulative usage to account for the fact that the effect of transferred knowledge manifests over a period of time. That is, counting KMS usage during concurrent or recent periods would overestimate the effect of KMS usage. Our modeling is also consistent with the learning curve literature in which the cumulative experience is considered a proxy for the stock of knowledge applied to perform a task (Argote and Epple 1990; Kim and Kim 2014; Mukhopadhyay et al. 2011).

A week is an appropriate time frame for our analysis since sales activities in grocery chains are driven by a weekly cycle (refer to the "Time" element in Table 1). Based on our in-depth interviews with managers at the research site, we identified the control variables that may explain week-to-week variations in sales in each store department. As we will discuss later in this paper, our model does not encounter any serious omitted variable bias issue due to unobserved heterogeneity. Our baseline model without interaction effects is specified below.

$$SALE_{iT} = v_i + \beta_0 + \beta_1 \cdot Log(LEMP_{iT}) + \beta_2 \cdot Log(KMSU_{iT}) + \beta_3 \cdot TRNG_{iT} + \beta_4 \cdot TINC_{iT} + \beta_5 \cdot TCOM_{iT} + \beta_6 \cdot Log(DWHU_{iT}) + \beta_7 \cdot TURN_{iT} + \beta_8 \cdot WEEK_T + \varepsilon_{1iT} \quad (1)$$

Here v_i is a constant term specific to department manager i that captures time-invariant department manager-specific effects such as department square footage and the manager's capability. Note that any store-specific time-invariant unobservable effects are also captured by this term. We take the log of $KMSU_{iT}$ to reflect the fact that an increase in acquired knowledge in a retail context may produce diminishing effects. $LEMP_{iT}$ is also log transformed to reflect a possible diminishing effect.[6] We control for other department manager-, store-, and chain-level characteristics that may change over time such as department manager's training on computer-related topics ($TRNG_{iT}$), trade area income ($TINC_{iT}$), trade area competition ($TCOM_{iT}$), department manager's usage of data warehouse ($DWHU_{iT}$), departmental employee turnover rate ($TURN_{iT}$), and weekly fixed effects ($WEEK_{iT}$).[7] ε_{1iT} is the idiosyncratic component of the error term. So that it would be comparable with KMS usage, the data warehouse usage was measured as a cumulative variable and log-transformed.

Our empirical approach is as follows: The baseline model is implemented with multiple alternative specifications. The first step is to ensure that the impact of KMS usage on store department sales is robust to heteroskedasticity, endogeneity, and different structure of error terms. We first use the conventional fixed effects model using robust standard errors clustered within each department manager. As for the possible endogeneity issue, we perform a two-stage least squares (2SLS) analysis. We take advantage of an event that could create exogenous variation in managers' KMS usage. The grocery chain's knowledge strategy group supporting the chain's KM initiative conducted an internal survey of repository users asking about 60 questions regarding user satisfaction, expectations, and usage patterns during the sample period. The group contacted 570 randomly selected users in stores and its headquarters, and 484 of them returned the survey (response rate = 85%). Of the 273 managers in our samples, 81 participated and responded to this survey between the 61st and 68th weeks of the 146-week period.

Our first instrument is a variable that indicates whether a department manager returned the survey in the immediate previous week. The rationale is that responding to such a detailed survey may raise managers' awareness of the repository KMS and drive them to explore it more in the short run. Our second instrument is a variable that captures whether a manager has participated and returned the survey any time before. In the longer term, a respondent may increase or decrease her usage level. If she is satisfied with the repository, she may continue using it more than she did before the survey. However, if not satisfied, she may use it even less than before. For example, stating pre-purchase expectations through a satisfaction survey may drive respondents to enhance their future involvement, focus more on the negative side of their experience, and react more negatively to a service or product later (Ofir and Simonson 2001, 2007). These possible correlations ensure the relevance of our instruments. However, given the group's random selection of respondents and a very high response rate, any shock on a department's sales performance is unlikely to be correlated with whether managers responded to the survey (exclusion restriction).[8] Finally, we examine an alternative specification of error terms with the first order autoregressive error terms AR(1). Table 4 summarizes relevant econometric issues and how they are addressed in this paper by additional analysis or robustness checks.[9]

Once we establish that KMS usage improves a manager's performance, we test the contingent effects. We selected the fixed effects model with a first order autoregressive error as our main model to test our hypotheses for the following reasons: First, we find strong evidence of the first order autoregressive error. As we know, autocorrelations depend on the time difference such that the autocorrelation between two adjacent weeks is stronger than that between two distant weeks. In contrast, the estimation using robust standard errors clustered within each department manager assumes the

---

[6]We have verified that our results are robust to using non-transformed variable for the labor input.

[7]The week fixed effects account for the chain-level seasonality in sales.

[8]A possible concern about these instruments may be that (1) managers are more likely to respond to the internal survey when they use the KMS more than others, and (2) managers who return the survey differ from those who were randomly selected to receive the survey. Thus, the instruments based on whether managers received an invitation to participate in the survey may appear to be more exogenous. We considered multiple variations of instrumental variable(s) based on whether managers "received" an invitation to participate in the survey instead of whether they filled out the survey. We have confirmed that the results using these alternative instruments are qualitatively similar to those obtained by using our main instruments based on whether they filled out the internal survey.

[9]To ensure the robustness of our estimation results, we also consider alternative model specifications. We try an FGLS (feasible generalized least squares) estimator with panel-specific AR(1) errors and a dynamic panel model using the Arellano-Bond estimator by including the lagged dependent variable as an explanatory variable. Finally, we consider an alternative operationalization of the KMS usage by allowing the knowledge acquired through KMS to depreciate over time. The results for these alternative specifications are presented in the appendix.

Table 4. Summary of Econometric Issues and Robustness Checks

Potential Econometric Issue	Robustness Check	Results
Endogeneity	2SLS analysis with instrumental variables	Satisfied. See Table 8.
Heteroskedasticity/autocorrelation of errors	Robust standard errors clustered within each manager	Satisfied. See Table 8.
Errors follow an AR(1) process	Fixed effects model with AR(1) errors	Satisfied. See Table 8.
Panel-specific AR(1) errors	FGLS estimator with panel-specific AR(1) errors	Satisfied. See Table A1.
Lagged dependent variable included as an explanatory variable	Dynamic panel model with the Arellano-Bond estimator	Satisfied. See Table A1.
Measurement of knowledge	Allowed knowledge depreciation at the rate of 1% to 10% per week	Satisfied. See Table A1.
Selection bias	Propensity score matching (PSM) method	Satisfied. See Table 10.

equi-correlated errors from the common shocks, which is rather unlikely in our case (Baum et al. 2010). Second, the effect size of KMS usage by using this model is the smallest of all those in the estimated fixed effects model, which ensures that our estimate is conservative. Third, the coefficients for other control variables in the selected model are most convincing among the models we estimated. Finally, due to the lack of appropriate instruments for interacted terms (e.g., KMS usage times alternative social sources of information and knowledge), we do not use the 2SLS approach in testing the interaction effects. Our Hausman test confirmed that the estimates from the 2SLS approach are not statistically different from the estimates obtained with our fixed effects model.

Next we estimate

$$\begin{aligned}SALE_{iT} = {} & v_i + \beta_0 + \beta_1 \cdot Log(LEMP_{it}) + \beta_2 \cdot Log(KMSU_{iT}) \\ & + \beta_3 \cdot TRNG_{iT} + \beta_4 \cdot TINC_{iT} + \beta_5 \cdot TCOM_{iT} \\ & + \beta_6 \cdot Log(DWHU_{iT}) + \beta_7 \cdot TURN_{iT} + \beta_8 \cdot WEEK_T \\ & + \beta_9 \cdot Log(KMSU_{iT}) \cdot ALTP_i + \beta_{10} \cdot Log(KMSU_{iT}) \\ & \cdot Log(DWHU_{iT}) + \beta_{11} \cdot Log(KMSU_{iT}) \cdot ALTS_i \\ & + \beta_{12} \cdot Log(KMSU_{iT}) \cdot TIIT_i + \beta_{13} \cdot Log(KMSU_{iT}) \\ & \cdot CIIT_i + \varepsilon_{2iT}\end{aligned} \qquad (2)$$

Five interaction terms involving KMS use ($KMSU_{iT}$) appear in Equation (2): alternative *physical* sources of information and knowledge ($ALTP_i$), alternative *social* sources of information and knowledge ($ALTS_i$), data warehouse use ($DWHU_{iT}$), *total* information intensity of task ($TIIT_i$), and *changing* information intensity of task ($CIIT_i$). All interacted terms are mean-centered to avoid collinearity. However, the direct effects of the four variables, $ALTP_i$, $ALTS_i$, $TIIT_i$, and $CIIT_i$ are not included in the model since they are time-invariant, and our model is estimated primarily by using the fixed effects model.

