Electronic Medical Records and Physician Productivity: Evidence from Panel Data Analysis

Abstract

Physician productivity is an important driver of key healthcare outcomes, such as quality of care, treatment costs and patient satisfaction, because physicians influence a vast majority of treatment decisions, and are central to the care delivery process. Thus, it is critical for researchers to understand how transformation technologies, such as electronic medical records (EMRs) impact physician productivity. While researchers and policy makers in the United States have suggested that the implementation of EMRs can have significant beneficial impacts on patient safety, health care quality and overall costs of care delivery, the effects of EMRs on physicians themselves have been understudied in the literature. In this paper, we examine the productivity impacts of EMR implementation on physicians. Our focus is to investigate if productivity impacts of EMR implementation depend on physician specialties and the duration for which the EMR has been implemented. This research is informed by extant work in physician productivity, IT productivity and task-technology fit theory. We use a unique panel dataset comprising 87 physicians specializing in internal medicine, pediatrics and family practice in 12 primary care clinics of an academic hospital in a large state in the western United States. Our dataset contains 3,186 physician-month productivity observations collected over 39 months. We employ random effects model on this panel dataset to estimate the impact of EMR implementation on physician productivity. We find that productivity impacts of EMR are contingent upon physician specialty and the time period for which an EMR has been implemented. Furthermore, we find that the stable stage impacts of EMR on various specialties are different from those in the transitory learning stage. These results emphasize the need for fine-grained analyses of productivity impacts of EMR implementation on physicians. We postulate that the fit provided by an EMR to the task requirements of physicians of various specialties is key to disentangling the productivity dynamics. We contribute to the nascent but emerging stream of literature that examines productivity implications of various information technologies among white color knowledge workers in the service industries.

Keywords

Electronic Medical Records, EMR, EMR Productivity, HIT, Health Informatics, IT Productivity, IT Value, Panel Data Analysis, Physician Productivity, Relative Value Units, Task-Technology Fit

Introduction

Health information technologies (HIT) in general, and electronic medical records (EMRs) in particular, have generated much excitement among researchers, payers, patients and policy makers in the United States. An EMR maintains comprehensive records of an individual's health-related information that is created, gathered, managed, and consulted by licensed clinicians and staff from *a single care providing organization*.[1] There is widespread belief among researchers that the use of EMRs can help eliminate pathologies present in clinical processes, and improve such important clinical metrics as quality of care, length of stay, readmission rates and medical errors that may result in preventable deaths (Fiks et al. 2011; Miller 2005; Shortliffe 2005; Zhou et al. 2009). Additionally, researchers have suggested that information availability and use at the point of care has potential not only to streamline healthcare processes but also to enhance the efficiency of care delivery (Ayal and Seidmann 2009; DesRoches et al. 2008; Goh et al. 2011; Jha et al. 2009; Ford et al. 2009). Not surprisingly then, policy makers in the U.S. have made a significant push to increase the adoption and use of EMRs among physicians through promoting and publicizing both incentives and eventual penalties (*HITECH Act* 2009).

EMRs have the potential to influence health care practice on many dimensions, including quality of care, medical errors, patient satisfaction, costs, revenues and physician productivity. This paper is focused on physician productivity – a measure of a physician's output weighed by input – which is important for several reasons. First, physician services currently account for 21% of national health expenditures in the U.S. (Hartman et al. 2009). According to statistics collected and published by the Centers for Disease Control and Prevention, there were about 956 million visits made to physician offices in 2008 (Sebelius et al. 2011). Hence physician productivity has a considerable impact on health care costs, besides affecting care delivery to patients, hospital staffing and workforce planning. Second, EMR technologies today require physician involvement not only in knowledge work, such as making decisions and choices based on patient information contained in the EMR, but also in data entry and system operation. This stands in stark contrast to many other industries, such as financial services, transportation, retail and

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1. Although sometimes used interchangeably, electronic medical records and electronic health records (EHRs) are different. Most importantly, while EMRs contain patient demographics, progress notes, problems, medications, vital signs, past medical history, immunizations, laboratory data and radiology reports from *one organization*, EHRs consolidate such information from multiple organizations such as hospitals, physician practices and laboratories, and provide a *unified assessment* of a patient's health history from *multiple organizations*.

telecommunications, where the top executives perform the knowledge tasks only, and delegate data entry and system operation to less-expensive employees at lower levels. Thus, the threat of a loss in productivity caused by the interference of EMRs with physician workflow and imposed by less efficient actions, such as the use of drop-down menus or free-text typing, both of which may be slower than dictating and using pen and paper, can cause physicians to resist EMRs (Agarwal et al. 2010; DesRoches et al. 2008; Jha et al. 2009). According to a recent study conducted by Medical Group Management Associates (MGMA), a prestigious professional organization of healthcare leaders and administrators, fear of productivity loss is the primary barrier to EMR use among physicians (Steele 2011).

Physician productivity considerations are, therefore, critical for EMR implementation and success in the long run. However, there is a lack of evidence demonstrating that EMRs increase the productivity of physicians (Cheriff et al. 2010; Stevens 2010). In contrast, there is already a robust literature studying the impact of health information technologies on quality of care, patient satisfaction, medical errors, costs and revenues (e.g., Aron et al. 2011; Ash et al. 2004; DesRoches et al. 2010; DeVore and Figlioli 2010; Furukawa et al. 2010; Linder et al. 2007; McCullough et al. 2010). More generally, there is surprisingly little formal research on the nature and dynamics of productivity impacts of EMRs on physicians. This is puzzling because physicians drive a vast majority of costs as well as treatment decisions in health services organizations, and it is widely understood that doctors' willingness to use EMRs is critical to their widespread diffusion (DesRoches et al. 2008; Jha et al. 2009; Menachemi 2006). Interestingly, productivity considerations are also largely absent from American Recovery and Reinvestment Act of 2009 and HITECH Act of 2009. This paper attempts to fill the gap in the literature by examining two research questions: 1) How do EMRs impact the productivities of physicians over a period of time? 2) How and why does this impact differ for physicians of different specialties?

We believe that central to this discourse is the nature of interactions physicians have with EMRs. These interactions can be classified into two categories, information review and information entry. The first category refers to physicians' use of an EMR to retrieve, review, aggregate and synthesize information, which help them learn about the patient's current and past health characteristics and enables better and faster decision making. The second category involves using an EMR to enter and document patient conditions, diagnoses, treatments and tests. Although physicians have long been accustomed to using the technology for the former, they have been responsible for the latter for only about a decade (Clayton et al. 2005). Additionally, the balance of times spent between the two sets of activities when physicians use EMRs is likely to differ for physicians of different specialties. These differences may be caused by the level of familiarity and past interactions with the patient, the nature and volume of patients seen in the clinic, and the usefulness of past data in treating the patient. Research in information systems (IS) has a longstanding tradition of analyzing productivity issues associated with information technologies (Barua and Mukhopadhyay 2000; Brynjolfsson and Hitt 1996; Menon et al. 2000). Additionally, research in health informatics (HI) recognizes the importance of interfaces and design in physician interaction with EMRs (Zheng et al. 2009). However, the interplay between physician productivity and EMR design issues has been understudied in the literature, including the time tradeoffs inherent between the two types of EMR uses, the impact of these tradeoffs on the productivities of physicians in different specialties and the resulting design implications for EMR have largely ignored in the literature. Our research attempts to address these issues, and falls at the novel intersection of health care, IT-enabled productivity and task-technology fit literature streams.

We draw upon the physician productivity literature to select a theoretically-grounded productivity measure used widely among healthcare researchers. We further draw upon two streams of well-established literature in information systems to inform our investigation on physician productivity. The first stream examines the productivity impacts of IT investments (Aral et al. 2006; Barua and Mukhopadhyay 2000; Brynjolfsson and Hitt 1996; Dewan and Kraemer 2000; Menon et al. 2000). There is broad consensus among researchers that IT investments and use have significant productivity impacts. Much of this research has focused on firm and industry levels, but individual-level studies, particularly those focused on knowledge and white-collar workers, are lacking in the literature (Aral et al. 2006; Bulkley and Van Alstyne 2004; Cheriff et al. 2010). The second stream, grounded in task-technology fit theory, suggests that performance impacts result from task-technology fit, i.e., when a technology provides features that support and fit the requirements of the task (Fuller and Dennis 2009; Goodhue and Thompson 1995). Thus, features of the technology that are brought to bear should correspond with the task requirements. Similar insights emerge from the economics literature where Bresnahan and Trajtenberg (1995) argue that the benefits of IT are contingent on the design and characteristics of applications and the context in which they are applied.

The data for our study were collected at an academic medical center associated with a large public university in western United States. We collected pre- and post-implementation productivity data on 87 physicians over a 39-month period, yielding 3,186 physican-month observations. The physicians work across 12 clinics and represent three specialties, Internal Medicine (IM), Pediatrics (Peds) and Family Practice (FP). Athey and Stern (2002) assert that without detailed, disaggregated and longitudinal data, it is difficult for researchers to discern IT impacts on various performance measures. Econometric analyses using such data at the individual level, as well as the use of contextual variables to assess IT value are limited in the IS literature (Chwelos et al. 2010; Kohli and Devaraj 2003). In this study, we attempt to address these gaps in the literature.

Related Literature and Conceptual Background

The conceptual foundations for our study draw upon research from three strands of work – physician productivity, IT-enabled productivity and task-technology fit. We rely on prior work in IS, economics and health policy and services to ground our research. Our review of the physician productivity literature provides us with insights on the wide variety of productivity measures that have been used by researchers, and helps us select a measure that provides a consistent meaning of productivity across various physician specialties. Prior work on IT-enabled productivity sensitizes us to the importance of data and measurement issues and the level at which productivity is measured. Finally, the task-technology fit literature helps us establish the context of IT use and explain the rationale for why some forms of IT, under certain circumstances, produce productivity gains, while others forms of IT don't. Next, we discuss each of these streams of literature.

Physician Productivity

Accurate measurement of and improvement in the productivities of knowledge workers are among the most important challenges facing managers in the developed countries (Drucker 1991). The conceptualization and measurement of physician input and output are central to revenue generation and physician compensation (Newhouse and Sinaiko 2007-2008; Tufano et al. 1999). However, productivity of knowledge workers such as physicians defies simple measurement because their outputs, appropriate and inappropriate outcomes, as well as inputs, time, knowledge, skills and relationships with other professional, are not directly comparable (Zaslove 2003). Hospitals, physician practices and institutional payers of health costs have used a variety of physician productivity measures, such as the number and type of patient encounters, time spent with patients, and dollars generated for the organization. These productivity measures, however, suffer from several limitations. For instance, the revenue generated by the physician is directly dependent on the insurance carried by the patient, and may not accurately reflect physician productivity.[2] Similarly, measures of time and patient encounters suffer from the limitation that not every office visit made by the patient or block of time spent by a physician with the patient is the same (Johnson and Newton 2002). For example, an hour spent providing critical care in the hospital is not the same as an hour spent counseling a patient in the office. Additionally, an office visit for common cold is not the same as another for severe chest pains.

