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Digitizing Work: Driving and Measuring Changes in Information Worker Time Use and Performance Via a Longitudinal Quasi-Experiment

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DRIVING AND MEASURING CHANGES IN INFORMATION WORKER TIME USE AND PERFORMANCE VIA A LONGITUDINAL QUASI-EXPERIMENT

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Abstract

We study the causal effects of digitizing work on information workers' time-use and performance at a large insurance firm. We make causal inferences and obtain unbiased estimates by exploiting a quasi-experiment: the phased introduction of Electronic Document Management (EDM) across multiple offices at different dates. We apply a difference-in-differences methodology to econometrically measure changes in a suite of performance metrics. We further triangulate on the effects of digitizing work via three complementary research techniques: extensive onsite interviews before, during and after implementation; detailed time use diaries and observation; and a series of surveys. In addition to large changes in time-use and performance, we find that digitization leads to a decline in the substitutable routine labor input and an increase in complementary non-routine cognitive labor input. We uncover a new micro-level mechanism, "IT-enabled slack", that explains how exactly IT can lead to payoff in terms of information worker performance.

Keywords: EDM, electronic document management, time use studies, differences-in-differences, productivity, IT payoff

Introduction

Causal effects in fields such as medicine are often estimated using controlled experiments. This is less common in the social sciences because it is often difficult or extremely expensive to control the setting (often organizations) and treatment (often major technology investments and business process changes). In addition to obscuring causality, it is also difficult to estimate an unbiased return to the adoption of new technologies (or the "average treatment effect") without experimental data (Bartel et al 2004, p. 221). In this paper, we are able to report on results from a , a large quasi-experiment in which the time of application of the technology and process intervention (in our case electronic document management technology or EDM) to various entities (in our case the offices) is "as if" it was randomly determined i.e. in which randomness is introduced by variations in specific office circumstances such as timing of the implementation of the technology that makes it appear as if the technological treatment was randomly assigned to the offices. In the context of a quasi-experiment, we use a four-pronged research study to holistically assess the causal impact of an enterprise IT (EDM) on the workers compensation division of a large insurance firm. EDM technology is used to manage documents and is often categorized as an information management tool. EDM has been defined as the "application of technology to save paper, speed up communications, and increase the productivity of business processes" (Sprague 1995, p.29). EDM implementation is literally one of the most visible manifestations of the ongoing move from analog to digital organizations, as paper document and manual routing are replaced by digital documents that are managed electronically. Its salience derives from two facts: valuable information in organizations is stored in the form of documents such as reports, forms, memos, letters etc. and business processes are often driven by document flows (Sprague 1995). Despite its salience, EDM has not received much attention from IS researchers. To the best of our knowledge, no systematic empirical study exists that assesses the business value of EDM. This particular research attempts to fill that void by empirically assessing the impact of EDM using four complementary methods: 1) extensive on-site observation and interviews, 2) detailed time use records, 3) office-wide surveys, and 4) accounting data on multiple intermediate and final performance metrics. We are able to address following questions: what are the net time savings, if any, that are attributable to EDM? What is the task level impact of EDM? How does that task-level impact translate to performance gains? More generally, we try to answer the following questions: What is the impact of digitizing work on tasks at the information worker level? How does the task-level impact of IT translate to performance gains? What are the micro-mechanisms that lead to IT payoff?

The motivation and theoretical basis of our work stems from the explanation offered by Autor et al (2003) for the observed skill-biased technical change or the "computer-skills" complementarity, which is the strong correlation between computerization and demand for higher-educated or college-educated labor. We contribute to the IT business value literature by demonstrating using a detailed empirical study how digitization of work changes task composition at the individual information worker level. We thereby build upon the work by Autor et al (2003), who use higher-level (*industry level, occupation level and education group* level) data.

Kohli and Devaraj (2003) do a meta-analysis of several firm-level IT impact empirical studies and make several recommendations for future IT payoff studies, including use of primary data and use of larger samples of panel data to assess lagged effects of IT. Though their recommendations are made in the context of firm-level studies, we believe that the suggestions would apply well to even single-firm in-depth field research studies. In an effort to improve our understanding of the true impact of IT, we gather detailed primary data from eight offices in the large insurance company that rolled out the enterprise technology during the course of the study. Our data is also cross-sectional time series that allows us to assess the lagged effects of the new technology. Longitudinal data analysis had been recommended by many researchers to deepen our understanding of the impact of technology (Lucas, 1993; Brynjolfsson and Hitt, 1996; Dewan and Min 1997). Lack of consideration of lag effects has been pointed as a potential reason for the observed productivity paradox (Brynjolfsson and Hitt, 1996). Though there are a few studies that have analyzed primary longitudinal data and looked at the effects of specific IT applications over time (Peffers and Santos 1996; Devaraj and Kohli, 2000), given the diversity of IT applications, more research that uses primary longitudinal data to assess the trend of IT payoff or the lagged effects of IT is highly desirable. It is in this vein that our field research study contributes in one of many ways to the IT impact literature.

The impact of IT at the enterprise level can be measured more accurately by examining its contributions at the intermediate or process level (Barua et al 1995; Mukhopadhyay et al. 1997b; Tallon et al 2000) where first-order effects may be observed since IT is often implemented in support of specific activities and processes (Ray, Muhanna, Barney 2005). Further, a deeper understanding of IT impact can be obtained by looking at the impact of individual IT applications on specific processes and tasks (Mukhopadhyay 1997b, Athey and Stern (2002)). At the firm level, the real impact of IT may be obscured because of aggregation problems: some applications may have a positive impact on certain tasks and processes, while others may have negative impact on those tasks and processes (Kauffman and Weill 1989; Mukhopadhyay 1997b). The aggregation issues at the firm level combined with the fact that most investment decisions are made at the application level, it becomes important to look at the impact of individual IT applications (Mukhopadhyay 1997b). Our research contributes to the IT impact literature by looking at the impact of a specific IT application, EDM, not yet examined in depth in the existing economics of information systems literature and an application particularly important for information workers. Further, we contribute methodologically to the process perspective in the IS literature by using time use studies and differences-in-differences econometric analyses to assess the micro-level impact of EDM at the activity and process level. There are several research studies that analyze pre- and post-introduction of IT data to quantify the impact of IT. For example, McAfee (2002) and Cotteleer and Bendoly (2006) use pre vs. post analysis to look at the impact of ERP (Enterprise Resource Planning) application on process output or operational variables such as lead time. Mukhopadhyay et al (1997a) use pre vs. post analysis to look at the impact of IT on labor productivity in toll collection (or specifically labor hours to complete different types of toll transactions). Athey and Stern (2002) present a differences-in-differences analysis of the impact of IT (in their case enhanced 911 technology) on the timeliness of emergency responses. Given the spectacular variety of IT applications and the great need to document the precise causal impact of IT at a micro-level, there is a dearth of application-specific differences-in-differences empirical studies. Our research study contributes to the IT impact literature by doing a rigorous differences-in-differences econometric analysis of the impact of EDM. Further, in documenting the impact of digitization of work, we uncover a micro-level mechanism as to how IT can lead to payoff in terms of higher performance.