Robustness Check: Propensity Score Matching Method

We note that different forms of selection biases may affect our results. Thus, we further conduct an analysis using the propensity score matching (PSM) method (Rosenbaum and Rubin 1983) as a robustness check. For instance, some department managers who are likely to benefit more from using KMS may choose to use KMS more which may bias the estimation of the KMS impact. The employee who is capable of using KMS better may be chosen as a department manager by a store manager although the chain does not discriminate on the basis of employee KMS usage. The PSM method has been often adopted in the IS literature (Caliendo et al. 2012; Mithas and Krishnan 2009; Smith and Telang 2009) as well as in the economics literature.

The first step of the PSM analysis is to define the treatment and outcome along with other covariates that may influence the choice of treatment. Out of 146 weeks in our original samples, we select the two most recent years (104 weeks). Since we are interested in the change in performance by a change in KMS usage, the outcome is the change in yearly sales measured in thousand dollars, $\Delta SALE_i = [SALE_{iY} - SALE_{iY-1}]$, where i indexes department manager (i = 1, 2,…, 273), Y indexes year (Y = 1 or 2), and Δ denotes the difference between the two years. For example, $SALE_{i2}$ denotes aggregate yearly sales in thousand dollars for department manager i in the most recent 52-week period. Because the cumulative KMS usage is a continuous variable, we redefine the treatment variable as $Treatment = 1$ if $[Log(KMSU_{iY-1}) - Log(KMSU_{iY-1})]$ is greater than the median of 273 managers. Otherwise, we code $Treatment = 0$. Note that this median split is often adopted when it is necessary to estimate the effect of IT by using a dichotomous treatment variable (e.g., Stiroh 2002). For robustness of our results, we use multiple specifications. We vary a set of variables used for matching and estimate the treatment effect using the nearest neighbor (NN) and Kernel matching methods. We use a logit model to calculate the propensity score. See the appendix for more details.

Supplementary Analysis: Opening Up the Black-Box

In the models above, we have assumed that every knowledge document in the repository KMS is uniformly helpful. We relax this assumption and examine how utilizing different types of knowledge may produce different performance outcomes and affect the contingent effects. Specifically, we ask: Does a certain set of knowledge from the KMS fit better with specific task environments? This analysis is inspired by Burton-Jones and Straub (2006) who emphasize that system usage should take the user, system, and type of tasks into account when examining task performance.

For our supplementary analysis, we consider one relevant dimension: life span of knowledge. Like a product whose value degrades over time, the value of knowledge may degrade as well (Birkinshaw and Sheehan 2002). Each piece of knowledge has an effective life span, beyond which it needs to be revised or discarded (Dennis and Vessey 2005). While the value of short life span knowledge degrades sharply, the value of long life span knowledge degrades more gracefully. We first examine if both types of knowledge have the same effect on performance. Since dynamic environments demand more up-to-date information and knowledge, short life span knowledge may fit well with such environments. That is, we expect that short life span knowledge works better for department managers whose tasks require more rapidly updated information and knowledge. For users in stable environments, however, long life span knowledge may generate more benefits. Thus, we also examine this question in an exploratory manner in this paper without a formal hypothesis. We estimate the following modified model:

$$\begin{aligned} SALE_{iT} = \delta_i + \gamma_0 + \gamma_1 \cdot Log(LEMP_{iT}) + \gamma_2 \cdot Log(SKSM_{iT}) \\ + \gamma_3 \cdot Log(LKMS_{iT}) + \gamma_4 \cdot Log(SKMS_{iT}) \cdot CIIT_i \\ + \gamma_5 \cdot Log(LKMS_{iT}) \cdot CIIT_i + \gamma_6 \cdot Z_{iT} \\ + \gamma_7 \cdot WEEK_T + \varepsilon_{3iT} \end{aligned} \quad (3)$$

Here i indexes department and T indexes week. δ_i is a constant term specific to department i to capture departmental heterogeneity. *KMSU* is split into two variables, *SKMS* and *LKMS*. $SKMS_{iT}$ denotes the cumulative usage of short life span knowledge measured by the cumulative number of knowledge documents with a short review cycle viewed by manager i until week T. Similarly, *LKMS* indicates the cumulative usage of long life span knowledge. These two variables are interacted with $CIIT_i$. We also include weekly fixed effects ($WEEK_T$) and Z_{iT}, a set of control variables used in Equation (2) such as $LEMP_{iT}$, $TRNG_{iT}$, $TINC_{iT}$, $TCOM_{iT}$, $TURN_{iT}$, and $DWHU_{iT}$. ε_{3iT} is the idiosyncratic error component. We use the fixed effects model with a first order autoregressive error term.

Operationalization of Variables

KMS Usage and Instruments. We measure the cumulative number of knowledge documents (*KMSU*) viewed by each manager by collecting the weekly level system-recorded repository usage by the manager in contrast with self-reported usage (Ahearne et al. 2008; Ko and Dennis 2011; Straub et al. 1995). We also collected the usage by peer department managers in their stores, which is used in our propensity score matching analysis. As described in the "Model Specification" section, we adopt two indicator variables as our instruments for repository KMS usage for our 2SLS analysis: whether the manager returned the chain's internal survey on user satisfaction in the immediate previous week (*SRVP*) and whether the manger has participated and returned the survey any time before (*SRVA*). These two variables capture the short- and long-term effects of answering the survey on the usage level.

Store Department Manager's Performance. The department manager-level performance is measured by the departmental weekly sales in thousand dollars (*SALE*). As discussed earlier, the store department sales is an appropriate and relevant measure of a department manager's performance because department sales is the key criterion used in evaluating department managers' overall performance and thus it is well aligned with managers' incentives at the research site.

Contingent Factors. To account for alternate sources of information and knowledge as well as task information intensity for department managers we used survey-based measures. The items and their validations are shown in Table 3. All survey items are measured based on a seven-point Likert scale from "Strongly Disagree" to "Strongly Agree." To ensure face and content validity of survey items, four iterative procedures were conducted: (1) a review of the instruments by faculty experts from different fields; (2) a pretest with university staff to confirm the readability of questionnaire; (3) item-by-item discussion with the head of knowledge strategy group, KnowLink training managers, and KnowLink administrators; and (4) a pilot test with 37 Ace Grocery employees. We reworded the items in a way that every employee could easily understand all of the questions. The third step included two formal sessions with Ace Grocery management and KnowLink specialists. For each session at least three employees attended to share opinions and correct the terms that may not be familiar to store personnel. The authors and Ace Grocery employees also had several informal discussions before the main survey. For data warehouse usage (*DWHU*), the cumulative number of data warehouse reports viewed by a department manager was counted based on system-recorded counts per user. More than 200 report types were used by the sampled department managers at least once during the period.

Control Variables. Labor input per department (*LEMP*) is measured by the total number of employees in the department in the previous month. Employee turnover rate (*TURN*) is measured by the percentage of employees who left the department in the previous month. A department manager's training on computer-related topics (*TRNG*) is computed as the cumulative number of training days on computer-related topics such as KMS, data warehouse, and other general computer skills. Trade area income (*TINC*) and trade area competition (*TCOM*) are coded as 1 if trade area income and competition are high, and 0 otherwise. This classification is based on an annual evaluation by the company's strategic planning department. Note that both of these variables were measured only three times during the sample period and have relatively small variations. A total of 145 dummy variables for 146 weeks were also coded and included in the model to account for seasonality in demand (*WEEK*).