Not surprisingly then, policy makers, clinicians, researchers and hospital administrators are all interested in the precise measurement of physician productivity (Fisher 2007-2008; Newhouse and Sinaiko 2007-2008). One emergent result is the use of work relative value units (WRVUs) to measure physician productivity (Clayton et al. 2005; Coleman et al. 2003). WRVUs are determined by committees of the American Medical Association (AMA), with representation from every specialty. WRVUs are comparable across all specialties, thus the productivity of a family practitioner can be directly compared with those of an emergency doctor, a cardiologist and a pediatrician. The measure is independent of any dollar amount generated,[3] thus limitations associated with patient charges, collections and insurance mix are excised away from RVU calculations. Furthermore, RVUs take into consideration the fact that not all patient encounters are the same. Thus, an hour spent with a patient in the operating room, performing an oncological surgery, yields a different RVU than the same amount of time spent counseling the patient in the office.

The work RVUs are intended to reflect four components: the complexity of the task; technical skill and physical effort; mental effort and judgment; and physician's psychological stress about inadvertent injury or illness caused to the patient due to treatment. The conceptualization and calculation of RVUs were influenced heavily by a study conducted by Hsiao and his colleagues (Hsiao et al. 1998). Their research led to the development of resource-based relative value scale (RBRVS), which are used to assign a work relative unit to every current procedure terminology (CPT) code (Maxwell and Zuckerman 2007-2008). Due to its conceptual grounding in the nature of

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2. Two doctors who are similar in every other aspect, but one sees largely private insurance patients and the other sees largely Medicare and Medicaid patients, will generate considerably different revenue streams.
3. RVUs are used to reimburse physicians, but the dollar amount a physician generates is not considered for their calculation.

physicians' work, and its widespread support by the AMA and the Centers for Medicare and Medicaid Services (CMS), the WRVU productivity measure has been widely adopted by healthcare researchers, payers and providers. In fact, it is the *de-facto* productivity measure used it the healthcare industry and among healthcare researchers. We use this measure in our study.

IT-enabled Productivity

There has been a longstanding tradition in the IS literature of analyzing productivity issues related with information technologies (Aral et al. 2006; Barua and Mukhopadhyay 2000; Brynjolfsson and Hitt 1996; Bulkley and Van Alstyne 2004; Hitt et al. 2002; Kohli and Devaraj 2003; Menon et al. 2000; Tambe and Hitt *forthcoming*). With almost two decades of concerted and rigorous research, the productivity paradox associated with IT has been resolved. Through the use of more extensive data, better measurements and more rigorous econometric techniques, researchers have found convincing positive relationships between IT and productivity at firm (Barua and Lee 1997; Brynjolfsson and Hitt 1996; Tambe and Hitt *forthcoming*), industry (Jorgenson and Stiroh 2000) and country levels (Dewan and Kraemer 2000). This research, valuable because it lays the foundation for future studies, is limited in two important ways.

First, extant IT productivity research is overwhelmingly concentrated on manufacturing industries (Aral et al. 2006). This disproportionate focus on manufacturing is not reflective of the U.S. economy, which is predominantly service-oriented. Additionally, large improvements in productivity in the last decade can be attributed to those taking place in the services sector of the economy (Triplett and Bosworth 2004). Thus, ironically, while the service industry is the largest employer of workers and user of information and information technologies, researchers know less about productivity mechanisms and magnitude changes in service industry than in the manufacturing industry (Aral et al. 2006). Furthermore, IT is arguably more relevant for the service sector. It is commonly accepted that the practice and delivery of healthcare is essentially an information-based science (Hersh 2002). Physicians use clinical information to diagnose and treat patients, health insurers use extensive claims databases to price their products and manage costs, and consumers are increasingly using the Internet to learn about treatment alternatives, search for providers, and transact with health insurers (e.g., Korp 2006; Slater and Zimmerman 2002). However, studies examining productivity implications of information technologies in the healthcare industry are sparse in the IS and HI literature.

Second, individual worker level productivity studies are lacking in the IS literature (Aral et al. 2006; Bulkley and Van Alstyne 2004). Research investigating the productivity of information and knowledge workers is particularly lacking in the literature. Measuring the productivity of white collar workers is markedly difficult as output produced by them is not as concrete and tangible as those for other professions (Aral et al. 2006), and attributing gains or impediments in productivity is difficult to attribute to one person. This may partially explain the lack of literature on productivity analyses for knowledge workers.

In their theoretical study, Bulkley and Van Alstyne (2004) discuss two views of information use – *homo economicus* and *homo computicus*. The first view suggests that information makes individuals more productive by reducing uncertainty and delays, and improving decision making and resource allocations. The value contributed by information in this perspective is the difference between informed and uninformed choices (Arrow 1962; Hirshleifer 1973). The second view suggests that information makes individuals more productive by enhancing the efficiency with which the problem space can be navigated and obtaining additional information that enhances knowledge and the search process. We believe that the second perspective, *homo computicus*, is particularly apt in our context. The rationale is that although physicians can make informed choices through both physical and electronic information, the efficiency with which the two means enable decision making is key to determining productivity impacts of EMR.

Task-Technology Fit

The task-technology fit (TTF) theory falls under the broad category of contingency theories that argue that the optimal course of action is dependent on internal and external circumstances. TTF theory posits that the use of a technology may result in different outcomes contingent upon its configuration and the task at hand (Dennis et al. 2001; Goodhue and Thompson 1995). TTF theory is the only organizational theory that attempts to formally and specifically examine the relationship between task requirements and technology characteristics (Maruping and Agarwal 2004), and is supported by significant empirical literature. The central tenet of TTF theory is that the alignment between task needs and system functionalities drive task performance (Goodhue 1995). Thus, when a technology provides features that support or "fit" the requirements of the user's task at hand, it leads to enhancements in performance. TTF theory provides additional insights beyond those offered by the research that suggests that the performance impacts of a technology are dependent on the use of the technology. However, more utilization of a system does not necessarily lead to higher performance if the task-technology fit is low.

The TTF theory suggests that it is important that the information processing features of the technology fit informational requirements of the task. For simple or single goal tasks, no information processing support may be required, but tasks that entail decision making and judgment, information processing adds significant value (Dennis et al. 2001; Zigurs and Buckland 1998). Information processing support entails ways to evaluate, gather and aggregate information as well as to organize and analyze information (Zigurs and Buckland 1998). Support of this nature may improve performance by reducing losses due to incomplete task analysis or by increasing gains due to synergy, encouraging the use of more information and promoting more objective evaluation (Dennis et al. 2001).

TTF theory has been used to examine performance at both group (e.g., Dennis et al. 2001; Fuller and Dennis 2009; Maruping and Agarwal 2004; Zigurs and Buckland 1998) and individual levels (Benbasat et al. 1986; Goodhue 1995; Goodhue and Thompson 1995). In our study, we use TTF at the individual level because we are interested in analyzing the WRVUs generated by individual physicians after the implementation of an EMR. To our knowledge, two prior studies have used TTF theory in the health IT context. Kilmon et al. (2008) utilize TTF as a diagnostic tool to evaluate the implementation of an electronic health record at a university hospital. They find that the implementation of the system is successful, but do not examine its performance impacts. Willis et al. (2009) use the TTF theory to examine the task-technology fit of an electronic health record system for registered nurses (RNs) at a regional health center in South Dakota. They find that the performance of RNs is significantly related to data quality and ease of use/training, and somewhat less significantly related to data compatibility. Thus, access to the right data at the right level of detail is a significant predictor of performance.

In summary, we draw upon physician productivity, IT-enabled productivity and TTF literature to ground our study. Three insights emerge from our synthesis of extant literature. First, there is wide consensus among researchers that WRVUs represents a robust measure of physician productivity. Second, while there is a significant body of literature that has examined IT-enabled productivity, studies investigating individual-level productivity, especially those for knowledge workers in service industries, are limited. Finally, although TTF theory is uniquely suited to study the relationship between task characteristics and technology features due to its focus on decision making, judgment and information processing, and hence to physicians' use of IT, insights from this theory have been applied rather narrowly in studies examining electronic medical or health records.

Empirical Framework

The Data

Our study was conducted in the context of outpatient visits in a large academic hospital located in an urban setting in the western United states. The hospital implemented the EPIC EMR system across 12 clinics over a period of time. The deployment of EMR took place one clinic at a time, starting in June 2004 and ending in October 2005. Our dataset includes monthly productivity data for each physician for several months before and after EMR introduction. The monthly data extends from May 2003 to July 2006, thus for each physician we have several, but varying number of, months of data before and after EMR deployment. Each physician in the data set was associated with a unique clinic and specialty during the entire data period. The clean nature of our data allowed us to control for extraneous effects that may obfuscate results if physicians shift clinics or specialties. An excerpt from the data is displayed in Table 1. The numbers of physicians and observations for each clinic-specialty pair are given in Tables 2 and 3. The dataset consisted of 3,189 observations covering 87 physicians across 12 clinics, but a careful perusal of data on productivity and number of days worked in various months showed that three observations suffered from typographical errors and incorrect data (e.g., number of days worked in a month = 115.5 is certainly incorrect). These observations were deleted, leaving us with 3,186 observations.

Physician productivity at this hospital is measured by WRVUs which measure the RVUs earned for clinical, rather than teaching or administrative, work. Because the focus of our study is to examine the impact of EMR on clinical productivity, we employ WRVUs as the measure of production. Our data set also included the number of days spent on clinical work by each physician each month, including fractional days. We define each physician's monthly productivity as the level of production per unit time, i.e., WRVUs divided by days worked on clinical tasks, computed from daily work logs at each clinic. Table 4 provides descriptive statistics and correlations between study variables.

[Insert Tables 1, 2, 3 and 4 about here]

Exploratory Data Analysis and Variable Coding

Our primary interest in this paper is in comparing physician productivity before and after EMR implementation, and in examining whether the nature of the physician's work - as defined by his/her specialty - has an effect on the direction and magnitude of influence. As a baseline model, we estimated a model which assumes that the impact of EMRs vary linearly with the amount of time elapsed since implementation. In other words, this model does not account for the differences between the learning and stable state phases. For this model, emrAGE, the actual number of months post-implementation of EMR, was included as the age variable. This model is encoded as Equation 1 on Page 14.