Theory and Hypotheses

The theoretical task model (Autor et al, 2003) is at the core of this research. According to the model, computerization has differential impact on different types of tasks. There are two types of tasks: routine and non-routine tasks. Routine tasks are those tasks that can be specified using a programmable set of instructions. Non-routine tasks on the other hand cannot be explicitly coded as a set of logical instructions, as the rules for performing these tasks are not clear. Routine and non-routine tasks are further classified as manual and analytic tasks. Examples of routine manual tasks include sorting and repetitive assembly, whereas routine analytic tasks include repetitive information-processing tasks such as calculations and record-keeping (Autor et al, 2003). Examples of non-routine manual tasks include driving a vehicle, cleaning, and mopping whereas non-routine analytic tasks include problem-solving and complex communications (Autor et al, 2003). Autor et al (2002) describe the kind of tasks that computers can do well: computers can perform tasks that can be fully described using procedural or rules-based logic i.e. “If-Then-Do” type of logic, which specifies the sequence in which tasks should be performed and what tasks need to be performed at different contingencies. Computers can however solve only “known problems”; they are not very good at responding to unexpected contingencies and they still do not have the capacity to do higher-order analytical and cognitive tasks that humans are good at (Autor et al 2002). Given the task framework and a description of the tasks that computers can do well, computerization and in our case digitizing work would have substantial substitution impact on routine tasks, both manual and analytic (Autor et al 2003). Computerization also “informates” (Zuboff, 1988) or in other words provides vast amounts of rich informational inputs, which can be very useful to information workers who typically have to employ higher-order cognitive skills to process the available information and make sense out of it. In this sense, computers complement information workers in their non-routine analytic tasks and can help them improve their productivity. As a concrete example, consider the availability of comprehensive online bibliographic searches for legal research: though this facility has greatly increased the information available for consumption, it has undoubtedly also positively impacted the quality of the research (Autor et al 2003).

With falling prices of computer technology and the strong substitutability of programmable tasks, there are economic pressures to substitute computers for humans in those routine tasks (Autor et al 2002). In their study of impact of digital check imaging on check processing at a bank, Autor et al (2002) demonstrate the loss of programmable or “routine” jobs held by high-school graduates when the new technology is introduced. At the same time, due to the strong complementarities between computerization and non-routine analytic tasks, increasing digitization of work should lead to higher demand for non-routine analytic labor input. Autor et al (2003) demonstrate at the *industry level, occupation level and education group* level that computerization is associated with reduced labor input of routine tasks (both manual and cognitive) and increased labor input of nonroutine cognitive (or analytic) tasks. We demonstrate in this research the same effect at the *individual information worker level* i.e. we demonstrate using a detailed empirical study how digitizing work changes task composition at the individual level. We test the hypothesis that digitization of work would lead to a decline in the substitutable routine labor input and an increase in non-routine cognitive labor input at the information worker level. Thus, we test whether non-routine cognitive labor input is a complement to digitization of work at the information worker level. We also assess at the individual level whether increases in the supply of routine informational inputs [made available thanks to digitization of work], both in quantity and quality, increase the performance of workers performing nonroutine tasks that demand those inputs (Autor et al 2003, p. 1285).

In our field research setting, we examine the impact of introduction of EDM on the task composition at the individual level. Prior to EDM, the information workers in our setting would need to supply a significant amount of routine labor input for their work. Pre-EDM, the information workers would need to type verbatim large sections of documents such as medical reports that were available only in paper form. Post-EDM, the paper documents were all scanned and made available in the electronic form. This obviated the need for the information workers to transcribe the paper documents. Thus, EDM directly impacted the supply of routine labor input, which was substituted away by the document management technology. Further, pre-EDM information workers would transcribe only certain sections of the documents that they deemed salient for their work purposes i.e. information in the paper documents was not completely captured. Information workers exercised significant discretion in deciding which pieces of information to type in verbatim into the information capture system, simply because there was not enough time in the day to transcribe complete copies of the documents. Information workers would apply different lenses to look at the same document. Thus, pieces of information interpreted to be important by one information worker may not be captured by another worker, who interpreted them to be less important. The incomplete information entered into the system was thus of a lower quality. Post-EDM, complete copies of the documents were available in electronic form. No information was lost. In other words, post-EDM, both the *quantity and quality* of routine informational inputs significantly increased. Since we hypothesize that increased supply of routine informational inputs should improve the performance of information workers who demand these inputs for their non-routine cognitive tasks (Autor et al 2003), we test the impact of shift in task composition of the workers on performance metrics.

In demonstrating a task shift at the information worker level, we also unpack the black box of IT impacting performance. We uncover a new mechanism as to how exactly IT can lead to significant payoff, especially in terms of information worker performance. A prominent model of IT payoff that tries to explain the mechanisms that lead to payoff from IT investments from a process point-of-view is the one proposed by Soh and Markus (1995). According to this model, investments in IT applications, skills, and projects represent creation of IT assets, which in turn if successfully deployed lead to IT impacts such as improved coordination and decision-making, and IT impacts at strategic points in the organization lead to higher organizational effectiveness (Soh and Markus, 1995; Devaraj and Kohli, 2000). It is well known that IT can help reduce cost, improve quality, or increase revenues; however, the micro-level mechanisms as to how IT helps achieve those impacts are often unclear. We show how IT can reduce time spent on certain activities and in reducing the time to complete those tasks, how it makes time available to do other value-adding tasks that involve interaction and higher-order cognitive and analytic skills. Without the introduction of IT, there would not be sufficient time to "pack" in many value-adding tasks in the workday. The routine labor tasks may often be necessary to do the non-routine labor tasks i.e. the routine labor tasks may not be ignored to make time for additional non-routine labor tasks. However, with the deployment of IT, some "slack" may develop, which would allow the information worker to "pack" in more units of value-adding tasks. This "IT-enabled slack" is the new construct that we propose to add to the literature. "IT-enabled slack" can lead to performance enhancements in two distinct ways: first, as described above, the slack allows information workers to spend more time on value-adding activities. These activities directly lead to performance improvements. Secondly, "IT-enabled slack" may allow for more personal time relaxing/resting at work or at home (less overtime), which in turn may lead to improvements in performance (Hamermesh, 1990). Just as Hamermesh (1990, p. 132-S) claims, "additional time spent in on-the-job leisure at least partly represents unproductive shirking rather than productive schmoozing," it is unlikely that all of the "on-the-job leisure" is productively used. That claim notwithstanding, from our interviews and econometric analyses, it does seem that the additional on-the-job leisure time leads to less stressed-out, happier and more productive employees.

Research Methodology and Data Collection

Since we were interested in the impact of EDM on information work, we focused our energies in our data collection and analysis efforts on the main information workers in the workers compensation division of the insurance company (whose name is withheld for confidentiality purposes). These information workers are called *case adjusters* or *case managers* and they handle insurance claims related to injuries suffered by employees on the job. The case managers refer to the injured employee as the *claimant* and the company in which the injured employee (IE) works and which has a service contract with the insurance company as the *customer*. Our primary research site was a single large office, where we focused most of our energies.

We conducted 17 unstructured interviews pre-EDM and 20 interviews post-EDM at various organizational levels (Operations Manager, Claims Manager, Team Manager, Case Manager, Nurses) in the office. The first set of interviews were conducted in the last week of March (2006) and the second set of interviews were conducted in the third week of August (2006). During the interviews, we focused on obtaining qualitative insights about the impact of EDM. Specifically, we wanted to know how case managers perceived personal and company benefits/costs of EDM, behavioral effects of EDM and EDM-related process changes, and how any time anticipated to be saved by EDM was re-allocated.

We also conducted office-wide self-reported time use studies at three different time points (one pre-EDM and two post-EDM) to give us a longitudinal sample of self-captured activity profiles of case managers. Pre-EDM time use study was conducted in the last week of March (2006) and post-EDM time use studies were performed in last week of August (2006) and in the second week of February (2007), approximately 4 and 10 months after EDM was implemented in the office (implementation period: April 20-24, 2006). With assistance from an internal team at the firm, we prepared a complete list of activities (or tasks) that would be performed by the case managers throughout the day. We invited a few managers and case managers to verify that the activity list was reasonably exhaustive. Case managers were asked to record every 10 minutes three pieces of information for each observation: approximate time of observation, category code (9 category codes capture main categories of activities), and activity code (each category contains several activities). We requested case managers to also record for each observation short descriptive details (notes) on the activity. This would allow us to correct any miscoded activities, provided the notes column was filled out accurately and with sufficient detail. 53 case managers yielded ‘usable’ activity data in the pre-EDM time use study. Case managers were excluded from the data set unless they had at least 40 ‘valid’ observations recorded throughout the day. ‘Valid’ observations are those that have both activity code and category code specified. 46 and 56 case managers yielded ‘usable’ activity data in the post-EDM (t=1) and post-EDM (t=2) study, respectively. However, because of absenteeism or non-availability of case managers due to job training on the day or inability to record at least 40 valid observations, there can be case managers that are not common across the pre-EDM and post-EDM time use datasets. For more usable comparison, we constructed a matched data set that included pre- and post-EDM data from case managers common to the three time use datasets. The matched data set contains 26 case managers. Note that the data was scrubbed where possible to reduce coding mistakes.