Supplementary Analysis. The codified documents in the chain's repository are marked with the date of creation and next review date. The grocery chain usually sets review cycles of documents as 3, 6, or 12 months, or longer. A majority of documents is reviewed a year after its creation. Therefore, the gap between the next and the last review date serves as the approximate life span of knowledge. We operationalized the usage of short (long) life span knowledge by the cumulative number of viewed documents with a review cycle of less than or equal to (longer than) 6 months. Since few documents have a 3 month cycle, we set 6 months as the cutoff point between short and long life span knowledge.[10] Table 5 summarizes all the variables used in this paper and their descriptions.

[10]According to this classification, more knowledge documents are classified as longer life span repository knowledge, and thus the correlation between cumulative repository use and longer life span repository knowledge use is very high (r = 0.99).

Results

Main Results

The descriptive statistics and correlations of variables are presented in Tables 6 and 7. The outcome and usage variables have been multiplied by a positive number to protect the confidential nature of the data.

Table 8 shows our estimation results of the direct effect of cumulative repository KMS usage on weekly sales. Model (1) *presents* the results from the standard fixed effects model with robust standard errors clustered within each department manager. It shows that the coefficient for repository KMS usage is positive and significant (β_{KMSU} = 4.318, p < 0.001). The estimated coefficient implies that 1 percent increase in the repository usage leads to an increase in weekly sales by 43.2 dollars.[11] If we assume that there are 200 stores and each store has approximately 10 departments,[12] a unit percent increase in the cumulative knowledge stock obtained from its repository KMS usage contributes to 86,400 dollars (43.2 × 200 × 10) on a weekly basis or increases chain-wide annual sales by 4.5 million dollars. Since a 1 percent increase in the cumulative KMS usage corresponds to viewing only one or two more documents in our dataset, the impact seems substantial. Overall R^2 in Table 8 excludes the fixed effects during calculation and is 10.38 percent. Within R^2 centers dependent and independent variables before R-squared computation and is 15.97 percent. The R^2 with fixed effects in Model (1) is 97.7 percent. As evidenced by the very high R^2 of the model, we believe that omitted variable bias is not a serious concern here.

Model (2) in Table 8 produces estimation results that address a possible endogeneity issue using 2SLS.[13] We observe that the estimated coefficient in this model is larger than those in the previous model (β_{KMSU} = 10.886, p < 0.05). Model (3) specifies a first order autoregressive error component. The

[11]When only variable x is logged, it is commonly interpreted that y increases by beta/100 when x is increased by 1 percent. As our y variable was in thousand dollars, 4.318 / 100 × 1000 = 43.2 dollars.

[12]The number of stores and the number of departments per store are similar at the research site.

[13]The first stage F-statistic is 34.7, which is far larger than the suggested threshold of 10 (Staiger and Stock 1997). The R^2s for the first stage were 72.6% (within), 22.7% (between), 36.5% (overall), and 91.5% (with fixed effects). The Sargan's test statistic, which tests the instrument exclusion restriction is, 1.453 (p = 0.228), showing that the null hypothesis that the instruments are valid cannot be rejected. Refer to the appendix for more first-stage results.

Table 5. Description of Variables

Variable	Description
$SALE_{iT}$	Sales in manager *i*'s department at week *t* (in thousand dollars).
$LEMP_{iT}$	The number of employees in manager *i*'s department in the previous month (measured monthly).
$KMSU_{iT}$	The cumulative number of knowledge documents viewed by department manager *i* until week *t*-1.
$TRNG_{iT}$	The cumulative number of days of computer-related training by department manager i before week *t*.
$TINC_{iT}$	Income level in department manager *i*'s trade area in week *t* (measured yearly). 1= high and 0 = low.
$TCOM_{iT}$	Competition level in department manager *i*'s trade area in week *t* (measured yearly). 1= high and 0 = low.
$DWHU_{iT}$	The cumulative number of data warehouse reports viewed by department manager *i* until week *t*-1.
$TURN_{iT}$	The employee turnover rate in manager *i*'s department in the previous month (measured monthly).
$WEEK_{T}$	A set of 145 dummy variables for weekly fixed effects.
$ALTS_{i}$	Alternative social knowledge sources for department manager *i* (mean value of four survey items).
$ALTP_{i}$	Alternative physical knowledge sources for department manager *i* (mean value of two survey items).
$CIIT_{i}$	Changing information intensity of task for department manager *i* (mean value of four survey items).
$TIIT_{i}$	Total information intensity of task for department manager *i* (four survey items).
$SKMS_{iT}$	Short life span knowledge acquired from cumulative KMS usage by department manager *i* until week *t*-1.
$LKMS_{iT}$	Long life span knowledge acquired from cumulative KMS usage by department manager *i* until week *t*-1.
$SRVA_{iT}$	1 if the internal survey was answered by department manager *i* any time before week *t* , and 0 otherwise.
$SRVP_{iT}$	1 if the internal survey was answered by department manager *i* in week *t*-1, and 0 otherwise.

Table 6. Descriptive Statistics

Variable	Description	N	Mean	Std. Dev.
$SALE_{iT}$	Department Weekly Sales in Thousand Dollars	39858	76.98	120.3
$Log(LEMP_{iT})$	Log of Department Employees	39858	2.24	0.70
$Log(KMSU_{iT})$	Log of Cumulative Repository Use	39858	4.32	1.55
$TRNG_{iT}$	Department Manager Training	39858	1.78	1.45
$TINC_{iT}$	Trade Area Income	39858	0.66	0.47
$TCOM_{iT}$	Trade Area Competition	39858	0.63	0.48
$Log(DWHU_{iT})$	Log of Data Warehouse Use	39858	7.27	1.77
$TURN_{iT}$	Department Employee Turnover Rate	39858	0.002	0.04
$ALTS_{i}$	Alternative Social Sources	38252	5.48	1.03
$ALTP_{i}$	Alternative Physical Sources	38982	5.67	1.18
$CIIT_{i}$	Changing Information Intensity of Task	38982	5.58	0.98
$TIIT_{i}$	Total Information Intensity of Task	38982	6.04	0.95
$Log(SKMS_{iT})$	Shorter Life Span Repository Knowledge Use	39858	1.06	1.15
$Log(LKMS_{iT})$	Longer Life Span Repository Knowledge Use	39858	4.26	1.56
$SRVA_{iT}$	Survey Answered by Department Manager Any Time Before	39858	0.16	0.37
$SRVP_{iT}$	Survey Answered by Department Manager in the Immediate Previous Week	39858	0.002	0.05

Table 7. Correlation of Variables

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1)	$SALE_{iT}$															
(2)	$Log(LEMP_{iT})$	0.62														
(3)	$Log(KMSU_{iT})$	0.11	0.47													
(4)	$TRNG_{iT}$	0.01	0.17	0.24												
(5)	$TINC_{iT}$	0.00	0.01	-0.06	0.22											
(6)	$TCOM_{iT}$	-0.03	0.01	-0.02	0.06	0.22										
(7)	$Log(DWHU_{iT})$	0.09	0.45	0.70	0.26	-0.05	-0.03									
(8)	$TURN_{iT}$	-0.02	-0.06	0.00	-0.01	-0.01	0.00	-0.01								
(9)	$ALTS_{i}$	0.07	0.11	0.07	0.05	0.04	0.03	0.14	0.02							
(10)	$ALTP_{i}$	-0.11	-0.06	0.06	0.02	0.12	0.02	0.04	0.01	0.41						
(11)	$CIIT_{i}$	0.07	0.16	0.11	0.04	0.00	-0.11	0.10	0.00	0.25	0.21					
(12)	$TIIT_{i}$	0.17	0.17	0.09	-0.03	-0.05	-0.13	0.11	-0.03	0.30	0.31	0.57				
(13)	$Log(SKMS_{iT})$	0.43	0.27	0.40	0.05	-0.06	-0.01	0.29	-0.01	-0.07	-0.08	0.06	0.04			
(14)	$Log(LKMS_{iT})$	0.11	0.48	0.99	0.24	-0.06	-0.03	0.70	0.00	0.08	0.06	0.12	0.10	0.34		
(15)	$SRVA_{iT}$	0.07	0.15	0.32	0.12	-0.05	0.01	0.22	0.00	-0.02	0.04	0.02	0.02	0.19	0.32	
(16)	$SRVP_{iT}$	0.01	0.01	0.02	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.10