The literature on the impacts of process-enabling information technologies, such as enterprise resource planning systems, suggests that the productivity impact of EMR may neither be a monotonic function of the duration of time after implementation, nor sufficiently modeled with a simple before-after bipartite classification. Technology implementation almost always exhibits (i) a learning period before (ii) a new stable steady-state emerges (Hitt et al. 2002; Robey et al. 2002). Specifically, there is first a sharp dive in productivity because new technology shocks the existing work systems (Brynjolfsson and Hitt 2000; Hitt et al. 2002), and then a recovery in productivity levels as workers become more familiar, and procedures become better aligned, with the new system. The initial drop is well-documented for large enterprise systems (Bendoly and Cotteleer 2008; Brynjolfsson and Hitt 2000; Hitt et al. 2002; Robey et al. 2002). EMR systems entail significant process modifications, as well as development of more complete and reliable patient data. Such changes, learning, and workflow adjustments enable a rebound in productivity, but this recovery process takes time and may, a priori, be of undetermined length. Once the technology has been absorbed – i.e., in a stable post-learning period – any further variations in productivity should be attributed to other factors and should reflect the variation pattern prior to EMR deployment. Productivity level after full absorption of the EMR technology can even exceed the original level if new technology improves workflows and makes work more efficient. Therefore, the productivity impact of EMR implementation can better be modeled by considering three distinct phases: pre-EMR, the learning period, which encompasses both shock and recovery, and a stable post-EMR phase.[4]

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[4]. Some authors have also proposed a subsequent sustained increase in productivity caused by organizational transformation and the implementation of follow-on technologies and modules, but noted that this process occurs over a substantially longer period and many organizations do not realize such transformation in the first couple of years after technology implementation (Ross and Vitale 2002). Our analysis is restricted to the pre-EMR/learning/stable periods because continuous improvement (e.g.,

Our initial explorations of the physician productivity data indicated a pattern that is consistent with this sequence. Figure 1 represents a Box and Whiskers plot. The solid line in the plot represents the median productivity level or 50th percentile, and the top and the bottom lines respectively represent the 75th and 25th percentile or the upper and the lower quartile.[5] We notice that there is a substantial drop in productivity in the two months during and immediately after EMR implementation relative to the pre-EMR period, followed by recovery for approximately the next 2-4 months. This suggests that it takes approximately 4 to 6 months – called the learning period – for the technology shock to be fully absorbed into the system. Hence, in order to model this non-linear dynamics of EMR productivity, we define two new dummy variables – learning phase and stable phase – in order to classify each observation as belonging to the pre–EMR phase (both learning and stable dummies are set to zero), the learning period (learning = 1, stable = 0), and the stable post-EMR phase (learning = 0, stable = 1). As noted above, there is some ambiguity, and no well-established theoretical or empirical guideline, regarding the length of the learning period, hence we estimated three alternative econometric models where the learning phase was set at 4 months, 5 months and 6 months respectively (models encoded as 2a, 2b and 2c on Page 14).[6] This was done to allow for flexibility across different clinics, and also served as a robustness measure. Recall, that EMR implementation in our study is at the clinic level, not the entire hospital level. The number of physicians in these clinics ranged from 1 to 14 (see Table 3). Thus, unlike other studies that examine the implementation of process-transforming technologies at the organizational level, and hence expect the learning phase to last up to one year due to coordination requirements, our exploratory data analysis demonstrates that shorter learning duration suffices at the clinic level.

[Insert Figure 1 about Here]

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add-on technological modules such as physician decision support) and transformation (e.g., changes in compensation practices and incentives, integration of treatment regimens with EMR, etc.) phases did not occur during our study period.

5. Figure 1 shows productivity variation from months 1 through 6; the pattern stays similar for all the post-implementation months beyond 6.

6. According to a Robert Wood Johnson foundation study, short-term productivity losses are a significant concern for hospitals and physicians (http://www.rwjf.org/files/publications/other/EHRReport0609.pdf). Practitioners have suggested to the American Medical Association (AMA) (http://www.ama-assn.org/amednews/m/2011/06/06/gse0610.htm) and to the Department of Health and Humans Services (http://healthit.hhs.gov) that hospitals keep patient volumes suppressed for three to six months post-implementation. In an online training video, the AMA suggests that hospitals reduce the number of patients by up to *50%* for the first week to allow them and staff to learn how to use new technologies, and allow physicians time to adjust to new workflows and routine changes. Medical Group Management Association (MGMA) found in a study conducted in 2007 that physicians' productivities stayed suppressed for six months and up to a year.

Going a step further, it is also evident, both from past literature and our data exploration, that there is sufficient variation within the learning period itself. That is, the dive and recovery sub-phases are distinctly observed in most large process-enabling IT implementations. This pattern is also evident from the productivity data displayed in Figure 1. Further analysis of the data demonstrates that productivity drop and recovery patterns are different for physicians of three specialties; both the relative length of the dive *versus* recovery phases, and the magnitude of changes, varies across time and physician specialty (Figures 2 and 3). Figure 2 shows the variations in productivity for physicians of different specialty from the month before EMR implementation to six months after EMR implementation. We note that in months 0 and 1, IMs experience a significant productivity drop. Peds and FPs also experience drops, but their fall is not as dramatic as IMs. We also notice that during the turbulent drop and recovery periods, the relative productivity levels change, with IMs, Peds and FPs trading places. Although IMs suffer a greater productivity loss initially, once the recovery phase is complete, they demonstrate higher productivity in the long run than FPs and Peds. Figure 3 demonstrates this more clearly. Figure 3 depicts physician productivities in 5 panels. The fifth panel – corresponding to 6+ months after EMR – shows that the level and relative order of productivities do not change significantly after 6 months. Additionally, IMs exceed their pre-EMR productivity level, but the productivity levels for Peds and FPs still lag behind their pre-EMR implementation productivities. A perusal of pre-EMR and the steady-state productivity levels (i.e., the first and last panels in Figure 3) demonstrates that the productivity gap between IMs and the other two specialties appears to increase after EMR implementation. In order to allow for such time- and specialty-specific differences, we create seven new variables, Month0 through Month6, to analyze productivity dynamics within the learning phase. $Month_i$ is coded 1 if the observation is i months after the EMR implementation month, otherwise it is coded 0.

[Insert Figures 2 and 3 about Here]

Notations and Symbols

The notations and symbols used in the study are discussed below:

Indices

- $c \in$ Clinics = {AB, AP, P, C, L, D, E, F, J, N, R, U}
- $s \in$ Specialty = {FP, IM, Peds}

- $i \in$ Physicians = {Docid 1, Docid 2, …. Docid 87}
- $t \in$ Months, calendar month-year, from May 2003 to July 2006.

Productivity and Employment

- WRVU(i, t) = Work RVUs for physician i in month t.
- DAYs(i, t) = Number of days worked by physician i in month t.
- Productivity(i, t) = WRVU(i , t) / DAYs(i, t) = Productivity of physician i in month t

EMR Implementation and Age

- emrGoLive(c) = Calendar month-year of EMR implementation at clinic c.
- emrDuration(c, t) = (t - emrGoLive(c)), the number of months between calendar month t and emrGoLive(c).

In order to account for the temporal nature of EMR impact, we define several additional variables:

- Learning Phase (c, t) = 0 if emrDuration(c, t) ≤ 0; 1 if $1 \leq$ emrDuration(c, t) $\leq L$ where $L \in \{4,5,6\}$; 0 if emrDuration(c, t) $> L$[7]
- Stable Phase (c, t) = 0 if emrDuration(c, t) $\leq L$ where $L \in \{4,5,6\}$; 1 if emrDuration(c, t) $> L$[8]
- Month0 (t) = 1 if emrDuration(c, t) = 0; 0 otherwise
- Month1(t) = 1 if emrDuration(c, t) = 1; 0 otherwise
- Month2 (t) = 1 if emrDuration(c, t) = 2; 0 otherwise
- Month3 (t) = 1 if emrDuration(c, t) = 3; 0 otherwise
- Month4 (t) = 1 if emrDuration(c, t) = 4; 0 otherwise
- Month5 (t) = 1 if emrDuration(c, t) = 5; 0 otherwise
- Month6 (t) = 1 if emrDuration(c, t) = 6; 0 otherwise[9]
- emrAGE(c, t) = 0 if emrDuration(c, t) ≤ 0; t - emrGoLive(c) if emrDuration(c, t) > 0

It is important to note here that because physicians are affiliated with the same clinic for the duration of the study, the age and implementation variables are the same for a physician and the clinic where he/she is employed.

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[7], [8.] : $L \in \{4,5,6\}$ because we have allowed the learning phase to vary from 4 to 6 months.

[9.] Different number of months is used depending on the model.

Data Analysis and Results

Estimation Strategy and the Econometric Model

The productivity of a physician i, specializing in specialty s, working in clinic c, in month t, is likely to be determined by the physician characteristics, the clinic characteristics, the specialty and number of months, at month t, that EMR technology has been available at the clinic. Thus, our empirical model accounts for these effects. Additionally, extant research suggests that the gender and experience of a physician can have a significant impact on his/her productivity (Conrad et al. 2002), hence we control for physician gender and experience in our study.[10] Finally, as our exploratory analyses indicate, the impacts of EMR are likely to be different for physicians in different specialties and this impact may vary over a period of time, thus our model must examine productivity variations by specialty and over a period of time. We employ the following empirical models to estimate physician productivity:

$$\text{Productivity}(i, t) = \beta_0 + \beta_1 * \text{Physician}(i) + \beta_2 * \text{Clinic}(c) + \beta_3 * \text{Specialty}(s) + \beta_4 * \text{Gender}(i) + \beta_5 * \text{Experience}(i) + \beta_6 * \text{emrAGE}(c, t) + \beta_7 * \text{Specialty}(s) * \text{emrAGE}(c, t) + \alpha_i + \varepsilon_{it} \quad (1)$$

$$\text{Productivity}(i, t) = \beta_0 + \beta_1 * \text{Physician}(i) + \beta_2 * \text{Clinic}(c) + \beta_3 * \text{Specialty}(s) + \beta_4 * \text{Gender}(i) + \beta_5 * \text{Experience}(i) + \beta_6 * \text{Learning Phase}(c, t) + \beta_7 * \text{Stable Phase}(c, t) + \beta_8 * \text{Specialty}(s) * \text{Learning Phase}(c, t) + \beta_9 * \text{Specialty}(s) * \text{Stable Phase}(c, t) + \alpha_i + \varepsilon_{it} \quad (2a, 2b, 2c)$$[11]