We further performed a much smaller direct observations time-use study for a group of 4 case managers, all residing in a physical ‘pod’ configuration and all handling a single customer’s account at the office. All four case managers in this time use study were observed personally by one of the researchers. The pre-EDM time use study was conducted in the last week of March (2006) and post-EDM time use studies were performed in the last week of August (2006) and first week of February (2007), approximately 4 months and 10 months after EDM was implemented in the office (April 20-24, 2006). The observations here were recorded every 12 minutes instead of every 10 minutes as in the office-wide time use study because only a single researcher was recording observations for all the four case managers in the pod. The time use study yielded a matched data set for 4 case managers at three points in time: pre-EDM, post-EDM(t=1) and post-EDM(t=2). Since case managers are expected to create what is called a ‘journal entry’ or an electronic record in an IT application called “ExPRS” after completing any significant activity, the journal entries are an electronic trail of their activities and analysis of the journal entry data can yield useful insights into distribution of activities of case managers Specifically, the journal entry data allows us to see the types of journal entries recorded by each of the case managers throughout the day. To validate our observations with objectively recorded data, we obtained journal entry data for the four case managers pre-EDM and post-EDM (t=1). This data allowed us to cross-check the observational data against hard, objective data recorded by the IT systems at the company. Overall, the self-reported as well as the direct observations time use studies helped us to assess the impact of EDM on the time allocated by employees to various activities at work and to evaluate the efficiency gains in terms of net time savings attributable to EDM.

We also administered to case managers two structured questionnaires (one pre-EDM survey and the other post-EDM survey) consisting of five sections, each containing several questions. The first four sections contained questions for which quantitative data or choice answers were requested. The last section contained open-ended questions written to gather qualitative data. The surveys were on the longer side (30 minutes to answer the survey) and were anonymous. 42 case managers responded to the pre-EDM survey. 66 case managers responded to the post-EDM survey. Thus, the pre-EDM survey and the post-EDM survey represented response rates of 57.5% (42/73) and 91.7% (66/72) respectively. The missing survey responses can be attributed to the length of the survey as well as to absenteeism. The survey instrument helped us to assess quantitatively and qualitatively the *perceived* impact of EDM (some key results are mentioned on page 10 in the survey data analysis sub-section).

We collected cross-sectional monthly data for the performance metrics for eight offices of the insurance company for the time period (Jan 2005 through Dec 2006) i.e. we have for most metrics, 24 months of data for the eight offices, in which EDM was rolled out at several points in time from Oct 2005 through Apr 2006. The specific dates for rollout of the EDM technology in the different offices were: **Office Code: 390** – October, 2005, **Office Code: 205** – February 2006, **Office Code: 555** – February 2006, **Office Code: 471** – March 2006, **Office Code: 413** – March 2006, **Office Code: 648** – March 2006, **Office Code: 608** – April 2006, **Office Code: 949** – May 2006

We looked at the following performance metrics:

Current Yr Closure Rate: Measures the % of claims closed that were opened in the current calendar year (CY).

Previous Year Closure Rate: Measures the % of claims closed that were opened in years prior to the current CY.

YTD Average Physical Therapy Paid Amount Per Claim: Measures the amount spent per claim on physical therapy costs.

YTD Average Chiropractor Paid Amount Per Claim: Measures the amount spent per claim on chiropractor care costs.

Retention Rate: Measures the case manager retention rate.

YTD Loss Leakage: Measures the total loss payout on the claims. Losses are defined as additional expenses that should not have been incurred on claims if best practices associated with medical management and disability management processes had been properly followed by the case managers.

Rolling12-months TTD Days: Measures the number of days of temporary total disability or number of days that a claimant is absent from work due to a work-related injury and is paid disability benefits.

We also collected cross-sectional monthly data for several other office-level cost metrics; however due to space considerations, we omit description and the analysis done on that data. Differences-in-differences econometric analyses on the objective performance data allowed us to isolate the causal impact of EDM on performance.

Data Analysis and Results

EDM Impact on Time Use: Four Case Managers/Single Customer Time Use Data Analysis

The four case manager time use study yielded a matched dataset of 149 observations pre-EDM, 153 observations post-EDM (t=1) and 175 observations post-EDM (t=2). A detailed pre- and post-EDM activity comparison for the UPS case managers is presented in Table 1. Each of the activities in the table is labeled as part of one of 10 activity groups in column 6: DOC PAPER, ACTIONPLAN, OTH DOC, OTH CASEMGMT, COMM, MEETING, OTH PAPER, EDM, OTH FILEWORK, PERSONAL. These activity groups described below are very useful in the analyses below. Note all % reported in Table 1 are arithmetic means or averages. The total time spent on each activity group is reported in column 7 (pre-EDM) and column 9 (average of post-EDM (t=1) and post-EDM (t=2)).

From the pre-EDM time-use data, we observe that on average 21.3% of the time of the case managers was spent documenting paper mail and paper faxes (a form of *routine labor input*) (see DOC PAPER activity group in table). Assuming that the case managers work for 8hrs and 15 minutes, this translates to approximately 1hr and 48 minutes or 108 minutes spent daily documenting paper mail & paper faxes. This form of documentation activity disappeared post-EDM as paper documents previously required to be typed in verbatim were now scanned in and available electronically i.e. 0% of the time post-EDM was spent documenting paper & paper faxes. Paper-related activity (excluding documenting paper mail & paper faxes) went down dramatically from 9.1% to 2.1% (see OTH PAPER activity group).

Table 1. Mean Time Use analysis on matched sample N=4 Single Customer Case Managers