Table 8. Estimation of the Effect of KMS Usage

	(1)	(2)	(3)
	FE with Robust SE	**2SLS**	**FE with AR(1)**
Intercept	35.534* (19.445)	24.949*** (8.108)	47.286*** (1.245)
Log of Department Employees	6.019 (7.796)	7.890*** (1.516)	3.095*** (1.083)
Log of Cumulative Repository Use	4.318*** (1.559)	10.886** (4.873)	2.877*** (0.456)
Log of Data Warehouse Use	1.353 (2.704)	-0.541 (1.416)	1.728*** (0.425)
Department Manager Training	-2.261*** (0.533)	-2.237*** (0.166)	-1.792*** (0.382)
Department Employee Turnover Rate	0.067 (2.191)	-2.096 (2.920)	-0.429 (2.760)
Trade Area Income	0.260 (2.468)	-0.294 (0.678)	1.076 (1.173)
Trade Area Competition	2.925 (2.943)	2.573*** (0.650)	1.753 (1.277)
Number of Observations	39,858	39,858	39,585
Number of Department Managers	273	273	273
R-Squared (Within)	15.97%	N/A	23.20%
R-Squared (Between)	13.22%	N/A	8.84%
R-Squared (Overall)	10.38%	N/A	6.19%

***Significant at 1%;** significant at 5 %; *significant at 10%. The numbers in parentheses are standard errors.

coefficient of the KMS usage is smallest in this model ($\beta_{KMSU} = 2.877$, $p < 0.001$). In all the estimated models, the effect of the KMS usage was positive and highly significant.[14]

The coefficient of repository KMS in Table 8 changes across the specifications. However, all of the coefficients show a consistently positive and significant effect of repository KMS usage. Furthermore, the Hausman test shows that the 2SLS estimates do not statistically differ from those in Model (3) ($\chi^2 = 1.82$, $p \approx 1.0$). Thus Model (3), with the smallest effect size of KMS repository usage, is preferred among the fixed effects models and is chosen to serve as our main model for further analysis.

We also discuss the coefficients of other variables although they are not the focus of our paper. First, the negative effect of computer-related training across models is somewhat unexpected. We believe that the effect of training itself is not positive once we control for KMS usage. This reflects that managers often had to drive to headquarters to receive training, which disrupts their work. Second, the coefficients for data warehouse and competition are somewhat unstable or counterintuitive in some models. We believe the most important reason for these results is the autocorrelation present in the model. Note that the coefficients of data warehouse and competition in Model (3) are more convincing. For example, in Model (3), the effect of data warehouse usage is positive and significant, and the effect of competition is not significant. We believe the reason for the insignificant effect of competition is partly due to little variation in the variable which was not only measured annually but also did not vary much within the 146-week period. Another possible reason may be that intensified competition helped managers receive more resources from the headquarters and inspired managers to innovate and make more improvements. For example, some of the chain's stores under higher competition fully renovated their stores to counter competition.

We now turn to the contingent effects (Table 9). We first estimate the influence of inserting each moderator separately into the model to obtain efficient coefficient estimates with limited collinearity. The full model with all the interaction terms is estimated last. We checked variance inflation factors (VIFs), which are below the strict threshold of 4.[15]

In Model (1) in Table 9, we find that the coefficient for the interaction term between repository KMS usage and alternative physical sources is in the expected direction and statistically significant ($\beta_{KMSU*ALTP} = -2.989$, $p < 0.001$). This result supports our hypothesis that the effect of the cumulative KMS usage is generally greater when a department manager is endowed with fewer alternative *physical* sources of knowledge (Hypothesis 2). Thus a 1 percent increase in the repository usage corresponds to an increase in weekly sales by 54.1 dollars at the 25th percentile of alternative physical sources but only by 9.3 dollars at the 75th percentile. Similarly, in Models (2) and (3), the coefficients of the interaction term between repository KMS usage and computerized knowledge sources or alternate social sources are in the expected direction and statistically significant ($\beta_{KMSU*DWHU} = -0.672$, $p < 0.001$; $\beta_{KMSU*ALTS} = 0.527$, $p < 0.1$). That is, repository KMS usage has less impact on department managers' performance when they already use data warehouse applications frequently (Hypothesis 3). The coefficient translates into an increase in weekly sales by 21 dollars for every 1 percent increase in the repository usage at the 25th percentile of data warehouse usage but only by 10.9 dollars at the 75th percentile of data warehouse usage. Although Hypothesis 4 is supported at $p < 0.1$ in Model (3), it is strongly supported in the full model, Model (6) ($\beta_{KMSU*ALTS} = 2.747$, $p < 0.001$). Thus, the effect of the cumulative KMS usage is greater in general when a department manager is endowed with more alternative *social* sources of knowledge (Hypothesis 4). With the coefficient in Model (3), a 1 percent increase in the repository usage leads to an increase in weekly sales by 24 dollars at the 25th percentile of alternative social sources but by 31.9 dollars at the 75th percentile. While more use of explicit knowledge from printed media or data warehouse reduces the impact of KMS that also provides explicit knowledge, a higher level of alternative social sources provides a mechanism to transfer tacit knowledge and enhances the impact of KMS. Thus, a firm that replaces existing social knowledge sources with a new repository KMS may gain little.

Model (4) in Table 9 shows that the impact of KMS usage is greater for those department managers who experience a higher level of total information intensity of task (Hypothesis 5). We find that the coefficient of the interaction term is in the expected direction and significant ($\beta_{KMSU*TIIT} = 1.027$, $p = 0.001$). Thus, a 1 percent increase in the repository usage leads to an increase in weekly sales by 22.1 dollars at the 25th

[14]See the appendix for the results from various alternative specifications. We confirmed that the results from alternative specifications strongly support the positive impact of repository KMS usage on performance.

[15]An alternative approach to diagnose multicollinearity is by using the condition number. The condition number at 10 begins to affect regression estimates; the number between 10 and 100 indicates moderate to strong dependencies; 100 or higher indicates a serious collinearity problem (Belsley et al. 1980). Some suggest 30 as a threshold. The maximum condition number in our models is 47, which does not raise a serious concern. Although some collinearity is present, it is not avoidable simply because of many dummy variables for time fixed effects. However, our results are robust to the collinearity issue because dropping all time fixed effects produces almost the same results as before, which pull the condition number below 30.

Table 9. Estimation of Interaction Effects (FE with AR(1))

	(1) ALTP	(2) DWHU	(3) ALTS	(4) TIIT	(5) CIIT	(6) FULL
Intercept	42.638*** (1.276)	72.149*** (1.751)	45.422*** (1.250)	50.269*** (1.278)	48.401*** (1.222)	59.735*** (1.772)
Log of Department Employees	3.198*** (1.110)	3.297*** (1.080)	2.672** (1.129)	2.613** (1.111)	2.806*** (1.080)	1.337 (1.093)
Log of Cumulative Repository Use	3.402*** (0.459)	1.811*** (0.493)	2.784*** (0.474)	2.767*** (0.464)	2.362*** (0.461)	2.246*** (0.487)
Repository Use* Alternative Physical Sources	-2.989*** (0.237)					-4.603*** (0.266)
Repository Use* Data Warehouse Use		-0.672*** (0.120)				-0.565*** (0.122)
Repository Use* Alternative Social Sources			0.527* (0.283)			2.747*** (0.307)
Repository Use* Total Information Intensity				1.027*** (0.314)		4.248*** (0.375)
Repository Use* Changing Information Intensity					-1.941*** (0.260)	-3.526*** (0.297)
Log of Data Warehouse Use	1.803*** (0.423)	-0.578 (0.590)	1.815*** (0.442)	1.637*** (0.433)	1.757*** (0.429)	0.638 (0.593)
Department Manager Training	-1.693*** (0.376)	-1.801*** (0.379)	-1.694*** (0.398)	-1.778*** (0.385)	-1.788*** (0.382)	-1.512*** (0.375)
Department Employee Turnover Rate	-0.898 (2.862)	-0.512 (2.758)	-0.754 (2.846)	-0.181 (2.779)	-0.506 (2.693)	-0.016 (2.775)
Trade Area Income	2.036* (1.191)	1.454 (1.169)	0.914 (1.221)	0.935 (1.181)	0.906 (1.183)	1.956* (1.156)
Trade Area Competition	1.600 (1.257)	1.389 (1.272)	2.005 (1.310)	1.838 (1.285)	1.653 (1.270)	1.847 (1.240)
Number of Observations	38,715	39,585	37,990	38,715	38,715	37,555
Number of Departments	267	273	262	267	267	259
R-Squared (Within)	23.53%	23.25%	23.05%	23.51%	23.44%	24.03%
R-Squared (Between)	5.17%	12.63%	7.14%	8.62%	7.02%	2.04%
R-Squared (Overall)	4.68%	6.30%	5.04%	5.71%	5.24%	2.44%