$$\text{Productivity}(i, t) = \beta_0 + \beta_1 * \text{Physician}(i) + \beta_2 * \text{Clinic}(c) + \beta_3 * \text{Specialty}(s) + \beta_4 * \text{Gender}(i) + \beta_5 * \text{Experience}(i) + \beta_6 * \text{Month0}(t) + \beta_7 * \text{Month1}(t) + \beta_8 * \text{Month2}(t) + \beta_9 * \text{Month3}(t) + \beta_{10} * \text{Month4}(t) + \beta_{11} * \text{Stable Phase}(c, t) + \beta_{12} * \text{Specialty}(s) * \text{Month0}(t) + \beta_{13} * \text{Specialty}(s) * \text{Month1}(t) + \beta_{14} * \text{Specialty}(s) * \text{Month2}(t) + \beta_{15} * \text{Specialty}(s) * \text{Month3}(t) + \beta_{16} * \text{Specialty}(s) * \text{Month4}(t) + \beta_{17} * \text{Specialty}(s) * \text{Stable Phase}(c, t) + \alpha_i + \varepsilon_{it} \quad (3)$$

$$\text{Productivity}(i, t) = \beta_0 + \beta_1 * \text{Physician}(i) + \beta_2 * \text{Clinic}(c) + \beta_3 * \text{Specialty}(s) + \beta_4 * \text{Gender}(i) + \beta_5 * \text{Experience}(i) + \beta_6 * \text{Month0}(t) + \beta_7 * \text{Month1}(t) + \beta_8 * \text{Month2}(t) + \beta_9 * \text{Month3}(t) + \beta_{10} * \text{Month4}(t) + \beta_{11} * \text{Month5}(t) + \beta_{12} * \text{Stable Phase}(c, t) + \beta_{13} * \text{Specialty}(s) * \text{Month0}(t) + \beta_{14} * \text{Specialty}(s) * \text{Month1}(t) + \beta_{15} * \text{Specialty}(s) * \text{Month2}(t) + \beta_{16} * \text{Specialty}(s) * \text{Month3}(t) + \beta_{17} * \text{Specialty}(s) * \text{Month4}(t) + \beta_{18} * \text{Specialty}(s) * \text{Month5}(t) + \beta_{19} * \text{Specialty}(s) * \text{Stable Phase}(c, t) + \alpha_i + \varepsilon_{it} \quad (4)$$

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10. We had access to all the data elements except physician experience. We obtained physician experience data from www.healthgrades.com, through a data field called "Years since Graduation." For implementation taking place in 200X, we subtracted 11-X from the experience in 2011 to arrive at the experience in 200X. Then we increased experience by 1/12 year for every subsequent month.

11. Models 2a, 2b and 2c correspond to learning durations of 4, 5 and 6 months respectively.

$$\text{Productivity}(i, t) = \beta_0 + \beta_1 * \text{Physician}(i) + \beta_2 * \text{Clinic}(c) + \beta_3 * \text{Specialty}(s) + \beta_4 * \text{Gender}(i) + \beta_5 * \text{Experience}(i) + \beta_6 * \text{Month0}(t) + \beta_7 * \text{Month1}(t) + \beta_8 * \text{Month2}(t) + \beta_9 * \text{Month3}(t) + \beta_{10} * \text{Month4}(t) + \beta_{11} * \text{Month5}(t) + \beta_{12} * \text{Month6}(t) + \beta_{13} * \text{Stable Phase}(c, t) + \beta_{14} * \text{Specialty}(s) * \text{Month0}(t) + \beta_{15} * \text{Specialty}(s) * \text{Month1}(t) + \beta_{16} * \text{Specialty}(s) * \text{Month2}(t) + \beta_{17} * \text{Specialty}(s) * \text{Month3}(t) + \beta_{18} * \text{Specialty}(s) * \text{Month4}(t) + \beta_{19} * \text{Specialty}(s) * \text{Month5}(t) + \beta_{20} * \text{Specialty}(s) * \text{Month6}(t) + \beta_{21} * \text{Specialty}(s) * \text{Stable Phase}(c, t) + \alpha_i + \varepsilon_{it} \quad (5)$$

The separation of the error term into two components is key to analyzing panel data. Two main categories of panel data models are used by researchers – fixed effects (FE) model and random effects (RE) model. In the FE model, α_i are allowed to be correlated with the regressors x_{it}, with the assumption that x_{it} are uncorrelated with the idiosyncratic error ε_{it}. In other words, the regressors are allowed to be correlated with the time-invariant component of the error. In the RE model, the assumption is that α_i are purely random, indicating that they are uncorrelated with the regressors and that regressors are completely exogenous (Cameron and Trivedi 2010).

The model was estimated using a panel dataset with N = 87 and T = 39 (observations on 87 physicians for 39 months). We hasten to add that our panel is unbalanced because different clinics within the hospital where physicians worked started implementing the EMR at different time periods. When used with panel data, standard applications of ordinary least squares (OLS) regression generates biased and inefficient parameter estimates as well as inaccurate standard errors. For OLS regression to yield proper results, the error processes must be independent and homoscedastic, but because panel data rely on repeat observations of the same unit across time, observations for particular units are, by definition, structurally related to one another. Thus, the use of OLS on panel data may result in heterogeneity bias (Baltagi 2005). Furthermore, unobserved characteristics, which may be correlated with both physician productivity and our included covariates can bias OLS results (Hausman and Taylor 1981).

Before estimating either the FE or RE model, we first evaluated our data for poolability. In other words, we assessed the suitability of the OLS model, which does not account for individual effects and implies constant intercept for all physicians. Thus, while the OLS model can be written as $y_{it} = a + x_{it} b + \varepsilon_{it}$, the panel models are written as $y_{it} = a + x_{it} b + \alpha_i + \varepsilon_{it}$. We used the *xtreg* command in Stata/SE 10 with the *fe* option to estimate the model. We found the F-statistic to be significant at p<.001 for all the models, hence, we can reject the null hypothesis that there is no individual-level heterogeneity, and excise away the pooled regression model from further consideration.

Next we evaluated the choice between FE and RE models. A fixed-effects analysis assumes that the subjects we are drawing measurements from are fixed, and that the differences between them are not of interest. So the researcher can look at the variance within each subject all lumped in together - essentially assuming that the subjects (and their variances) are identical. By contrast, a random-effects analysis assumes that the subjects are randomly drawn samples from a larger population, and that therefore the variance between them is interesting and can tell us something about the larger population. Fixed effects methods completely ignore the between-person variation and focus only on the within-person variation, whereas random effects models allow the regression coefficients to vary across subjects. Thus, there is a trade-off between bias and sampling variability. Fixed effects methods tend to reduce bias at the expense of greater sampling variability. Another major difference between the models is related to inference. A fixed-effects analysis can only support inference about the group of measurements, such as firms, countries, individuals, etc. actually examined. A random-effects analysis, by contrast, allows inferences about the larger population (Chellappa et al. 2010). Further, random effects models do not require that subjects be measured on the same number of time points and the time points need not be equally spaced (Chellappa et al. 2010). As discussed earlier, we have an unbalanced panel. Because of our interest in allowing regression coefficients to vary across subjects, our desire to generalize study results among other primary care physicians, and the nature of our data, we believed that random effects model would be more suitable to our study context.

We conducted the Hausman test to econometrically confirm our rationale. The issue here is whether there is significant correlation between the unobserved physician-specific random effects and the regressors. If there is no such correlation, then the random effects model may be more powerful and parsimonious. If there is such a correlation, the random effects model would be inconsistently estimated and the fixed effects model would be the model of choice. The null hypothesis is that there is no correlation. If there is no statistically significant difference between the covariance matrices of the two models, then the correlations of the random effects with the regressors are statistically insignificant. Hausman test statistic has a Chi-Square distribution with degrees of freedom equal to the number of regressors. We find that Hausman test statistic is insignificant with p-value > 0.1 for all the estimation models, suggesting that the random effects model is the appropriate choice in our context. RE model is also more efficient in estimating our highly unbalanced panel. However, if an unbalanced panel is being used, one needs to take note of the possibility that the causes of missing observations are endogenous to the model. In other words, the different time periods when the EMR implementations begin may be endogenous.[12]

Model Estimation and Results

We used Stata/SE 10 for estimating our econometric models. The default option for standard errors in Stata is the conventionally derived variance estimator for generalized least-squares (GLS) regression (i.e., *vce(conventional)*). We used GLS estimation with robust standard errors option (i.e., *vce(robust)*) because these estimations are robust to misspecifications, cross-sectional heteroscedasticity and within-panel (serial) correlation. It is important to note that this option leaves coefficient estimates largely untouched; only the standard errors produced by the default option are impacted. Clinic AB, IMs and male respectively served as bases for clinics, specialty and gender.

Our key interest in this study is to examine the temporal productivity implications of EMR implementation across physicians of different specialty. Our results are shown in Tables 5 and 6. Table 5 presents estimation results for equations 1, 2a, 2b and 2c (see Page 14). It is important to remember that we have allowed the learning phase to be 4, 5 or 6 months, and thus get three empirical models corresponding to equation 2. Table 6 presents estimation results for equations 3, 4 and 5. Table 5 primarily lets us evaluate if there is a significant interaction between specialty, and learning and stable phases. Table 6 takes a deeper look into the learning phase and allows us to understand the dynamic within it.

[Insert Tables 5 and 6 about Here]

All the four models in Table 5 are statistically significant, as is evident from model fit statistics. These statistics confirm that the null hypothesis that all the coefficients are zero can be safely rejected and that the model is significant. We conducted the Breusch-Pagan Lagrange Multiplier (BPLM) test to confirm the appropriateness of the RE model. The χ^2 (1) statistic was significant at $p<0.001$ for every model, suggesting the applicability of RE models. The estimated standard deviation of α_i (sigma_u) is lower than the estimated standard deviation of ε_{it} (sigma_e) for every model, suggesting that the idiosyncratic component of the error is more important than the individual-specific error. The Wooldridge test for serial correlation suggests that there is no serial correlation. We fail to reject the null in

12. We also analyzed our data using fixed effects models. The FE approach does not provide estimations for time invariant variables, but otherwise, our key results stay the same qualitatively. In other words, neither the direction nor the significance of coefficients changes qualitatively for our study variables. These results are available from the authors.

every model as evidenced by p>0.1 for every model. The Wald test for heteroscedasticity suggests that it is present in all four models, as suggested by p<.001 in every model. Thus, we reject the null of homoscedasticity and conclude heteroscedasticity. As discussed, we use the *robust* option to control for heteroscedasticity. We notice that the same pattern holds for all the models in Table 6. Next we discuss the results from the two Tables sequentially.