**Note all % are means or arithmetic averages*

		PRE-EDM (N=4)					POST-EDM avg of (t=1) (N=4), (t=2) (N=4)	
Org. Category	**Activity**	**cat.**	**act.**	**activity%**	**ACTIVITY GROUP**	**%**	**ACTIVITY GROUP**	**avg %**
Doc	Sorting Incoming Mail	1	1	1.3	OTH PAPER			
Doc	Documenting Paper Mail + Paper Faxes	2	1	21.3	DOC PAPER	**21.3**	**DOC PAPER**	**0.0**
Doc	Documenting Action Plan/Initial Assessment	2	3	6.6	ACTIONPLAN	**7.2**	**ACTIONPLAN**	**10.9**
Doc	Writing Journal Entries	2	4	9.1	OTH DOC	**9.7**	**OTH DOC**	**9.0**
Doc	Financial Notes	2	5	1.9	OTH CASEMGMT	**7.3**	**OTH CASEMGMT**	**9.4**
Comm	Phone	3	1	22.5	COMM	**28.4**	**COMM**	**39.1**
Comm	Voicemail	3	2	1.3	COMM			
Comm	E-mail	3	3	4.7	COMM			
Comm	In-person meeting	3	4	2.5	MEETING	**2.5**	**MEETING**	**7.0**
Comm	Sending Paper Fax	3	5	0.6	OTH PAPER	**9.1**	**OTH PAPER**	**2.1**
Comm	Putting Together Paper Items to Mail / Fax	3	7	0.6	OTH PAPER			
Comm	Manage EDM Inbox (Complete/Forward Notifications)	3	9	0.0	EDM	**0.0**	**EDM**	**8.3**
Filework	Accessing Paper File	4	1	0.6	OTH PAPER			
Filework	File Sorting/Removing Duplicates	4	2	0.0	OTH PAPER			
Filework	Copying Files	4	3	1.3	OTH PAPER			
Filework	Electronic Formwork	4	4	1.3	OTH FILEWORK	**2.6**	**OTH FILEWORK**	**0.6**
Filework	Paper Formwork	4	5	0.0	OTH PAPER			
Filework	Payments	4	6	1.3	OTH CASEMGMT			
Filework	Printing from Systems (ExPrs, EDM, Etc.)	4	7	1.3	OTH PAPER			
Filework	Closing File from System	4	8	1.3	OTH FILEWORK			
Filework	Accessing EDM File	4	9	0.0	EDM			
Filework	Dragging & Dropping documents/right-faxes to EDM	4	11	0.0	EDM			
Filework	Complete EDM Document Properties	4	13	0.0	EDM			
Case Mgmt	RTW Plans	5	6	0.6	ACTIONPLAN			
Case Mgmt	Making decision to accept/reject referral	5	9	0.0	OTH CASEMGMT			
Case Mgmt	Medical Management	5	8	4.1	OTH CASEMGMT			
Case Mgmt	Recording Statements	5	11	0.0	OTH CASEMGMT			
Case Mgmt	Documenting Claim Screen / Details	5	12	0.6	OTH DOC			
Case Mgmt	Reviewing Paper Files	5	13	1.6	OTH PAPER			
Case Mgmt	Reviewing EDM Files	5	14	0.0	EDM			
Personal	Break	6	1	1.9	PERSONAL	**11.3**	**PERSONAL**	**12.4**
Personal	Lunch	6	2	9.4	PERSONAL			
Personal	Other	6	4	0.0	PERSONAL			
Administration	Printing / Stapling Incoming Right Faxes	7	1	0.6	OTH PAPER			
Administration	Drop Filing (both picking out and putting away docs)	7	8	1.3	OTH PAPER			
Other	Other Task	9	1	0.6	OTHER			

As seen from Table 1, the key result is that the level of documentation activity went down dramatically and time spent documenting seems to have been re-allocated towards significantly higher communication activity (a *non-routine cognitive labor input*). The documentation activity (composed of 'DOC PAPER' and 'OTH DOC' activity groups or specifically, documenting paper mail and paper faxes, writing electronic journal entries, documenting claim screen/details) went down from 31% to 9% (a reduction of 71%), whereas communication activity ('COMM' activity group or specifically phone/voicemail/e-mail activities) or a form of *non-routine cognitive labor input* went up from 28.4% to 39.1% (an increase of 38%). In particular, phone-based communication went up from 22.5% to 31.5% (an increase of 40%). Post-EDM, time on other value-adding, non-routine activities involving critical thinking went up. Specifically, time spent on in-person meetings (see 'MEETING' activity group in Table 1) went up from 2.5% to 7.0% and time spent on writing/updating action plans (see 'ACTIONPLAN' activity group in Table 1) went up from 7.2% to 10.9%. EDM also introduced new activities in the post-EDM time use data. These EDM-related activities identified as part of the 'EDM' activity group in Table 1 took 8.3% of the time post-EDM. Of this 8.3%, 4.3% was devoted to new activities that had no close pre-EDM counterparts. Specifically, 4.3% of time was devoted to managing EDM inbox (which much like an e-mail inbox was continuously populated with new documents scanned into the system), uploading documents to EDM (case managers were supposed to upload electronically faxed documents to EDM themselves) and completing EDM document properties (each EDM document had seven identifying properties for case managers to fill in). Personal activities (see 'PERSONAL' activity group in Table 1) went up from 11.3% to 12.4% (an increase of about 10%). Specifically, the activities in this group were personal break, lunch, and other personal time-off at work. EDM introduced some potentially performance-enhancing, stress-reducing *slack* that is captured in the increase in the personal activities. Notably, the time use study would fail to capture the time spent at home by case managers on work-related activities such as documenting paper. From interviews, we did find that pre-EDM, many case managers were taking paper documents home to catch up on their document posting activity; however this was eliminated with the introduction of EDM: case managers that we talked to agreed that EDM cut down on overtime as well as on time spent doing office-related work at home. In other words, EDM introduced considerable "slack" in the work lives of the case managers.

To validate the results based on observational data from the time use study, we next analyzed the computer-captured 'journal entry' data for each of the four case managers for the pre-EDM and post-EDM (t=1) days they were observed. As mentioned earlier, case managers were expected to create what is called a 'journal entry' after completing any significant activity; the journal entries are thus an electronic trail of their activities. The results were striking and validated the observations made by us in the time use study. Specifically, we observed that paper medical report transcription activity (a *routine labor input*) for all case managers dramatically dropped. For all but one case manager, the activity was eliminated post-EDM. This would validate our observation from the time use study that documentation activity dropped significantly post-EDM. The total number of physician or claimant or customer contact journal entries increased substantially from pre-EDM to post-EDM. This would validate our observation from the time use study that communication activity increased significantly post-EDM. The results of the analysis on the journal entry data are graphically shown in Figure 1. Note that the "Physician + Claimant + Customer Contacts" chart (on the right side of the figure) aggregates the information in "Physician Only", "Claimant Only" and "Customer Only" Contact data, which is not shown below for brevity. The disaggregated data showed that communication contacts to each of the parties (physician, claimant, customer) in general increased post-EDM.

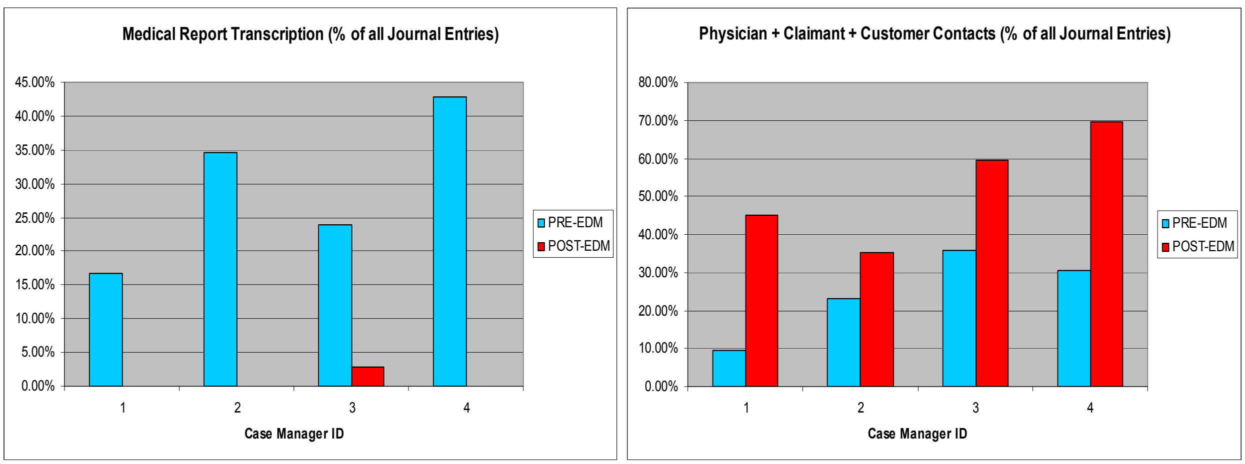

Figure 1. Pre-EDM vs. Post-EDM Journal Entries (4 Case Manager/Single Customer Pod)