***Significant at 1%;**significant at 5 %;*significant at 10%. The numbers in parentheses are standard errors.

percentile of total information intensity but by 37.5 dollars at the 75th percentile. In Model (5), the coefficient of the interaction between repository KMS usage and changing information intensity of task (Hypothesis 6) is negative and significant as expected ($\beta_{KMSU*CIIT}$ = -1.941, $p < 0.001$). A 1 percent increase in the repository usage leads to an increase in weekly sales by 34.9 dollars at the 25th percentile of changing information intensity but by 10.7 dollars at the 75th percentile. Model (6) estimates Equation (2) and presents the estimation results of the model with all variables. The overall patterns are preserved in the full model in comparison with the previous separate estimations. We conclude that all research hypotheses are supported. All models in Table 9 have an adequate level of goodness-of-fit. For example, the R^2 with fixed effects in the full model is 97.8 percent.

As a robustness check, the results from the propensity score matching method to address a possible selection bias are summarized in Table 10. Model (1) estimates the treatment effect using the nearest neighbor (NN) matching method. Model (2) adds sales in the prior year as a matching variable. Model (3) uses the Kernel matching method as the matching algorithm. All subjects fall inside the common support except in Model (3). With the Kernel matching algorithm, eight subjects were outside the common support and dropped from the analysis. The balancing property was reasonably well satis-

Table 10. Propensity Score Matching Method Results

	(1) NN Matching	(2) NN Matching with Current Sales	(3) Kernel Matching
Average treatment effect on treated	378.71	417.32	405.52
Standard errors	142.23	165.20	137.50
t-value	2.66	2.53	2.95
Number of observations	273	273	265
Outside the common support	0	0	8

fied in the three models. More details about the analysis including the logit model results, matching quality, and model sensitivity can be found in the appendix. Based on the results, we find that the average treatment effect on treated ranges is between 378.71 and 417.32; the effect size is translated into increased department annual sales between 378,710 and 417,320 dollars if a manager increased her usage of repository KMS more than the median level increase in KMS usage by managers in our sample. When we estimate the same model using ordinary least squares (OLS), the estimated effect size is 381.18, which differs little from the effect size in the PSM analysis (see the appendix). We conclude that our interpretation of the KMS impact is robust to a selection bias and credible.

In addition to the robustness check, we find additional evidence that supports the effect found in this study was related to KMS usage. First, since KMS usage is voluntary at our research site, managers have no incentive to use KMS unless usage helps them improve their performance. Neither is there intrinsic motivation for managers to use KMS. Second, from our on-site observations and interviews, we have identified many anecdotal scenarios that using KMS actually helps managers make informed decisions and facilitate employees' learning of business processes in the stores. Finally, if such an unobserved factor as mangers' ingenuity is relevant and accounts for their performance, there is no good reason for our moderating effects to be significant. To the extent that our theoretical expositions are sensible, our work on the contingent factors serves as a type of identification strategy.

Supplementary Analysis: Opening Up the Black-Box

In this subsection, we further examine whether a certain set of knowledge acquired from the KMS fit better with specific task environments by distinguishing different types of knowledge as described in Equation (3). We first estimate the direct effects of short and long life span knowledge in Model (1), Table 11. Interestingly, only the usage of long life span knowledge is statistically significant ($\gamma_{SKMS} = 0.743, p = 0.104$; $\gamma_{LKMS} = 2.630, p < 0.001$). This is possibly because short life span knowledge depreciates rapidly, or short life span knowledge is effective only under certain conditions. When we interact the two types of knowledge with changing information intensity of task, we find that the effect of short life span knowledge also becomes statistically significant ($\gamma_{SKMS} = 1.167$, $p < 0.05$; $\gamma_{LKMS} = 1.948$, $p < 0.001$). It is interesting to note that the effect of long life span knowledge is still greater than that of short span knowledge at the average level of CIIT. Both short and long life span knowledge are negatively moderated by changing information intensity of task ($\gamma_{SKMS*CIIT} = -1.026$, $p < 0.05$; $\gamma_{LKMS*CIIT} = -1.294$, $p < 0.001$). Thus, a 1 percent increase in cumulative long life span knowledge leads to an increase in weekly sales by 27.0 dollars at the 25th percentile of changing information intensity but by 10.9 dollars at the 75th percentile. However, a 1 percent increase in cumulative short life span knowledge increases weekly sales less and by 17.7 dollars only at the 25th percentile of changing information intensity and by 4.8 dollars at the 75th percentile.

We expected that $\gamma_{SKMS*CIIT}$ would be positive indicating that short life span knowledge is more useful under a higher level of changing information intensity of task. Interestingly, short life span knowledge is less useful under a high level of *CIIT* although it improves performance at the average level of *CIIT*. At the maximum level of *CIIT*, 1.417 in a mean-centered scale, the coefficient for the cumulative usage becomes 0.115 (= 1.948 – 1.294* 1.417) for long life span knowledge while it becomes -0.287 (= 1.167 – 1.026* 1.417) for short life span knowledge. That is, when the task environment becomes turbulent requiring rapidly updated information and knowledge, short life span knowledge even hurts performance. This finding may signal a major challenge for repository KMS in which codified knowledge, by its nature, is unable to keep pace with more dynamic environments. This is understandable because short life span knowledge in our context relates to documents that are updated at most every

Table 11. Short Versus Long Life Span Knowledge (FE with AR(1))

	(1) Direct Effects Only	(2) Interaction with *CIIT*
Intercept	47.082*** (1.248)	48.222*** (1.225)
Short Life Span Repository Knowledge Use	0.743 (0.457)	1.167** (0.463)
Long Life Span Repository Knowledge Use	2.629*** (0.459)	1.948*** (0.466)
Short Life Span Repository Knowledge Use × Changing Information Intensity		-1.026** (0.471)
Long Life Span Repository Knowledge Use × Changing Information Intensity		-1.294*** (0.321)
Log of Department Employees	3.011*** (1.084)	2.602** (1.082)
Log of Data Warehouse Use	1.793*** (0.424)	1.881*** (0.428)
Department Manager Training	-1.801*** (0.382)	-1.779*** (0.383)
Department Employee Turnover Rate	-0.408 (2.760)	-0.425 (2.693)
Trade Area Income	1.098 (1.173)	0.815 (1.185)
Trade Area Competition	1.791 (1.277)	1.596 (1.272)
Number of Observations	39,585	38,715
Number of Department Managers	262	267
R-Squared (Within)	23.20%	23.44%
R-Squared (Between)	11.15%	10.80%
R-Squared (Overall)	7.51%	7.23%

***Significant at 1%;** significant at 5 %; *significant at 10%. The numbers in parentheses are standard errors.

three months whereas they should probably be updated more frequently to enable managers to react to changing demand and supply conditions on a daily basis when their task environment changes fast (e.g., as with perishable products). Our analysis shows why using repository KMS may sometimes result in unexpected performance outcomes.

Discussion

In this study, we attempted to understand when the use of KMS lifts performance using data from a retail grocery chain. We found a substantial positive impact of managers' usage of the repository KMS on their performance, as measured by weekly department sales. We estimated the effect of KMS usage in dollar values. Based on the situated knowledge performance framework, we found that the positive impact of KMS usage is greater under fewer alternate physical or computerized knowledge resources (e.g., data warehouse). In contrast, the impact of repository KMS usage is enhanced in the presence of rich alternative social sources of knowledge. We also showed that the repository KMS usage produces higher benefits for managers whose task environments require a greater volume of information and knowledge. However, an increased need for rapidly updated information and knowledge induces a misfit between users' knowledge needs and the relatively stable knowledge available from KMS. In these instances, the effect of KMS usage is lessened. Overall, our study reveals that while the impact of KMS on performance is mediated by actual usage, the size of the impact is determined by the mix of alternate knowledge sources available to users and by their task environments.