The interpretation of the coefficients in RE models is complicated because they include both the within-entity and between-entity effects. In general, the coefficients represent the average effect of the variables over the dependent variable as they change across time and between cross-sections by one unit. Our results suggest that the constant term is significant in every model in Table 5. Further, being in clinics C, D and J is negatively associated with productivity in comparison to clinic AB. Surprisingly, in contrast to other researchers (e.g., Conrad et al. 2002), we find that gender is not significantly related to physician productivity. Additionally, we find that physician experience is not significantly related to productivity. In interpreting the coefficients associated with study variables, we adopt the following approach – we examine models 2, 3 and 4 together and model 1 separately. Focusing on model 1, which models learning and stable phases as a running variable, number of months, our results indicate that both FPs and Peds are significantly less productive than IMs as emrAGE increases. More importantly, this model suggests that Peds and FPs perform worse than IMs in every time duration, which clearly is not the case. Recall that this model assumes that physician productivity varies linearly with emrAGE, and hence ignores the dynamic nature of productivity and learning and stable phases associated with technology implementation. Focusing on models 2, 3 and 4, our results consistently indicate FPs are less productive in the stable phase in comparison to IMs. Peds also demonstrate a decrease in productivity in the stable phase in comparison to IMs, although their decrease is less significant than that of FPs. Our results also indicate that during the learning phase, FPs and Peds are no different statistically from IMs with regard to their productivity.

The three estimation models reported in Table 6 confirm the long-term productivity impact for differences in specialties discussed above, and extend the analysis to cover the dynamics within the learning phase. As mentioned earlier, the constant term is significant in every model in Table 6. Being in clinics C, D and J is still negatively associated with productivity in comparison to clinic AB. Gender and physician experience are still not significantly related to physician productivity. Finally, FPs are less productive in the stable phase in comparison to IMs. Peds also demonstrate a decrease in productivity in the stable phase in comparison to IMs, although their decrease is less significant than that of FPs. Internal medicine doctors appear to exhibit a larger and somewhat longer initial drop in productivity, however they recover and exceed their pre-EMR productivity levels in the stable phase.

All three specialties exhibit a substantial drop in productivity immediately after EMR implementation (i.e., months 0 and 1). Before we examine the monthly variations during the learning phase, we note that during the month of EMR implementation (Month 0), the productivities of Peds is not statistically different from those of IMs, whereas the productivities of FPs are substantially lower than those of IMs. This fact is reflected in all the models in Table 6. However, the pattern becomes rather interesting as the months transition from 1 to 6. We notice that in Models 3, 4 and 5 in Table 6, the productivities of Peds improve significantly in comparison to those of IMs in the first month. The advantage enjoyed by Peds is dissipated away in Month 2 and onward in all the Models. Although FPs are significantly worse off than IMs in Month 0, their productivities improve in comparison to IMs and they become statistically indistinguishable from IMs in Months 1, 2 and 3. In all subsequent months, their productivities are significantly lower than IMs. This pattern is consistent in all the Models, 3, 4 and 5, in Table 6.

A recent National Research Council report states that clinicians spend more time entering data than using it, which might suggest that the information entry aspects of EMR can dominate the overall effect on productivity (Stead and Lin 2009). Additionally, researchers claim that while EMRs make audit, research and billing more efficient, they may render the clinical work to be less efficient. However, our research suggests that it would be more useful to examine such statistics and observations at a finer-grained level that accounts for differences in workflow due to systematic differences such as physician specialty. A few other notable studies, including a 2008 Congressional Budget Office study (Orszag 2008), and an MGMA study funded by the US government (Gans 2005), have cautioned that EMRs may reduce overall physician productivity. Again, our research points to the importance of examining this impact by specialty and also separating the short-run changes from the long-run effect. In a recent study, Cheriff et al. (2010) found that the implementation of EHR systems at Cornell Weill center improved the productivity of physicians in the ramp-up phase (up to 5 months post go-live) in comparison to the pre-implementation stage, with productivities in the post ramp-up phase being even higher. In contrast, we do not find an unequivocal increase in productivity among physicians. Furthermore, while they do not find any difference on productivity implications on specialty category (surgical vs. medical), we find significant differences among the three specialties examined in this study.

Endogeneity Issues

The RE model assumes that regressors in the model are completely exogenous. Physicians' specialties, the clinics where they worked and their gender were time invariant for the duration of our study, and we can assume that these variables are exogeneous. These variables are not determined within the context of EMR productivity because each physician in this study was born with a gender; chose a specialty during his / her medical school and internship, years and decades before he / she joined the academic hospital in California; and was assigned to various clinics by the management years before EMR implementation began. Similarly, we can assume that physician experience is not determined within the context of EMR productivity because each physician graduated several years before EMR implementation of productivity data collection began at the academic medical center we studied.

EMR implementation decisions are made at the clinic level. Can this decision be assumed to be exogenous or do clinics choose to implement endogeneously? Thus, can the month of EMR implementation in various clinics, and hence various variables such as learning phase, stable phase, EMR age, etc. be assumed to be exogenous? Controlling for endogeneity of adoption decision is difficult. Unfortunately, the exact reason for choosing the order of implementation of EMR was not revealed to us, and this makes it hard to control for endogeneity. To instrument the clinics' EMR adoption decision, we need to have a set of valid predictors of a clinic's EMR adoption decision. We do not have such data and hence the problem is intractable (Gao et al. 2010), which is a limitation.

Our focus in this research is to examine how the productivity of physicians in multiple specialties evolve over time after EMR implementation. Thus, our foremost concern is to understand the interaction effects shown in the equations 2a, 2b, 2c, 3, 4 and 5 (see Page 14). Prior research shows that the magnitude of bias is reduced when the interacting factors are close to zero (Harrison 2008). Most of the interacting terms in our models are binary variables, and so the impact of endogeneity bias may not be significant on our results (Gao et al. 2010; Harrison 2008). Further, while endogeneity problem is severe in cross-sectional data and pooled data, analyzed using OLS model, given that we use panel data models, endogeneity problems are likely to be restrained (Chellappa et al. 2010).

We addressed the potential endogeneity issues in several ways. A common way to handle endogeneity between the independent and the dependent variables is to lag the dependent variable (Chellappa et al. 2010; Gopal and Gao 2009; Wooldrige 2002). Being able to lag variables and examining issues of reverse causality between them is one of the central advantages of panel data. As is evident, several variables in our study are time invariant and lagging them will not have any impact. It is important to note here that we do not believe that physicians' productivities can causally influence EMR implementation month. Table 7 below shows that there is no discernible pattern between physician productivities in a clinic and the EMR implementation time at that clinic. However, as suggested in the literature (Chellappa et al. 2010; Gopal and Gao 2009; Wooldrige 2002), we introduced a one month lag in physician productivity to reduce the impact of simultaneity and reverse causality between the IV and the DV, and analyzed our panel data again. Our key results are robust to this change. We find that our results for Models 1, 2a, 2b and 2c in Table 5 stay qualitatively the same for the interaction terms.[13] Our results for interaction terms for Models 3, 4 and 5 in Table 6 stay qualitatively the same for stable duration, but the interaction terms associated with Month0 through Month6 for both Peds and FPs are shifted forward by one month.[14]

Susarla et al (*forthcoming*) use another approach to address endogeneity. They use the Hausman-Taylor (HT) estimation technique, which enables estimations of panel-data RE models through an instrumental variable (IV) approach, in which some, but not all, covariates are correlated with the unobserved individual-level effects (Hausman and Taylor 1981). We use Stata/SE 10 to estimate the HT model. We indicate that the EMR implementation month related variables (e.g., such as learning phase, stable phase, EMR age, Month0, etc.) are endogenous regressors. Our results indicate that for all models in both Tables 5 and 6, our key results stay the same qualitatively.[15]

[Insert Table 7 about Here]

While it is not possible to completely dismiss the effects of endogeneity in our study, the consistent results we obtain from a wide variety of different analyses provides evidence for the robustness of our main results.

Discussion

[13, 14, 15.] These results are available upon request from the authors.

Implementations of information technologies in various contexts and the resulting productivity impacts are enduring research issues among IS scholars. Although a significant amount of research has been done in the domain, the new and emerging context of EMR use in the healthcare industry, which is rife with workflow complications, and specialty-specific differences, in addition to regulations and institutional histories, provide a fertile ground to conduct individual-level productivity studies on physicians. A number of researchers (e.g., Cheriff et al. 2010; DesRoches et al. 2008; Goh et al. 2011; Menachemi 2006) have suggested that the actual effects of EMR implementation on physician productivity have been understudied. The lack of insights on physician-level impacts of EMR implementation tends to prejudice doctors who are skeptical of how technologies apply to them. To date, however, there are few rigorous studies in IS that have attempted to examine these aspects using panel data. Further, to our knowledge, productivity impacts of EMR implementation across different physician specialties have not been studied before.

Our goal in this paper was to examine the impacts of EMR implementation on physician productivity across different specialties and to uncover the dynamic and temporal nature of these impacts. Our empirical analysis is limited to three categories of primary care specialties, pediatrics, internal medicine, and family practice. Our analysis suggests that the three physician specialties differ significantly in terms of how they absorb EMR technology, and on the long-run productivity impact of EMR technologies. The post-EMR productivity levels for Internists settled slightly above the pre-EMR levels, despite there being a substantial productivity drop in the months immediately after EMR implementation. Compared with pediatricians and family practitioners, Internists experience greater productivity gains in the long run, irrespective of the length of the learning phase (4, 5, or 6 months).

Why might the different categories of primary care exhibit differences in how they absorb EMR and in the overall impact on physician productivity? To understand this, we return to the two ways in which EMRs affect physician workflow, and examine whether inherent differences in work patterns and in the use of information, across specialties, can account for the observed differences in productivity impacts of EMR technologies. In other words, we examine if the tasks performed by physicians in various specialties and the features offered the implemented EMR fit.

The first aspect of EMR, information review, enables physicians to retrieve and synthesize information quickly and efficiently. Traditional, paper-based, patient records pose substantial challenges in both retrieval of the patient file, possibly from a different location or administrative unit, and in locating and searching for specific information from a patient's health history. EMRs can speed up retrieval and search of information. Moreover, EMR systems facilitate combination, aggregation and synthesis of multiple pieces of data for physicians. For instance consider an internal medicine specialist examining a patient who has had a series of lab tests (e.g., WBC count, CRP levels, etc.) over the past few months, and suppose that this physician is interested in looking at one particular series (CRP). With the traditional paper record, the physicians would need to extract this data which might be scattered over several pages in the file, and collate the information. An EMR, in contrast, makes such data easy to retrieve, and moreover, facilitates visual display of test results as a line graph over time. Thus, from a *homo computicus* perspective of information use, EMRs enhance the alacrity with which physicians can obtain additional information about disease conditions, search for more relevant information and navigate the knowledge base embedded in EMR, resulting in improved information review, synthesis and medical decision making.