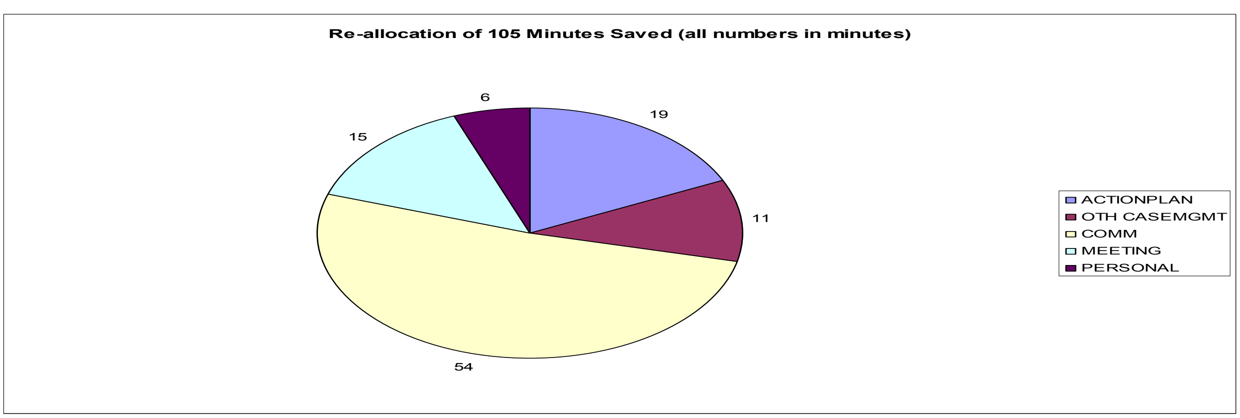

Figure 2. Re-Allocation of Net Time Savings (4 Case Manager/Single Customer Pod)

Next, we compute using the time use data the time savings that may be attributable to EDM and how the time saved is reallocated by the case managers. The net EDM-related time savings from this small case manager study seems to be at least 105 minutes. This corresponds to 20% of 505 minutes available in the entire workday. We arrive at 20% as follows (note gains/losses based on average of post-EDM (t=1) and post-EDM (t=2) compared with pre-EDM): reduction in documenting paper mail & paper faxes (gain of 21.3% or 108 minutes), reduction in paper-related activities (gain of 7% or 35 minutes), reduction in other documentation activity (gain of 0.7% or 4 minutes), and increase in EDM-specific activities (loss of 8.3% or 42 minutes). The 105 minutes (105=108+35+4-42) saved on account of EDM seems to be reallocated as follows (note average of post-EDM (t=1) and post-EDM (t=2) used below): more time on action plans (see ACTIONPLAN activity group in Table 1) (19 mins), more time on other case mgmt (such as financial notes (eg. reserving), payments, medical case management activity, recording statements) (see OTH CASEMGMT activity group) (11 mins), more time on communication activity (i.e. phone/e-mail/voicemail) (see COMM activity group) (54 mins), more time on in-person meetings (see MEETING activity group) (at least 15 mins) and more personal time (see PERSONAL activity group) (at least 6 mins). This is shown graphically in Figure 2.

EDM Impact on Time Use: Office-Wide Case Manager Time Use Data Analysis

The office-wide case manager time use study yielded a matched dataset of 2905 observations pre-EDM, 2763 observations post-EDM (t=1) and 3125 observations post-EDM (t=2). From the pre-EDM time-use data, we observed that on average 7.8% of the time of the case managers was spent documenting paper mail and paper faxes (a form of *routine labor input*). Assuming that the case managers work for 8hrs and 15 minutes, this translates to approximately 39 minutes spent daily documenting paper mail & paper faxes. This form of documentation activity reduced to 1.8% post-EDM, a reduction of 77%. This is generally consistent with what was observed in the four case manager time use study. Paper-related activity (excluding documenting paper mail & paper faxes) went down dramatically from 7% to 4.8%, a reduction of 31%. This is also consistent with what was observed in the four case manager time use study.

The key result again is that the level of documentation activity went down dramatically and time spent documenting seems to have been re-allocated towards significantly higher communication activity (a *non-routine cognitive labor input*). The documentation activity (composed of 'DOC PAPER' and 'OTH DOC' activity groups or specifically, documenting paper mail and paper faxes, writing journal entries, documenting claim screen/details) went down from 21.3% to 11.5% (a reduction of 46%), whereas communication activity ('COMM' activity group or specifically phone/voicemail/e-mail activities) went up from 26.4% to 32.5% (an increase of more than 23%). In particular, phone-based communication went up from 19% to 22.5% (an increase of 18%). The above results are again consistent with what was observed in the four case manager time use study.

As observed in the four case manager time use study, EDM introduced new activities in the post-EDM office-wide time use data. These EDM-related activities identified as part of the 'EDM' activity group took 7.6% of the time post-EDM. Personal activities went up from 10.9% to 13.7% (an increase of 26%). Specifically, the activities in this group were personal break, lunch, and other personal time-off at work. EDM introduced some potentially performance-enhancing, stress-reducing slack that is captured in the increase in the personal activities. Time spent on in-person meeting activity went down from 10.9% to 5.3% (decrease of 51%). This is *not* consistent with what was observed in the four case manager time study, where an increase in in-person meeting activity was observed. However, given that all employees, including managers, had online access to documents post-EDM, there would be need for fewer in-person meetings.

For completeness, we also performed the mean time use analysis on the full sample of case managers. We have 53 case managers in the pre-EDM time use study, 46 managers in post-EDM (t=1) time use study and 56 case managers in the post-EDM (t=2) time use study. The results (not shown for lack of space) were consistent with what was observed in the matched sample. Since means can be subject to outlier-effects, we performed various other analyses to check the robustness of our main results. Specifically, we computed medians of times spent on various activities and also performed non-parametric analysis (or counts analysis) on the activities. All of these confirmatory analyses (not shown here for brevity) were broadly consistent with the mean analysis discussed above.

Next, we compute using the office-wide time use data the time savings that may be attributable to EDM and how the time saved is reallocated by the case managers. The net EDM-related time savings from this small case manager study seems to be at least 51 minutes. This corresponds to 10.1% of 505 minutes available in the entire workday. We arrive at 10.1% as follows (note gains/losses based on average of post-EDM (t=1) and post-EDM (t=2) compared with pre-EDM): reduction in documenting paper mail & paper faxes (gain of 6% or 30 mins), reduction in paper-related activities (gain of 2.2% or 11 mins), reduction in other documentation activity (gain of 3.9% or 20 mins), reduction in in-person meeting activity (gain of 5.6% or 28 mins) and increase in EDM-specific activities (loss of 7.6% or 38 mins). The 51 minutes (51=30+11+20+28-38) saved on account of EDM seems to be reallocated as follows (note average of post-EDM (t=1) and post-EDM (t=2) used below): more time on communication activity (i.e. phone/e-mail/voicemail) (see COMM activity group) (31 mins), more time on other case mgmt (such as financial notes (eg. reserving), payments, medical case management activity, recording statements of claimants) (see OTH CASEMGMT activity group) (3 mins), and more personal time (see PERSONAL activity group) (17 mins).

When we examine data from our time use study of four case managers, we find a net time savings of 105 minutes per day attributable to EDM. In contrast, when we analyze data from the office-wide time use study in which we have a matched sample of 26 case managers, we obtain a net time savings of 51 minutes. Each result comes with its own set of caveats: the larger time use study result is based on a larger data sample and hence is potentially statistically more reliable; however, the observations there are recorded by the employees themselves and it is not possible to ascertain that the same standard of judgment has been used to code the various activities. Although we requested case managers to document comments for each of the activities on the observation sheets, the instructions were not always followed. Further, case managers varied in their diligence in recording reasonably detailed comments for the activities. Both of these factors limited our ability to correct mis-codings. The difference between the net time savings numbers largely stems from the difference in the pre-EDM times spent on documenting paper mail and paper faxes in the two time use studies. While the pre-EDM four case manager time use study indicated that 21.3% of time was spent on documenting paper mail and paper faxes, the office-wide time use study indicated that only 7.8% of time spent on the same activity. This number is critical to the net time savings calculations. In our efforts to find out the reason behind the discrepancy, we found out that many case managers were simply not posting medical documents as they did not have enough time at work; they would simply send the paper documents to paper file upon receipt. Many case managers would not do paper medical document transcription at work during regular hours: some would stay overtime or do it at home. These factors would directly impact the time recorded for the particular documentation activity in the pre-EDM state. The four case manager study, albeit small, is potentially more accurate as all observations were taken by a single person and hence calibration error is minimized. In addition, the pre-EDM survey indicated that the average time spent transcribing paper medical reports was 103 minutes, which was much closer to what was observed in the smaller time use study.