Our study contributes to the IT business value literature in two ways. First, we advance the IT business value research by examining the value of KMS by drawing upon the KM literature. Although Devaraj and Kohli (2003) suggest actual system usage as a main driver of performance impact, it is often not clear why the same level of KMS usage may produce differential impacts for different employees. Our study demonstrates how the IT value research can be extended to study the contingent impact of an IT artifact by leveraging the theoretical base on the artifact as well as the specific business context in which the system is used. Our study takes into account the types of systems, users, and tasks to understand the differential impact of IT as emphasized by Burton-Jones and Straub (2006).

Second, we also contribute to the IT business value literature by examining how the value of using one IT application may diminish with increasing use of another system. While some studies have examined the effects of implementing multiple systems, applications, or modules, they rely on aggregate spending at the firm level or simple adoption data in measuring IT inputs. In the spirit of Devaraj and Kohli, such interaction effects between IT systems can be better estimated when the actual usage of different systems is examined simultaneously. Our finding adds further insights into why IT investments may not always produce expected outcomes. We believe the value of using one system may in fact go down with an increased use of another system when both serve a similar purpose either directly or indirectly. For example, both repository KMS and data warehouse can be viewed as investments in "informational" IT assets (Aral and Weill 2007) and may overlap each other as part of an internal- and system-oriented knowledge sourcing strategy (Choi and Lee 2012).

The key contribution of this study to the KM literature lies in performing a critical empirical test of the situated knowledge performance framework based on fine-grained objective and longitudinal data while broadening its theoretical scope. There has been speculation that the task-level performance impact of codified knowledge may be neither quantifiable nor substantial (e.g., Gilmour 2003). Haas and Hansen (2005) found a negative impact of using KMS on task performance in a management consulting context. Gallivan et al. (2003) conducted a qualitative case study and found a provisional negative outcome of KMS in a help desk setting. More recently, Ko and Dennis (2011) extended this view; their study highlighted that it may take some time before the benefit of reading codified knowledge documents is realized. It is notable that only Ko and Dennis have studied the contingent impact of KMS usage by using objective usage and performance data in a longitudinal setting. Compared to Ko and Dennis, however, we perform a series of robustness checks to buttress our findings. Our study is also unique in that we could differentiate the types of knowledge in our supplementary analysis. We showed that all knowledge is not created equal and that the contingent effect may also depend on the types of knowledge utilized. Thus, our empirical study with detailed objective data on usage, performance, and characteristics of sourced knowledge as well as our conduct of various robustness checks adds credibility to the validity of the situated knowledge performance framework.

Moreover, we have extended the situated knowledge performance framework by covering the task situations that have not received much attention previously. In prior studies, the experience of users has been the main factor that created contingency. Haas and Hansen (2005) suggested a team's experience level and the number of competitors involved in each bid as the moderator of the relationship between KMS usage and bidding success. Gallivan et al. suggested that the possible reason for the decreased performance is the lagged performance effect because users take time to learn to use KMS effectively. Experience of users plays an important role in alleviating the lagged performance effect (Ko and Dennis 2011). Thus, our study sheds new light on KMS value beyond the Haas and Hansen's (2005) framework and other related studies in several ways. First, while prior studies indicated that poor performance outcomes may attenuate as users accumulate more experience, our findings highlight a more fundamental challenge. We show that the lower impact of KMS may sometimes be rooted in task environments. Second, to the best of our knowledge, we are the first to examine the alternative knowledge channels and users' task environments as moderators of the KMS usage impact. A consideration of interactions between KMS and other knowledge channels, including traditional and computerized sources, yields deeper insights into the design of KMS. Third, while Haas and Hansen (2005) did not specify which aspect of competition reduces the value of using KMS, we are more specific in isolating the characteristics of tasks that determine the value of KMS. Note that our findings extend prior studies on the fit between knowledge and task environments from a non-KMS context (Aral et al. 2012; Das 2003; Sorenson 2003) to a KMS context.

Our study has several important managerial and practical implications. First, with limited resources, firms should provide KMS support to groups with greater potential benefits. In particular, if a firm deploys its resources to create electronic documents for its repository, it is important to understand which user groups benefit more from accessing that knowledge. Understanding the differential impact of IT is particularly important for enterprise-wide applications such as ERP, CRM, and KMS that are deployed for a diverse set of users. Second, the knowledge structure within a company should be carefully planned and designed. Needless to say, if the duplication of contents from different knowledge sources is not coordinated carefully, there will be more inconsistent information and higher expenditure of resources. Our study also implies that in such conditions with abundant codified knowledge available through alternative channels or for managers requiring a higher level of changing information and knowledge, it may be more beneficial to pursue a "personalization strategy" instead of a "codification strategy" (Hansen et al. 1999). Third, managers should consider possible overlaps between different computer assets as well. A commonly held view has been that different computer assets complement each other (Aral et al. 2006; Tanriverdi 2005), but we show that complementarities between applications may not always exist. Thus management should not treat two IT applications separately but should attempt to consider the joint effects of both applications. Finally, knowledge workers as users of repository KMS have to clearly understand the potential benefit and cost of reusing codified knowledge. Although there is some measureable performance gain, search and contextualization of codified knowledge is not trivial. As shown in our study, while repository KMS is a useful source of knowledge to obtain a large number of codified knowledge documents, it may not be very useful in dynamic environments where the information and knowledge required for tasks change quickly. Firms should devise a mechanism by which codified knowledge documents can be updated depending on the appropriate life span of knowledge as well.

Conclusion

Although our results show strong support for our hypotheses, our work is not without limitations. First, as a field study, the generalizability of our findings may be limited. Nevertheless, field studies have been used in the IT business value literature when it comes to examining the process level impact or the IT usage impact (Ashworth et al. 2004; Davamanirajan et al. 2006; Mukhopadhyay, Lerch, and Mangal 1997; Mukhopadhyay and Mangal 1997). As a trade-off, we were able to develop more context-specific models.

The second limitation relates to our survey. Although we have counted the exact number of knowledge documents and reports viewed by department managers for the repository KMS and data warehouse, we were not able to precisely measure the frequency of knowledge acquisition from traditional sources. Instead, we asked about the overall accessibility, availability, and utility of knowledge from traditional sources. Furthermore, we measured traditional alternate sources only once. The underlying assumption is that a department manager's alternate sources do not vary much over time or are quasi-fixed over at least the two-year time period. At our research site, department managers were typically recruited internally and had a low turnover rate, thus somewhat alleviating this concern.

Third, we did not consider actual knowledge contents and assumed that the utility of the documents did not vary much. It was not feasible to evaluate the value of every single document in the repository KMS of our research site. In fact, the value of each electronic knowledge document may differ over time even for the same manager, a possibility that cannot be easily captured in a field setting.

Fourth, we were not able to use 2SLS when testing the contingent effects. If we are to use 2SLS to estimate the coefficients of interaction terms, we need instruments for the interacted terms in addition to the instruments for the KMS usage. One possibility is to use (instrument for KMS usage) × (contingent factor) as an instrument for the interaction term. Using this approach, we obtained qualitatively similar results. However, this approach is deemed less appropriate because the exogeneity of the instruments for interacted variables are not guaranteed. Nevertheless, the endogeneity was not a serious concern according to the Hausman test, which ensures there is little contamination from endogeneity in our estimation of the interaction effects.

Fifth, our estimate of the impact of KMS usage does not take into account the cost of implementing and operating KMS. Creating and updating knowledge documents also requires additional human and financial resources. However, our discussions with the KMS management indicate that the revenue impact of KMS usage, based on our conservative estimate, far exceeds the cost of KMS implementation and operation at the research site.

Finally, our PSM method transformed KMS usage into a dichotomous treatment variable, which limits quantifying the size of the effects precisely. Because of the nature of our KMS usage variable that deviated from normal distribution, we were not able to adopt the version of PMS that uses a continuous treatment effect. However, our PSM analysis was used as a robustness check rather than quantifying the annual impact.