We note here that medical information review and synthesis requires significant cognitive processing, and hence a change in the manner in which physicians receive information is likely to place considerable learning burden on them in the initial stage. This is akin to academicians making a shift from physical copies of journal articles to purely electronic ones. However, after physicians assimilate the new information review and synthesis workflows, EMR technologies should provide a significant productivity boost. The extent to which physicians receive such a boost would depend on the weight of information review in their work practice. Physicians who rely substantially on a patient's health history are more likely to achieve greater efficiency in information retrieval. In contrast, physicians who either have lesser use for past history, or tend to have greater mental recollections about the patient, will enjoy relatively lower benefits from the information retrieval capabilities of an EMR. Among the three specialties we considered - internal medicine, pediatrics, and family practice - we would expect that internal medicine physicians would obtain highest benefits from EMR, assuming that IMs see the most "new patients" while family practitioners, and to a lesser extent pediatricians, tend to be already more familiar with their patients because of their frequent interactions with patients. Additionally, IMs are more likely to see patients whom other doctors have previously examined and perhaps generated substantial data regarding their health history, and have greater use of health history and statistics in treating the patient.

The second mechanism is information entry. EMR technologies provide and often require an alternative mode for physicians to enter information such as documentation about the visit. This aspect of EMR requires a higher level of technological skills, including in typing sentences or paragraphs and in navigating a hierarchy of forms or check-boxes to enter visit details. Physicians are required to enter both structured and unstructured data in patients' electronic records. Because of access restrictions placed on patients' electronic records, doctors can no longer rely on nurses to enter information about patients for which they are directly responsible. For many physicians, this new mode can consume greater amount of time relative to, for instance, scribbling notes, dictation, or checking on Yes/No boxes on a paper form. Through this mechanism, EMRs can compromise physician productivity. Again, the negative effect is likely to be greater for physicians whose routine work requires greater amounts of documentation. Our discussions with the physicians and administrators at the hospital indicated that EMRs impose a more substantial information entry burden on pediatricians and family practitioners in comparison to Internists.

Combining the two mechanisms, it appears that the differences in the information work across different specialties can explain the observed variations in impact of EMRs on physician productivity. Internists see sick adults, with whom they are not as familiar as pediatricians and family practitioners tend to be with their patients. EMRs can quickly provide relevant facts about the patient's health. Our discussions with the medical staff at the research site suggest that Internists, in general, do less data entry and more data synthesis and decision making. Additionally, because they tend to specialize in certain disease conditions, they become proficient in accessing and synthesizing information about those conditions. In such cases, the EMR's replacement of the old paper health record is substantially, and positively, impactful, once the learning period, when the cognitive load on physicians to learn and modify existing paper-based information review and synthesis schema and workflows are replaced with new schemas and workflows, is over, and the new technology is integrated into physicians' daily operations. Family practitioners are the first line of defense for patients against many different illnesses. Patients go to see FPs for a wide variety of medical conditions, necessitating information entry on widely different medical conditions, making it difficult for them to master informational requirements for specific medical conditions. According to National Ambulatory Medical Care (NAMC) survey, FPs accounted for 224 million visits, out of 956 million visits in 2008 (http://www.cdc.gov/nchs/data/ahcd/namcs_summary/namcssum2008.pdf), the highest number reported by any physician specialty. Additionally, while information entry requirements are high for FPs, their numbers have been plunging since the 1990's, making a bad situation much worse. Pediatricians spend substantial time in well-baby care and other activities that do not require considerable review of past patient data. Hence they do not benefit much from the superior IT capabilities for data retrieval, review and visualization. On the other hand, in addition to creating documentation for newborns, they are required to make substantial documentation for infants children and adolescents after each visit because they serve as the primary medical resource for them and these patients visit them for many different conditions. Peds therefore face a significant burden of entering data through computer forms and menus, as against paper-and-pad checklists that are filled while moving between rooms.

Recall that we do not find any significant impact of physician gender or experience, which can serve as a proxy for age, on post-EMR productivity. In contrast, Conrad et al. (2002) find that experience has a small but significant impact on productivity. Furthermore, they find that female physicians are significantly less productive than male physicians. While Conrad et al. used the annual cost and physician compensation and production surveys reported by MGMA for the year 1997, we believe that the availability of a longer and more fine-grained panel dataset allows us to more accurately estimate the impact of gender and experience. Our results indicate that there is a need to assess these impacts with more detailed data as cross-sectional analyses may not reveal the nature of actual impacts. From a policy perspective, our results suggest that both younger and older doctors, as well as both male and female doctors, can be trained on new technologies, and be equally productive after a period of time.

The divergence in EMR impact has useful implications for design of future EMR technologies. In many EMR implementations, such as at our study site, the EMR interface is a desktop computer tethered to other hardware in the room and used via a standard keyboard and mouse interface. Every physician uses the same interface to interact with the EMR. It appears that this standard design is not an effective replacement for the pen-paper-pad tool which Peds and FPs can use efficiently to document and enter visit information. Our results suggest that IMs may be more productive with voice-activated search and analysis feature, and FPs and Peds may find voice-enabled data input into EMR more helpful. Moreover, the absence of huge productivity gains, substantial enough to overcome the implementation costs, indicates that healthcare providers may not have full incentives to incur the substantial costs of EMR deployment. This tradeoff, of course, plays out differently for different types of hospital structures. A fully integrated system, such as Kaiser Permanante may be able to capture benefits resulting from increase in quality of care and long-term patient health, but disaggregated health systems and hospitals may hesitate to make suitable investments unless health insurance companies provide different reimbursement rates or begin to track longer-term outcomes in a pay-for-performance model. This suggests that the prospects for medium-term investments in health care information technologies are tied both to the design/architecture of these technologies as well as to the nature of economic incentives provided to health care delivery organizations. Our results also suggest that productivity measurements are turbulent during the first few months after EMR implementation across different physician specialties, and thus the management should not make long-term policy decisions regarding EMR use during this period.

Limitations of the Research

Prior to discussing the research and pragmatic implications of our findings, we acknowledge some limitations that provide opportunities for further extending our study. First, while our focus on examining productivity implications of EMR on physicians associated with one clinic for the duration of the study and their association with one university hospital provided us with a unique setting that controlled for a number of confounding factors, some may wonder about boundary conditions and generalizeability of our findings. We hasten to add that our use of random effects model allows us to generalize the results. Additionally, to the extent that workflow and informational needs of FPs, Peds and IMs are expected to be similar across different organizational settings, we would expect our results to be applicable. However, we strongly recommend other researchers to expand the scope of our study and examine productivity impacts of EMR across a large number of specialties and in multiple hospitals with varying levels of ownership, academic status (academic or community) and profit focus (for or not-for profit).

Second, extant research in health informatics has used several additional productivity measures such as charges and visit volume (Cheriff et al. 2010). Many of these measures have been shown to have severe limitations, and CMS as well as private insurance companies use the WRVU measure for payment purposes, it would be appealing to compare to examine the productivity impacts of EMRs on multiple productivity measures. However, because of lack of data on measures such as charges and visit volume, we are unable to extend our results. We hope that future research will gather data on these productivity measures and provide a comparison across them. We recognize that productivity does not fully capture performance and value in a clinical setting; other measures such as quality of care, revenues generated or patient satisfaction may be equally, if not more, important.

Third, we are unable to account for the time doctors spend training on the new system. Additionally, doctors may spend a significant amount of time before and after an actual patient encounter, as also in coordinating care with other doctors and supervising other health professionals such as nurse practitioners and physician assistants (Johnson and Newton 2002). These are limitations associated with the WRVU measure, and our study suffers from them as well.

Finally, due to lack of data, we are unable to link our physician-level productivity measure with hospital-level with financial or operational measures. Our primary purpose in this paper was to emphasize the fact the physician productivity is the missing piece of the EMR value puzzle. In other words, while researchers have examined various measures of EMR adoption and use and the performance impacts of EMR for other entities, their effects on one of the most consequential entities – physicians – have not been examined in detail. However, it may be insightful to examine the productivity impacts of EMR on physicians along with other performance measures.

Research Contributions and Implications

Despite the limitations identified earlier, this paper makes several contributions to extant research in health informatics, IT productivity and task-technology fit. First, to the best of our knowledge, this study is the first to examine physician-level productivity impacts of EMR implementation using a panel data spread across 39 months and rigorous econometric methods. In the health informatics literature, researchers have debated about the impact of EMRs on physicians. In the absence of a study using a panel data of considerable length, they have fallen back on anecdotal evidence to suggest that these technologies enhance physician productivity. Concurrently, the IT productivity literature has lamented the absence of individual-level productivity studies in the services sector, especially for white-collar, knowledge and information workers (Aral et al. 2006). Our study extends the research in both health informatics and IT productivity literatures. As alluded by Aral et al. (2006), it is difficult to attribute gains or impediments in productivity to one person, but the productivity measure used in this study, WRVU, allows us to isolate how individual physicians perform pre- and post- EMR implementation, because it is captured at the individual level. Thus, multiple physicians collaborating on a treatment earn individual WRVUs that are well-understood in the healthcare industry. Second, our study and results demonstrate that technological innovations such as EMRs can indeed impact physician productivity, but the nature, direction and magnitude of such changes are contingent on the nature of work performed by the knowledge workers (e.g., physicians) and vary systematically over time, demonstrating a big dive initially, followed by some a recovery phase, and then a steady-state that may be higher or lower than pre-technology levels based on the task-technology fit. The key insight from our study is that such impacts vary considerably across specialties. Third, our results show, with remarkable consistency across different formulations, that when EMR implementation is examined in the context of clinics rather than hospitals, the productivity of physicians suffers for a short duration, in months 0 and 1, before climbing back up. Thus, while the benefits of EMR may be far from certain, our study suggests that the continued deep decline in productivity feared by physicians may not materialize. Finally, this study shows that the concept of information retrieval to information entry ratio can be important for explaining productivity differences across different physician specialties. This concept can also be extended to other contexts such as management and IT consulting and applied in various individual-level IT productivity studies.