EDM Impact on Time Use: Survey Data Analysis

The survey provided useful data to triangulate the results of EDM impact on time use as well as data to assess EDM-related time savings that would not be easy to capture through a time use study. According to the pre-EDM survey, the average time spent transcribing paper medical reports was 103 minutes, which corresponded remarkably well with what was observed in the four case manager time-use study. Post-EDM the time spent typing in medical reports declined to 17 minutes, a statistically significant change (Note we tested statistical significance of difference between pre-EDM and post-EDM numbers obtained from the surveys using two-sample unequal variance t-test). The number of times per week a case manager would need to go to the filing area to retrieve a paper file declined from 6.3 (pre-EDM) to 2.3 (post-EDM), a statistically significant decline. Notably, the time to search for the desired document in the electronic claim file is only 20.7 seconds as opposed to 18.2 minutes pre-EDM with paper files. The number of paper faxes that a case manager would send per week (a time-consuming process) declined from 9.2 (pre-EDM) to 4.7 (post-EDM), a statistically significant decline. The above survey results on perceived time savings are broadly consistent with the time savings observed in the time use studies. Further, these results amplify the time savings attributable to EDM obtained through analysis of time use data, as the time use methodology may fail to capture savings such as those related to searching or sending paper faxes.

Econometric Analyses

As mentioned in the Introduction, we have here in this field research study a large quasi-experiment, in which the time of application of the intervention (in our case the EDM technology) to various entities (in our case the offices) is "as if" it was randomly determined i.e. in which randomness is introduced by variations in specific office circumstances such as timing of the implementation of the technology that make it appear as if the technological treatment was randomly assigned to the offices. Although the first office where EDM was implemented was consciously chosen on the basis of its size and performance (it was a large and reasonable, although not top, performer), the timing of implementation at remaining offices was chosen in a random fashion with no systematic procedure or criteria used to determine the sequence of implementation. This allows us to use the OLS (Ordinary Least Squares) regression technique to assess the causal impact of EDM by incorporating the treatment variable as a regressor in the model. If the treatment variable is "as if" randomly determined, OLS is an unbiased estimator of the causal effect (Stock and Watson, 2007). Specifically, we use the differences-in-differences regression technique to isolate the impact of EDM intervention on various performance metrics. Differences-in-differences (D-in-D) is an effective technique to isolate the effect of an intervention/treatment (such as the introduction of a new technology) on the dependent variable of interest. The D-in-D estimator is the difference between the "average change in the variable of interest for the treatment group or the group that received the technological intervention" minus "the average change in the variable of interest for the control group or the group that did not receive the technological intervention." We use time fixed effects as well as office fixed effects in testing whether EDM (or treatment which appears as an independent variable in the regression) has any impact on the performance metric (or the dependent variable). The inclusion of office fixed effects and time fixed effects removes omitted variable bias resulting from exclusion of unobserved variables that vary across offices but are constant over time and variables that vary over time but are constant across offices. The mathematical representation of the general model that we estimate is presented below:

$$Y_{it} = \beta_0 + \beta_1 X_{it-l} + \beta_2 \mathbf{W}_{it} + \gamma_2 D2_i + \ldots + \gamma_n Dn_i + \delta_2 B2_t + \ldots + \delta_{12} B12_t + \eta CY + u_{it}$$

where $\beta_0, \beta_1, \beta_2, \gamma_2, \ldots, \gamma_n, \delta_2, \ldots, \delta_{12}, \eta$ are regression coefficients that need to be estimated, i = 1,2,…,n indicates the office, t = 1,2,…, 12 indicates the monthly time period, Y is the dependent variable, X_{it-l} is the binary treatment variable X_{it} lagged 'l' periods (X_{it} equals 1 if office i has received the treatment by time t and zero otherwise), $\mathbf{W}_{it}$ is a vector of pertinent control variables, $D2_i \ldots Dn_i$ are the binary variables for the offices, $B2_t \ldots B12_t$ are the binary variables for the months (to control for seasonal time effects), CY is the binary variable for the calendar year which equals 1 for year 2006 and u is the error term. Note binary variables for office 1 and time period 1 are excluded from the regression model to eliminate perfect multi-collinearity. Also note that the treatment variable in the model is lagged as appropriate, as EDM may have the maximum impact on a particular metric after some time. The exclusion of seasonal (time) effects and the use of the lagged treatment variable makes the actual timing (or month) of implementation not important in the estimation of the coefficient on the treatment variable. We essentially compare the performance metric trend pre-EDM and post-EDM taking into account potential lagged impact, after excluding office effects and seasonal time effects. The lags may differ for different models as EDM may be expected to impact different metrics at different time periods. Note that the above model looks quite similar to a fixed effects model; the differences-in-differences feature of the model arises from the use of the binary treatment variable X_{it} (Stock and Watson, 2007).

We found that introduction of EDM was associated with the following effects on the performance metrics (Table 2):

1) improvement in ability to meet or beat current year closure rate monthly goals that are dynamic in nature. This effect is observed at a 1-period lag and is statistically significant. (number of observations N=192). The logistic regression result implies that EDM increased the predicted log odds of meeting/beating current year closure rate goals by 1.78. Equivalently, EDM multiplied predicted odds of meeting/beating current year closure rate goals by e1.78=5.93.
2) increase in the current year closure rate. This effect observed at a 1-period lag is however not statistically significant (number of observations N=192). The regression result implies a 0.9% increase in the current year closure rate associated with the implementation of EDM in the offices.
3) decrease in the previous clear closure rate. This effect observed at a 1-period lag is however not statistically significant (number of observations N=184).
4) decrease in the YTD avg. amount paid for physical therapy on a per-claim basis. This effect observed at a 3-period lag is significant at the 1% level (number of observations N=176). The regression result implies a reduction of $111 or 19% drop in the YTD average amount paid for physical therapy on a per-claim basis that is associated with the implementation of EDM in the offices.
5) decrease in the YTD avg. amount paid for chiropractor care on a per-claim basis. This effect observed at a 2-period lag is significant at the 1% level (number of observations N=176). The regression result implies a reduction of $154 or 28% drop in the YTD average amount paid for chiropractor care on a per-claim basis that is associated with the implementation of EDM in the offices.

6) increase in the claim service team professionals (or case managers) retention rate. This effect observed at a 1-period lag is significant at the 1% level (number of observations N=168). The regression result implies a 7% increase in the retention that is associated with the implementation of EDM in the offices.
7) decrease in YTD loss leakage (i.e. losses associated with leakage or overpayments when best practices associated with medical management and disability management are not followed). This effect observed at a 4-period lag is however not statistically significant (number of observations N=176). The regression result implies a 4% decrease in the loss leakage that is associated with the implementation of EDM in the offices.
8) increase in TTD days (12 months rolling average) (i.e. number of days of temporary total disability for which disability benefits have to be provided). This effect is observed at a 4-period lag and is statistically significant at the 5% level (number of observations N=192). The point estimate though statistically significant implies only a 2% increase in TTD days that is associated with the implementation of EDM.

The detailed fixed effect pooled regressions are shown in table 2. The variable names used in the models (see table 2) are: EDM TREAT, which is the binary treatment variable appropriately lagged, TOT. STAFF, which is the total claim processing staff strength of the office, INC. CLAIM, which is the total number of incoming claims. Note that we do not show the office dummies for sake of confidentiality.