The business value of IT has been one of the core IS research questions. Although many studies have enhanced our understanding of how IT creates value for firms, further research should be conducted to fully understand the mechanisms that create value in various settings. One possible direction is to investigate the contingent impact of enterprise-wide applications in which a great deal of IT investments is made. Moreover, our research can be extended to examine issues such as how negative interaction effects between different knowledge sources may take place, whether different channels may be integrated over time, and how users may react to any conflict between different knowledge sources. Another interesting question would be the factors leading to sourcing knowledge from different knowledge channels. At a micro level, social sources of knowledge can be further differentiated by who provides relevant knowledge. We hope that our study paves the way toward such integrative studies.

Acknowledgments

The authors thank the senior and associate editors, the three anonymous reviewers, all seminar participants at the National University of Singapore and the Singapore Management University, Rahul Telang, Linda Argote, Sandra Slaughter, Dennis Rousseau, Robert Kauffman, Dorothy Leidner, and Millie Myers for their helpful comments and suggestions. The authors also thank Bob Guy, Russ Ross, and their colleagues for help in gaining access to the datasets in the research site. This research was partially supported by the Yonsei Business Research Institute and the Singapore Ministry of Education Academic Research Fund, NUS (R-253-000-067-133).

References

Agarwal, R., and Lucas, H. C. 2005. "The Information Systems Identity Crisis: Focusing on High-Visibility and High-Impact Research," *MIS Quarterly* (29:3), pp. 381-398.

Ahearne, M., Jones, E., Rapp, A., and Mathieu, J. 2008. "High Touch through High Tech: The Impact of Salesperson Technology Usage on Sales Performance via Mediating Mechanisms," *Management Science* (54:4), pp. 671-685.

Alavi, M., and Leidner, D. E. 2001. "*Review*: Knowledge Management and Knowledge Management Systems: Conceptual Foundations and Research Issues," *MIS Quarterly* (25:1), pp. 107-136.

Aral, S., Brynjolfsson, E., and Van Alstyne, M. 2012. "Information, Technology, and Information Worker Productivity," *Information Systems Research* (23:3), pp. 849-867.

Aral, S., Brynjolfsson, E., and Wu, D. J. 2006. "Which Came First, IT or Productivity? The Virtuous Cycle of Investment and Use in Enterprise Systems," in *Proceedings of the 27th International Conference on Information Systems*, Milwaukee, WI, pp. 1819-1840.

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

Argote, L., and Epple, D. 1990. "Learning Curves in Manufacturing," *Science* (247:4945), pp. 920-924.

Armstrong, J. S., and Overton, T. S. 1977. "Estimating Nonresponse Bias in Mail Surveys," *Journal of Marketing Research* (14:3), pp. 396-402.

Ashworth, M., Mukhopadhyay, T., and Argote, L. 2004. "Information Technology and Organizational Learning: An Empirical Analysis," in *Proceedings of the 25th International Conference on Information Systems*, Washington, DC, pp. 481-492.

Banker, R. D., and Kauffman, R. J. 2004. "The Evolution of Research on Information Systems: A Fiftieth-Year Survey of The Literature In Management Science," *Management Science* (50:3), pp. 281-298.

Barua, A., Kriebel, C. H., and Mukhopadhyay, T. 1995. "Information Technologies and Business Value: An Analytic and Empirical Investigation," *Information Systems Research* (6:1), pp. 3-23.

Barua, A., and Mukhopahdyay, T. 2000. "Information Technology and Business Performance: Past, Present and Future," in *Framing the Domains of IT Management Research: Glimpsing the Future Through the Past,* R. W. Zmud (ed.), Cincinnati, OH: Pinnaflex Educational Resources, pp. 65-84.

Baum, C., Nichols, A., and Schaffer, M. 2010. "Evaluating One-Way and Two-Way Cluster-Robust Covariance Matrix Estimates," paper presented at the Stata Conference 11, Boston, Boston, MA.

Baum, J .R., and Wally, S. 2003. "Strategic Decision Speed and Firm Performance," *Strategic Management Journal* (24:11), pp. 1107-1129.

Belsley, D. A., Kuh, E., and Welsch, R. E. 1980. *Regression Diagnostics: Identifying Influential Data and Sources of Collinearity*, New York: John Wiley and Sons.

Birkinshaw, J., and Sheehan, T. 2002. "Managing the Knowledge Life Cycle," *MIT Sloan Management Review* (44:1), pp. 75-83.

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

Brynjolfsson, E., Hitt, L. M., and Yang, S. K. 2002. "Intangible Assets: Computers and Organizational Capital," *Brookings Papers on Economic Activity* (1), pp. 137-198.

Burton-Jones, A., and Gallivan, M. J. 2007. "Toward a Deeper Understanding of System Usage in Organizations: A Multilevel Perspective," *MIS Quarterly* (31:4), pp. 657-679.

Burton-Jones, A., and Straub, D. W. 2006. "Reconceptualizing System Usage: An Approach and Empirical Test," *Information Systems Research* (17:3), pp. 228-246.

Caliendo, M., Clement, M., Papies, D., and Scheel-Kopeinig , S. 2012. "Research Note—The Cost Impact of Spam Filters: Measuring the Effect of Information System Technologies in Organizations," *Information System Research* (23:3, Part 2), pp. 1068-1080.

Choi, B., and Lee, J. N. 2012. "Complementarities and Substitutabilities among Knowledge Sourcing Strategies and Their Impact on Firm Performance," *Journal of the Association for Information Systems* (13:7), pp. 498-545.

da Cunha, J. V. 2013. "A Dramaturgical Model of the Production of Performance Data," *MIS Quarterly* (37:3), pp. 723-748.

Das, A. 2003. "Knowledge and Productivity in Technical Support Work," *Management Science* (49:4), pp. 416-431.

Davamanirajan, P., Kauffman, R. J., Kriebel, C. H., and Mukhopadhyay, T. 2006. "Systems Design, Process Performance, and Economic Outcomes in International Banking," *Journal of Management Information Systems* (23:2), pp. 65-90.

Dennis, A., and Vessey, I. 2005. "Three Knowledge Management Strategies: Knowledge Hierarchies, Knowledge Markets, and Knowledge Communities," *MIS Quarterly Executive* (4:4), pp. 399-412.

Devaraj, S., and Kohli, R. 2003. "Performance Impacts of Information Technology: Is Actual Usage the Missing Link?," *Management Science* (49:3), pp. 273-289.

Eisenhardt, K. M., and Martin, J. A. 2000. "Dynamic Capabilities: What Are They?," *Strategic Management Journal* (21:10-11), pp. 1105-1121.

Gallivan, M. J., Eynon, J., and Rai, A. 2003. "The Challenge of Knowledge Management Systems: Analyzing the Dynamic Processes Underlying Performance Improvement Initiatives," *Information Technology & People* (16:3), pp. 326-352.

Gilmour, D. 2003. "How to Fix Knowledge Management," *Harvard Business Review* (81:10), pp. 16-17.

Glazer, R. 1993. "Measuring the Value of Information: The Information-Intensive Organization," *IBM Systems Journal* (32:1), pp. 99-110.

Grant, R. M. 1996. "Prospering in Dynamically-Competitive Environments: Organizational Capability as Knowledge Integration," *Organization Science* (7:4), pp. 375-387.

Gray, P. H., and Meister, D. B. 2004. "Knowledge Sourcing Effectiveness," *Management Science* (50:6), pp. 821-834.

Gupta, A. K., and Govindarajan, V. 2000. "Knowledge Flows Within Multinational Corporations," *Strategic Management Journal* (21:4), pp. 473-496.

Haas, M. R., and Hansen, M. T. 2005. "When Using Knowledge Can Hurt Performance: The Value of Organizational Capabilities in a Management Consulting Company," *Strategic Management Journal* (26:1), pp. 1-24.

Haas, M. R., and Hansen, M. T. 2007. "Different Knowledge, Different Benefits: Toward a Productivity Perspective on Knowledge Sharing in Organizations," *Strategic Management Journal* (28:11), pp. 1133-1153.

Hansen, M. T., Nohria, N., and Tierney, T. 1999. "What's Your Strategy for Managing Knowledge?," *Harvard Business Review* (77:2), pp. 106-116.

Huber, G. P., and Daft, R. L. 1987. "The Information Environments of Organizations," in *Handbook of Organizational Communication,* F. Jablin, L. Putnam, K. Roberts and L. Porter (eds.), Newbury Park, CA: Sage Publications, pp. 130-164.