This study can be extended in several possible ways. First, while we examined EMR implementation in the ambulatory primary care setting, future research can enhance the scope of study by contrasting EMR implementations in multiple setting such as in-patient setting, surgery departments and emergency rooms, in addition to the primary care setting. Information entry and retrieval mechanisms are likely to manifest themselves in multiple ways, thus providing promising opportunities to compare and contrast productivity implications of EMR. Second, from a task-technology fit theory perspective, several task traits, such as complexity, routineness, uncertainty, variety and ambiguity have been posited to be relevant because these characteristics influence the amount and nature of information processing (Goodhue and Thompson 1995; Zigurs and Buckland 1998). Additionally, TTF has been used predominantly to assess user evaluations of performance and fit along eight different dimensions - data quality, data locatability, authorization, data compatibility, ease of use, production timeliness, system reliability and relationship with users. Future research can posit explicit hypotheses on how task traits may differ for different physicians working in diverse conditions, and how these traits may influence the fit on multiple dimensions. We believe that observational data, including those obtained from time and motion studies, in addition to secondary data obtained from productivity and schedule logs, and survey data can be used to examine the fit issues in detail.

Conclusion

As health services organizations endeavor to implement EMRs and hope for a synergistic impact on many performance metrics, it becomes important for researchers to analyze how the new technologies influence a critical group of stakeholders in the healthcare industry – the physicians. This paper evaluated the productivity impact of EMR technologies on physicians, and examined how this impact evolves over time and whether this impact varies by physician specialty. We used a unique, long panel dataset to provide evidence and insights on productivity implications of EMR on physicians. This paper contributes to extant knowledge on individual-level productivity impacts of IT in the service industry, a context which has been understudied in the literature. We contribute to policy and practice discussions by emphasizing the need for granular analyses, taking into consideration specialties, temporal nature of productivity and fine-grained data. We hope that this paper stimulates further research in the domain, contributing to our enhanced understanding of how information technologies impact individual-level productivity, especially among white-color and knowledge workers.

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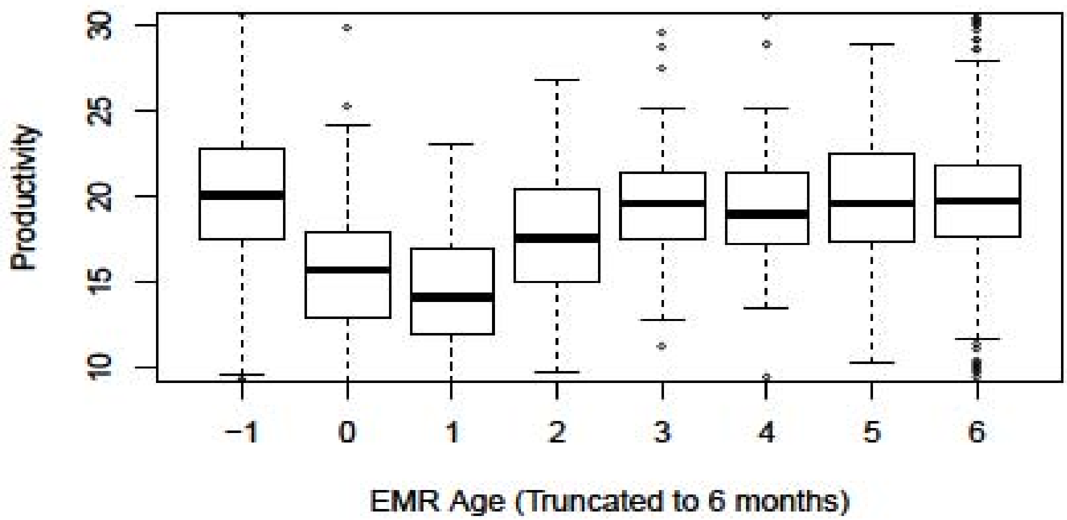

Figure 1: Physician Productivity Variation across Time without Considering Specialties

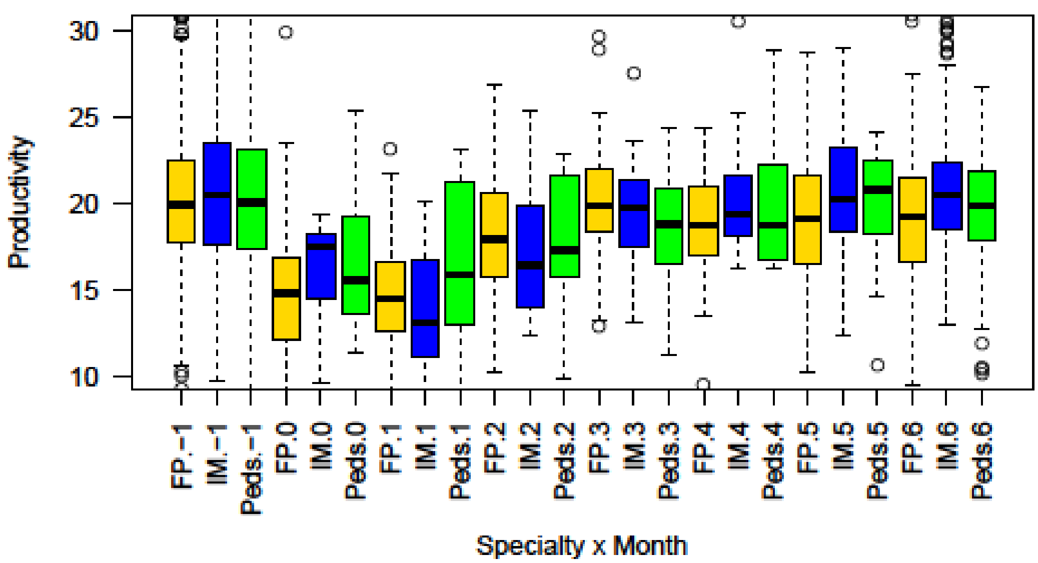

Figure 2: Productivity Variation before and after EMR Implementation, for Each Specialty

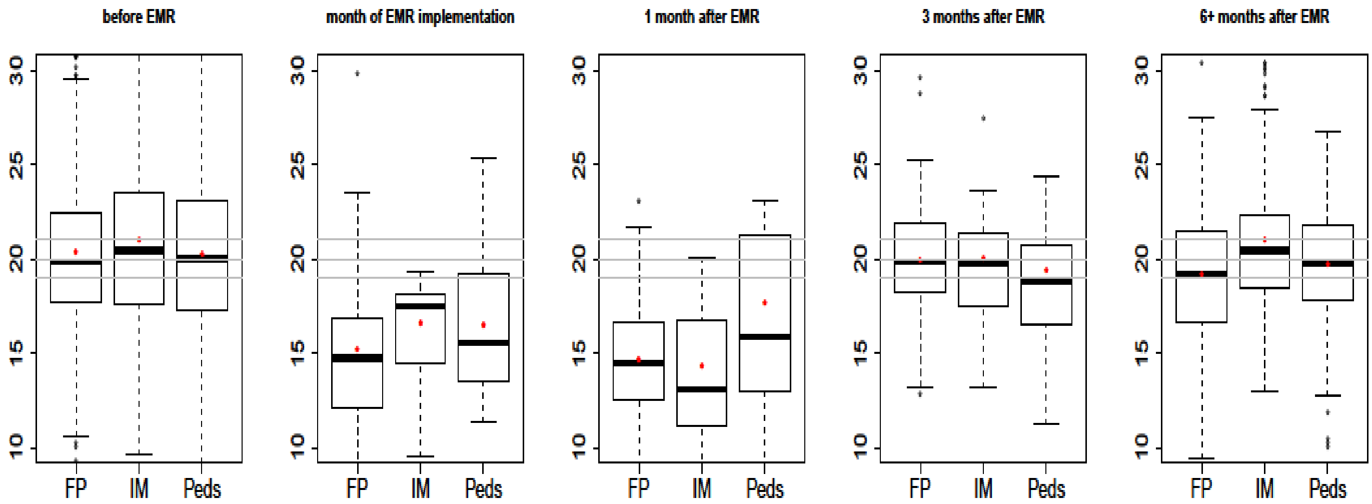

Figure 3: Physician Productivity over Time for Different Specialties

Table 1: Sample Data

Observation Number	Doc ID	Month ID	Gender	Clinic	Specialty	# Days Worked	WRVUs	Productivity
300	8	28	F	AP	IM	19.14	318.80	16.66
800	29	34	M	D	FP	11.57	260.67	22.53
1250	34	9	F	D	Peds	8.90	58.6	6.58

Table 2: Number of Observations by Specialty and Clinic

	AB	AP	P	C	L	D	E	F	J	N	R	U	Total
FP	155	0	260	78	0	259	269	193	0	158	156	0	1,528
IM	0	114	0	117	39	31	23	99	335	38	231	0	1,027
Peds	117	0	0	78	0	31	0	132	0	0	117	156	631
Total	272	114	260	273	39	321	292	424	335	196	504	156	3,186

Table 3: Number of Physicians by Specialty and Clinic

	AB	AP	P	C	L	D	E	F	J	N	R	U	Total
FP	4	0	7	2	0	7	7	5	0	5	4	0	41
IM	0	3	0	3	1	1	1	4	9	1	7	0	29
Peds	3	0	0	2	0	1	0	4	0	0	3	4	17
Total	7	3	7	7	1	9	8	13	9	6	14	4	87

Table 4: Descriptive Statistics and Correlations among Variables

Variables	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Clinic AB (1)	.09	.28	1																	
Clinic AP (2)	.04	.19	-.06*	1																
Clinic P (3)	.08	.27	-.1*	-.06*	1															
Clinic C (4)	.09	.28	-.09*	-.06*	-.09*	1														
Clinic L (5)	.01	.11	-.03	-.02	-.03	-.03	1													
Clinic D (6)	.10	.30	-.1*	-.06*	-.1*	-.1*	-.04*	1												
Clinic E (7)	.09	.28	-.1*	-.06*	-.1*	-.1*	-.04*	-.11*	1											
Clinic F (8)	.13	.34	-.12*	-.08*	-.12*	-.12*	-.04*	-.13*	-.12*	1										
Clinic J (9)	.11	.31	-.11*	-.07*	-.1*	-.11*	-.04*	-.12*	-.11*	-.13*	1									
Clinic N (10)	.06	.24	-.08*	-.05*	-.08*	-.08*	.03*	-.09*	-.08*	-.1*	-.09*	1								
Clinic R (11)	.16	.37	-.13*	-.08*	-.13*	-.13*	-.05*	-.15*	-.14*	-.17*	-.15*	-.11*	1							
Clinic U (12)	.05	.22	-.07*	-.04*	-.07*	-.07*	-.03	-.08*	-.07*	-.09*	-.08*	-.06*	-.1*	1						
PEDs (13)	.20	.40	.18*	-.1*	-.15*	.07*	-.06*	-.09*	-.16*	.11*	-.17*	-.13*	.04*	.5*	1					
IMs (14)	.32	.47	-.21*	.28*	-.21*	.07*	.16*	-.16*	-.17*	-.08*	.5*	-.07*	.13*	-.16*	-.34*	1				
FPs (15)	.48	.50	.06*	-.19*	.31*	-.12*	-.11*	.22*	.28*	.02	-.33*	.17*	-.15*	-.22*	-.48*	-.66*	1			
Gender (16)																				
Experience (17)																				
Productivity (16)	20.03	5.02	.05*	.12*	.01	-.13*	.09	-.12*	-.08*	.11*	-.09*	-.01	.1*	.007	-.02	.1*	-.07*	1		