The above effects of EDM on various performance metrics are consistent with expectations. Although the effect of EDM on the current year closure rate is not statistically significant, the point estimate is positive and more importantly the ability to beat current year closure rate goals is positively impacted by EDM (and this effect is statistically significant). Most cases can be closed when the claimant returns to work in modified duty or full duty positions. Returning the claimants back to work in such positions often requires critical communication on the part of the case managers with all the three key parties involved: medical providers or doctors, customers or the employers of the injured workers and the claimants. We do know from the time use studies that EDM greatly frees up time to do this important value-adding communication activity and we do see level of this activity jump post-EDM. Importantly, most of the current year cases have most of their documents (such as medical reports) in the electronic form. Access to these documents is much easier and faster with EDM. This improves the speed of communications. From the survey, we know from the case managers perspective that one of the top three perceived benefits of EDM is faster access to claim documents (the other two being less time documenting paper mail, and better information sharing with other groups/individuals). Hence EDM would be expected to positively impact the ability of offices to meet/beat their monthly current year closure rate targets. Just as the effect of EDM on current year closure rate is positive, its effect on previous year closure rate is negative (note the point estimate is negative although the effect is again not statistically significant). Given that previous year closure rate measures the closing of cases opened in years prior to the current year, most of these cases do not have their documents in the electronic form (note that the offices did not attempt to migrate any of the prior year old cases to EDM). Even though some of the freed up time because of EDM would be devoted to increased communication activity related to the older cases, follow-up activity and communication in general is slowed or held up because the documents belonging to those cases are not easily accessible. Hence, EDM would not be expected to positively impact previous year closure rate. The above findings on closure rates are consistent with findings in previous research, in which adoption of new technologies has been shown to reduce production time in the stage of production where the technology is of value (Bartel et al 2004, p. 220). Further, the positive impact on current year closure rate and the negative impact on previous year closure rate seems to reduce the likelihood of Hawthorne effect, which refers to the effect of observation on people's behavior or performance.

It is interesting to see the statistically significant effects of EDM on physical therapy costs and chiropractor care costs on the claims. The reduction in these costs critically depends on the ability of case managers to manage medical treatment of claimants and ensure that only treatment that is medically necessary is covered. The claim step process that case managers engage in to achieve medical cost savings is technically labeled within the firm as "medical management." Medical management requires timely utilization of various medical resources available to the case managers to manage the medical costs and timely and regular follow-up with treating doctors and the claimants. The regular follow-up allows the case manager to determine whether the claimant is making objective progress. For example, in the context of physical therapy, it is important for the case manager to determine whether the injured worker is making objective progress in the therapy process. In the context of chiropractor care, it is important for the case manager to check whether improvement is evident within two weeks of start of care. EDM frees up time to engage in value-adding medical management, which crucially involves communication activity (note that we see evidence of higher communication activity from the time use studies). Further, from the survey, we know that approximately 48% of the respondents said that time freed up because of EDM allowed them to spend more time to follow-up on activities outlined in their action plans.

Table 2. Differences-In-Differences Fixed Effects Pooled Regressions

	Dependent Var.							
Independent Var.	**Beat Current Yr. Closure Rate Goal**	**Current Yr. Closure Rate**	**Previous Yr. Closure Rate**	**Avg. Physical Therapy Paid**	**Avg. Chiropractor Care Paid**	**Staff Retention Rate**	**Loss Leakage**	**Temporary Total Disability (TTD)**
	TREAT LAG=1	TREAT LAG=1	TREAT LAG=1	TREAT LAG=3	TREAT LAG=2	TREAT LAG=1	TREAT LAG=4	TREAT LAG=4
	LOGIT (N=192)	OLS (N=192)	OLS (N=184)	OLS (N=176)	OLS (N=176)	OLS (N=168)	OLS (N=176)	OLS (N=192)
EDM TREAT	1.778** (0.738)	0.005 (0.008)	-0.006 (0.007)	-111.175*** (20.116)	-154.59*** (23.674)	0.054*** (0.020)	-0.001 (0.0009)	0.687** (0.275)
TOT. STAFF	0.152* (0.090)	0.001 (0.0007)	0.0004(0.001)	-7.856*** (2.038)	-2.87 (2.047)			0.037 (0.040)
INC. CLAIM	0.001 (0.001)	-2.71e-06 (0.000014)	-1.19e-05 (0.00002)					
FEB	-2.397** (0.941)	0.331*** (0.014)	0.037** (0.0167)	121.196*** (35.969)	110.439*** (34.717)	0.058 (0.040)	0.0002 (0.0007)	0.238 (0.336)
MAR	-2.510** (0.928)	0.460*** (0.012)	0.080*** (0.0155)	158.928*** (36.765)	177.27*** (35.037)	0.042* (0.022)	-0.0004 (0.0009)	0.739** (0.358)
APR	-1.202 (0.964)	0.517*** (0.012)	0.113*** (0.015)	215.312*** (37.164)	272.276*** (39.970)	0.007 (0.015)	-0.0005 (0.0009)	0.830** (0.413)
MAY	-0.935 (0.989)	0.555*** (0.011)	0.149*** (0.015)	216.254*** (36.177)	291.177*** (37.878)	0.008 (0.014)	0.0005 (0.0011)	1.273*** (0.421)
JUN	-1.055 (0.996)	0.581*** (0.011)	0.183*** (0.015)	239.921*** (38.322)	303.909*** (37.773)	-0.004 (0.012)	0.0001 (0.0010)	1.321*** (0.386)
JUL	-0.937 (1.043)	0.603*** (0.0122)	0.210*** (0.016)	250.334*** (42.072)	312.658*** (40.683)	-0.008 (0.013)	0.0007 (0.0011)	1.017*** (0.376)
AUG	-2.812** (1.005)	0.622*** (0.011)	0.244*** (0.016)	263.871*** (42.738)	335.501*** (42.947)	-0.005 (0.014)	0.0004 (0.0012)	1.159*** (0.409)
SEP	-2.047* (1.049)	0.641*** (0.012)	0.269*** (0.016)	208.256*** (39.057)	275.933*** (39.169)	0.004 (0.013)	0.0008 (0.0012)	1.051** (0.417)
OCT	-1.631 (1.049)	0.658*** (0.012)	0.292*** (0.016)	173.479*** (37.886)	241.965*** (38.526)	0.007 (0.014)	0.0016 (0.0012)	0.610 (0.452)
NOV	-1.054 (1.122)	0.673*** (0.012)	0.317*** (0.018)	136.052*** (38.406)	212.260*** (39.578)	-0.001 (0.013)	0.0005 (0.0012)	0.791 (0.484)
DEC	-0.398 (1.103)	0.685*** (0.012)	0.348*** (0.018)	121.543*** (38.701)	204.914*** (40.158)		0.0005 (0.0012)	0.682 (0.447)
YEAR	1.917** (0.840)	0.013*** (0.011)	0.008*** (0.010)	-107.531*** (23.366)	-40.806 (26.332)	-0.040** (0.019)	0.0014* (0.0007)	0.715** (0.309)
R^2	LOGIT	0.999	0.993	0.990	0.9885	0.996	0.990	0.999
F-stat (p-value)	LOGIT	24031 (0.0)	1903.59 (0.0)	976.56 (0.0)	996.67 (0.0)	4055.89 (0.0)	1430.12 (0.0)	10784.65 (0.0)

Huber/White standard errors (accounting for heteroskedasticity issues) are reported in parentheses for OLS regressions.

Note: coefficients for office dummies not shown for sake of confidentiality

*** indicates significance at the 1% level

** indicates significance at the 5% level

* indicates significance at the 10% level

Importantly, EDM allows for chronologically sorting of documents that allows case managers to quickly and accurately assess whether objective progress in the treatment program is being made, and if any changes in doctors/medications/therapy would help. The finding that EDM has a highly positive impact on the ability of case managers to reduce physical therapy costs and chiropractor care costs is especially significant in light of data from the interviews in which case managers revealed that pre-EDM they often did not document/post therapy notes into the claim files as they did not have time to do so. Lack of documentation of these notes would make it more likely for case managers to miss important warnings and chances to reduce therapy costs.