Kim, K. K., Shin, H. K., and Kong, Y. I. 2013. "Potential Complementary Knowledge, Collaborative Elaboration, and Synergistic Knowledge," *Asia Pacific Journal of Information Systems* (23:1), pp. 107-132

Kim, S. H., and Kim, B. C. 2014. "Differential Effects of Prior Experience on the Malware Resolution Process," *MIS Quarterly* (38:3), pp. 655-678.

Ko, D. G., and Dennis, A. R. 2011. "Profiting from Knowledge Management: The Impact of Time and Experience," *Information Systems Research* (22:1), pp. 134-152.

Kogut, B., and Zander, U. 1992. "Knowledge of the Firm, Combinative Capabilities, and the Replication of Technology," *Organization Science* (3:3), pp. 383-397.

Kohli, R., and Grover, V. 2008. "Business Value of IT: An Essay on Expanding Research Directions to Keep Up with the Times," *Journal of the Association for Information Systems* (9:1), pp. 23-39.

Levitt, B., and March, J. G. 1988. "Organizational Learning," *Annual Review of Sociology* (14), pp. 319-340.

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

Mithas, S., and Krishnan, M. S. 2009. "From Association to Causation via a Potential Outcomes Approach," *Information Systems Research* (20:2), pp. 295-313.

Mithas, S., and Whitaker, J. 2007. "Is the World Flat or Spiky? Information Intensity, Skills, and Global Service Disaggregation," *Information Systems Research* (18:3), pp. 237-259.

Mudambi, R. 2008. "Location, Control and Innovation in Knowledge-Intensive Industries," *Journal of Economic Geography* (8:5), pp. 699-725.

Mukhopadhyay, T., and Kekre, S. 2002. "Strategic and Operational Benefits of Electronic Integration in B2B Procurement Processes," *Management Science* (48:10), pp. 1301-1313.

Mukhopadhyay, T., Kekre, S., and Kalathur, S. 1995. "Business Value of Information Technology: A Study of Electronic Data Interchange," *MIS Quarterly* (19:2), pp. 137-156.

Mukhopadhyay, T., Lerch, F. J., and Mangal, V. 1997. "Assessing the Impact of Information Technology on Labor Productivity: A Field Study," *Decision Support Systems* (19:2), pp. 109-122.

Mukhopadhyay, T., and Mangal, V. 1997. "Direct and Indirect Impacts of Information Technology Applications on Productivity: A Field Study," *International Journal of Electronic Commerce* (1:3), pp. 85-100.

Mukhopadhyay, T., Rajiv, S., and Srinivasan, K. 1997. "Information Technology Impact on Process Output and Quality," *Management Science* (43:12), pp. 1645-1659.

Mukhopadhyay, T., Singh, P. V., and Kim, S. H. 2011. "Learning Curves of Agents with Diverse Skills in Information Technology-Enabled Physician Referral Systems," *Information Systems Research* (22:3), pp. 586-605.

Nahmias, S. 1977. "Ordering Perishable Inventory When Both Demand and Lifetime Are Random," *Management Science* (24:1), pp. 82-90.

Nayyar, P., and Bantel, K. 1994. "Competitive Agility: A Source of Competitive Advantage Based on Speed and Variety," in *Advances in Strategic Management* (Volume 10), P. Shrivastava, A. S. Huff, and J. E. Dutton (eds.), Greenwich, CT: JAI Press, pp. 193-222.

Nonaka, I. 1994. "A Dynamic Theory of Organizational Knowledge Creation," *Organization Science* (5:1), pp. 14-37.

Ofir, C., and Simonson, I. 2001. "In Search of Negative Customer Feedback: The Effect of Expecting to Evaluate on Satisfaction Evaluations," *Journal of Marketing Research* (38:2), pp. 170-182.

Ofir, C., and Simonson, I. 2007. "The Effect of Stating Expectations on Customer Satisfaction and Shopping Experience," *Journal of Marketing Research* (44:1), pp. 164-174.

Pee, L. G., Kankanhalli, A., and Kim, H. W. 2010. "Knowledge Sharing in Information Systems Development: A Social Interdependence Perspective," *Journal of the Association for Information Systems* (11:10), pp. 550-575.

Porter, M. E., and Millar, V. E. 1985. "How Information Gives You Competitive Advantage," *Harvard Business Review* (63:4), pp. 149-160.

Rosenbaum, P. R., and Rubin, D. B. 1983. "Assessing Sensitivity to an Unobserved Binary Covariate in an Observational Study with Binary Outcome," *Journal of the Royal Statistical Society Series B-Methodological* (45:2), pp. 212-218.

Smith, M. D., and Telang, R. 2009. "Competing with Free: The Impact of Movie Broadcasts on DVD Sales and Internet Piracy," *MIS Quarterly* (33:2), pp. 321-338.

Sorenson, O. 2003. "Interdependence and Adaptability: Organizational Learning and the Long-Term Effect of Integration," *Management Science* (49:4), pp. 446-463.

Staiger, D., and Stock, J. H. 1997. "Instrumental Variables Regression with Weak Instruments," *Econometrica* (65:3), pp. 557-586.

Stiroh, K. J. 2002. "Information Technology and the US Productivity Revival: What Do the Industry Data Say?," *American Economic Review* (92:5), pp. 1559-1576.

Straub, D., Limayem, M., and Karahanna-Evaristo, E. 1995. "Measuring System Usage: Implications for IS Theory Testing," *Management Science* (41:8), pp. 1328-1342.

Sung, T. K. 2008. "Competitive Advantage of IT and Effects on Strategy and Structure: Knowledge-Intensive vs.Manufacturing Industries," *International Journal of Technology Management* (41:3-4), pp. 359-378.

Sykes, T. A., Venkatesh, V., and Johnson, J. L. 2014. "Enterprise System Implementation and Employee Job Performance: Understanding the Role of Advice Networks," *MIS Quarterly* (38:1), pp. 51-72.

Szulanski, G. 1996. "Exploring Internal Stickiness: Impediments to the Transfer of Best Practice Within the Firm," *Strategic Management Journal* (17), pp. 27-43.

Tanriverdi, H. 2005. "Information Technology Relatedness, Knowledge Management Capability, and Performance of Multibusiness Firms," *MIS Quarterly* (29:2), pp. 311-334.

Teece, D.J., Pisano, G., and Shuen, A. 1997. "Dynamic Capabilities and Strategic Management," *Strategic Management Journal* (18:7), pp. 509-533.

Uzzi, B. 1997. "Social Structure and Competition in Interfirm Networks: The Paradox of Embeddedness," *Administrative Science Quarterly* (42:1), pp. 35-67.

Weill, P. 1992. "The Relationship Between Investment in Information Technology and Firm Performance: A Study of the Valve Manufacturing Sector," *Information Systems Research* (3:4), pp. 307-333.

Zuckerman, P. 1994. "America's Silent Revolution," *U.S. News & World Report* (117:3), p. 90.

About the Authors

Seung Hyun Kim is an associate professor of Information Systems at the School of Business, Yonsei University. He received his Ph.D. and M.S. from Carnegie Mellon University, and his bachelor's degrees in economics, applied statistics, and business administration from Yonsei University. His primary research interests include economics of information security, knowledge management, and mobile commerce. His work has been published in leading academic journals including *MIS Quarterly, Information Systems Research,* and *Communications of the ACM*.

Tridas Mukhopadhyay is Deloitte Consulting Professor of e-Business at Tepper School of Business and Carnegie Mellon University in Qatar. His research interests include strategic use of information technology, business value of information technology, eBusiness applications, and software development productivity. His recent papers examine enterprise blogging, virtual currency in digital games, e-mail advertising, and offshore software projects.

Robert E. Kraut is the Herbert A. Simon Professor of Human-Computer Interaction in the School of Computer Science and Tepper School of Business Carnegie Mellon University. He received his Ph.D. in Social Psychology from Yale University in 1973, and has previously taught at the University of Pennsylvania and Cornell University, and was a research scientist and manager at AT&T Bell Laboratories and Bell Communications Research. He has broad interests in the design and social impact of computing and computer-mediated communication. He conducts research on everyday use of the Internet, the design of online communities, technology and conversation, and collaboration in work groups.