The positive effect of EDM on the retention rate of the case managers is also interesting. From the interviews, we do know that EDM has cut down on overtime work for case managers. Also, pre-EDM many case managers would take home work, especially documenting paper mail type of work. The documenting mail work would be perceived as low-skilled "secretarial work" and not the real and more interesting case management work that case managers wanted to do. This could be frustrating to some of the case managers. Post-EDM, this type of low-skilled "secretarial work" was dramatically reduced. EDM also resulted in a dramatic reduction in paper documents sitting on the desks of the case managers. Pre-EDM, the paper documents would simply pile up on the work desk, waiting for the case manager to "work" them. The rising pile of paper documents on the desk would cause mental frustration to the workers. Post-EDM, the number of backlogged documents sitting on the desk showed a dramatic drop. EDM helped case managers stay more organized and removed their feeling of being overwhelmed by all the paper on their desks. Lastly, the time use studies indicate higher level of personal time at work, which would imply lower level of work-related stress. All of the factors above would indicate that EDM made work more pleasant for the case managers, and this is reflected in the positive impact on the retention rate.

Finally, the EDM effects on the loss leakage and the temporary total disability metrics are also interesting. Though the effect on the loss leakage metric is not statistically significant, the point estimate is negative and consistent with expectations. As indicated previously, loss leakage captures the overpayments when best practices associated with medical management and disability management are not followed, where medical management and disability management are technical terms for processes used within the firm to describe case direction that results in medical cost savings and indemnity savings respectively. Controlling or reducing loss leakage critically depends on the ability of the case managers to stay on top of their cases and do continuous follow-up with medical providers, customers and claimants. Communication activity is key and timely assigning helpful resources such as nurses and investigators on the files is paramount to controlling leakage. The freed up time because of EDM allows higher level of value-adding communication activity and more time for thoughtful case management and investigation. Importantly, EDM also allows case managers to chronologically sort documents and more easily/quickly detect what is known as "injury creep" (similar to "scope creep" in IT projects), in which the treatment currently being paid for is for an injury that is not related to the original covered injury at work. Further, EDM makes timely receipt of important documents (such as claimant work status reports from doctors) more likely as external parties such as doctors simply fax them to the e-fax numbers of the case managers post-EDM. This makes it easier for case managers to cut off benefits in a more timely fashion, reducing possible overpayments. Given above reasons, EDM would be expected to reduce loss leakage. The higher closure rate and higher TTD (or number of temporary total disability days for which indemnity benefits are provided) are consistent. Since closure rate is the paramount performance metric, the case managers in their efforts to close out the cases may, after negotiating with the customer (or the employer of the injured worker) and the injured worker, pay out a higher number of disability days.

Discussion and Conclusions

We have used a four-pronged research study to holistically assess the causal impact of an enterprise IT (EDM) on the workers compensation division of a large insurance firm. Through pre- and post-EDM interviews, time use studies, surveys and importantly analysis of office-level objective performance data, we have qualitatively and quantitatively documented the causal impact of EDM. Through our "insider econometrics" empirical study (Bartel et al, 2004), in which we focused on the operations of a single firm, we assessed the impact of EDM at the process and office level. Insider insights obtained through direct contact with the managers and information workers were key in this type of "insider econometrics" study, as they reduced concerns about endogeneity bias and omitted-variable bias in the results (Bartel et al, 2004). Much of the IT impact research is unable to say definitively whether either business process changes or information technology implementation caused the demonstrated effects on performance (McAfee, 2002). Since we have access to a quasi-experiment in this study, our analysis of longitudinal data here is able to isolate unbiased estimates of the causal effects of information technology. Further, there were few substantive business process changes with the introduction of EDM in our setting. With the rollout of the technology, the management at the insurance firm decided to make the work process change that medical providers and other parties would be encouraged to send all correspondence to the electronic fax (RightFax) numbers so that case managers would see the faxed documents as e-mail attachments. This process change obviously increased the work associated with uploading the e-mailed documents to the EDM system and subtracted from the EDM-related time savings. Since we focus on a single firm, the results about digitization of work are applicable to the firm studied and future research may need to study other settings to obtain broader generalizibilty; in any case, we believe that the approach that we employ may be widely applicable in future research.

We demonstrated how EDM changed task composition at the individual level. EDM led to a significant decline in the substitutable routine labor input and an increase in non-routine cognitive labor input at the information worker level. Prior to EDM, the information workers in our setting would need to supply a significant amount of routine labor input for their work: they would need to type verbatim large sections of documents such as medical reports that were available only in paper form. Post-EDM, the paper documents were all scanned and made available in the electronic form. This obviated the need for the information workers to manually transcribe the paper documents. Thus, EDM directly impacted the supply of routine labor input, which was substituted away by the technology. In reducing the time to complete various routine tasks, EDM made time available to do other value-adding tasks that involved interaction and higher-order cognitive and analytic skills. With the deployment of IT, some "slack" ("IT-enabled slack") developed, which led to performance enhancements in two distinct ways: first, the slack allowed information workers to spend more time on value-adding communication activities, which directly led to performance improvements. Secondly, "IT-enabled slack" allowed for more personal time relaxing/resting at work or at home (less overtime), which in turn led to less stressed-out, happier and more productive employees. EDM also brought about an outward shift in the supply (and quality as well) of routine informational inputs which complemented the non-routine cognitive labor input (such as interactions and communications) in the sense that they likely increased the performance of workers doing nonroutine tasks that demanded those inputs. We demonstrated the impact of shift in task composition of the workers on performance metrics at the office level.

Mukhopadhyay et al (1995) have proposed several benchmarks to evaluate IT impact research. The first benchmark is theoretical foundation of the research. Our research has a strong theoretical foundation in the task model proposed by Autor et al (2003), which we described in detail in the Theory section above. The second benchmark concerns methodological issues. Our access to a quasi-experiment which makes available experimental controls alleviates the problem of confounding factors affecting the results. Further, the fact that this is an "insider econometrics" study, in which we gathered insider insights through direct contact with managers and information workers, reduces concern about endogeneity bias and omitted-variable bias in the results (Bartel et al, 2004). The third benchmark concerns modeling issues. Our analysis is at the application level, which eliminates aggregation-related issues associated with firm-level analyses (Mukhopadhyay 1997b). The fourth benchmark concerns the quality of data. We had unprecedented access to gather primary data through firm databases, firm reports and manuals, employee observations and interviews. Given that the firm collected the performance data through fairly-long established methods and used them for appraisals and planning, it is safe to assume that the quality of data is high.

We make several contributions in this research study. First, our research contributes to the IT impact literature by documenting the significant impact of a specific IT application, electronic document management, not yet examined sufficiently empirically in the economics of information systems literature despite its salience in the context of information management. Second, we demonstrate using a detailed empirical study how digitization of work changes task composition at the individual information worker level. Though the relationship between our task level findings and results from the performance metrics regressions is inferential (i.e. we are unable to test for the relationship directly), our personal observations and insider insights lead us to believe that the link between changes in task composition at the individual level and performance improvements at the office level is strong. Third, we unpack the black box of IT impacting performance and uncover a new micro-level mechanism ("IT-enabled slack") as to how exactly IT can lead to significant payoff, especially in terms of information worker performance. Fourth, we contribute methodologically to the process perspective in the IS literature by using time use studies and differences-in-differences econometric analyses to assess the impact of EDM at the activity and process level. Given the spectacular variety of IT applications and the great need to document the precise causal impact of IT at a micro-level, there is a pressing need for application-specific, differences-in-differences quasi-experimental empirical studies. Our research study addresses that need by assessing the impact of EDM using a quasi-experiment.

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