*p<.05

Table 5: Physician Productivity Variation during Learning and Stable Phases

Variables	Model 1: Linear Impact model		Model 2a: Learning Duration / Ramp-up Phase = 4 months		Model 2b: Learning Duration / Ramp-up Phase = 5 months		Model 2c: Learning Duration / Ramp-up Phase = 6 months	
	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error
Constant	22.42***	(1.64)	22.05***	(1.63)	22.03***	(1.59)	21.96***	(1.59)
Clinic AP	1.10	(2.67)	1.23	(2.62)	1.15	(2.61)	1.22	(2.57)
Clinic P	-0.63	(1.73)	-0.49	(1.74)	-0.48	(1.71)	-0.45	(1.69)
Clinic C	-3.29*	(1.48)	-3.32*	(1.47)	-3.34*	(1.46)	-3.32*	(1.54)
Clinic L	1.95	(3.61)	2.02	(3.63)	2.00	(3.62)	2.04.	(3.56)
Clinic D	-3.54*	(1.47)	-3.29*	(1.48)	-3.28*	(1.46)	-3.24*	(1.44)
Clinic E	-3.06	(1.61)	-2.67	(1.61)	-2.66	(1.59)	-2.60	(1.57)
Clinic F	0.23	(1.43)	0.57	(1.42)	0.60	(1.40)	0.68	(1.39)
Clinic J	-3.74*	(1.61)	-3.44*	(1.59)	-3.41*	(1.56)	-3.39*	(1.57)
Clinic N	-2.63	(2.94)	-2.37	(1.92)	-2.38	(1.90)	-2.33	(1.87)
Clinic R	-0.75	(1.42)	-0.52	(1.41)	-0.53	(1.40)	-0.49	(1.39)
Clinic U	-0.35	(2.02)	-0.03	(2.07)	-0.03	(2.05)	0.06	(2.00)
Pediatrics (Peds)	-1.24	(1.12)	-1.64	(1.11)	-1.69	(1.11)	-1.68	(1.10)
Family Practice (FP)	-0.008	(0.96)	-0.16	(0.95)	-0.20	(0.95)	-0.20	(0.95)
Physician Gender	-0.07	(0.64)	-0.18	(0.64)	-0.20	(0.64)	-0.21	(0.63)
Physician Experience	-0.034	(0.03)	0.002	(0.03)	0.006	(0.03)	0.008	(0.03)
Learning Duration	--	--	-2.35***	(0.42)	-1.43***	(0.37)	-1.18***	(0.36)
Stable Duration	--	--	0.81**	(0.25)	0.61**	(0.25)	0.69**	(0.25)
Peds * Learning Duration	--	--	1.28	(0.81)	0.37	(0.78)	0.67	(0.62)
EMR Age	0.09***	(0.017)	--	--	--	--	--	--
Peds * Stable Duration	--	--	-0.78†	(0.42)	-0.78†	(0.42)	-0.81†	(0.45)
FP * Learning Duration	--	--	-0.31	(0.50)	-0.37	(0.45)	-0.50	(0.43)
FP * Stable Duration	--	--	-1.55***	(0.31)	-1.35***	(0.31)	-1.39***	(0.32)
Peds * EMR Age	-0.09**	(0.03)	--	--	--	--	--	--
FP * EMR Age	-0.13***	(0.02)	--	--	--	--	--	--
Model Fit Statistis	Wald χ^2 (18) = 66.51 Prob > χ^2 = 0.000		Wald χ^2 (21) = 153.17 Prob > χ^2 = 0.000		Wald χ^2 (21) = 126.87 Prob > χ^2 = 0.000		Wald χ^2 (2.1) = 118.11 Prob > χ^2 = 0.000	
Standard Deviation	Sigma_u: 2.56 Sigma_e: 3.55		Sigma_u: 2.57 Sigma_e: 3.51		Sigma_u: 2.54 Sigma_e: 3.53		Sigma_u: 2.51 Sigma_e: 3.54	
BPLM Test	χ^2 (1) = 5583.7; p<0.000		χ^2 (1) = 6236.7; p<0.000		χ^2 (1) = 6193.6; p<0.000		χ^2 (1) = 6143.52; p<0.000	
Test for Heteroskedasticity	χ^2 (87) = 1205.4; p<0.000		χ^2 (87) = 1088.7; p<0.000		χ^2 (87) = 983.8; p<0.000		χ^2 (87) = 965.4; p<0.000	
Wooldridge Test for Autocorrelation	F(1,86) = 1.58; p=0.21		F(1,86) = 1.61; p=0.22		F(1,86) = 1.64; p=0.22		F(1,86) = 1.66; p=0.22	
N	3,186		3,186		3,186		3,186	

Note: Clinic AB, Specialty IM and Gender Male served as the bases

†:p<.1; *:p<.05; **:p<.01; ***:p<.001

Table 6: Physician Productivity Variation during Learning Months and Stable Phase

Variables	Model 3: Learning Duration / Ramp-up Phase = 4 months		Model 4: Learning Duration / Ramp-up Phase = 5 months		Model 5: Learning Duration / Ramp-up Phase = 6 months	
	Coefficient	Std. error	Coefficient	Std. error	Std. error	Std. error
Constant	21.64***	(1.65)	21.64***	(1.60)	21.63***	(1.59)
Clinic AP	1.43	(2.62)	1.43	(2.54)	1.43	(2.56)
Clinic P	-0.32	(1.72)	-0.32	(1.67)	-0.31	(1.68)
Clinic C	-3.30*	(1.49)	-3.29*	(1.44)	-3.30*	(1.46)
Clinic L	2.19	(3.68)	2.18	(3.56)	2.18	(3.60)
Clinic D	-3.02*	(1.49)	-3.02*	(1.44)	-3.02*	(1.46)
Clinic E	-2.32	(1.59)	-2.32	(1.54)	-2.32	(1.56)
Clinic F	0.96	(1.44)	0.97	(1.40)	0.98	(1.42)
Clinic J	-3.19*	(1.59)	-3.19*	(1.54)	-3.17*	(1.56)
Clinic N	-2.12	(1.89)	-2.11	(1.83)	-2.11	(1.85)
Clinic R	-0.32	(1.41)	-0.32	(1.38)	-0.33	(1.38)
Clinic U	0.34	(2.08)	0.34	(2.02)	0.36	(2.03)
Pediatrics (Peds)	-1.71	(1.15)	-1.71	(1.11)	-1.70	(1.12)
Family Practice (FP)	-0.16	(0.99)	-0.15	(0.96)	-0.15	(0.96)
Physician Gender	-0.28	(0.63)	-0.28	(0.61)	-0.28	(0.61)
Physician Experience	0.03	(0.03)	0.03	(0.03)	0.03	(0.03)
Month0	-3.58***	(0.62)	-3.58***	(0.62)	-3.57***	(0.61)
Month1	-6.79***	(0.73)	-6.79***	(0.73)	-6.78***	(0.73)
Month2	-3.05***	(0.59)	-3.05***	(0.60)	-3.04***	(0.59)
Month3	-0.60	(0.47)	-0.60	(0.47)	-0.60	(0.47)
Month4	0.20	(0.54)	0.20	(0.55)	0.21	(0.55)
Month5	--	--	0.91	(0.67)	0.91	(0.67)
Month6	--	--	--	--	1.16*	(0.64)
Peds * Month0	-0.77	(1.11)	-0.77	(1.11)	-0.78	(1.11)
Peds * Month1	3.99*	(1.67)	3.99*	(1.67)	3.98*	(1.67)
Peds * Month2	1.77	(1.17)	1.77	(1.17)	1.76	(1.17)
Peds * Month3	-0.14	(1.74)	-0.15	(1.74)	-0.16	(1.74)
Peds * Month4	-0.70	(1.05)	-0.71	(1.05)	-0.72	(1.05)
Peds * Month5	--	--	0.15	(0.92)	-0.68	(0.90)
Peds * Month6	--	--	--	--	-0.71	(0.96)
FP * Month0	-2.15*	(0.81)	-2.15*	(0.82)	-2.15*	(0.81)
FP * Month1	0.96	(0.80)	0.96	(0.80)	0.96	(0.80)
FP * Month2	1.13	(0.71)	1.13	(0.72)	1.13	(0.71)
FP * Month3	0.33	(0.60)	0.33	(0.60)	0.33	(0.60)
FP * Month4	-1.54*	(0.67)	-1.55*	(0.67)	-1.54*	(0.67)
FP * Month5	--	--	-1.99**	(0.78)	-2.02**	(0.78)
FP * Month6	--	--	--	--	-2.54***	(0.80)
Stable Duration	0.56*	(0.25)	0.53*	(0.26)	0.48*	(0.26)
Peds * Stable Duration	-0.80*	(0.42)	-0.82*	(0.43)	-0.86*	(0.45)
FP * Stable Duration	-1.62***	(0.31)	-1.59***	(0.32)	-1.49***	(0.32)
Model Fit Statistics	Wald χ^2 (32) = 669.22 Prob > χ^2 = 0.000		Wald χ^2 (36) = 673.99 Prob > χ^2 = 0.000		Wald χ^2 (39) = 673.80 Prob > χ^2 = 0.000	
Standard Deviation	Sigma_u: 2.75 Sigma_e: 3.35		Sigma_u: 2.46 Sigma_e: 3.35		Sigma_u: 2.48 Sigma_e: 3.35	
BPLM Test	χ^2 (1) = 7086.42; p<0.000		χ^2 (1) = 7085.75; p<0.000		χ^2 (1) = 7090.68; p<0.000	
Test for Heteroskedasticity	χ^2 (87) = 1829.71; p<0.000		χ^2 (87) = 1828.63; p<0.000		χ^2 (87) = 1825.8; p<0.000	
Wooldridge Test for Autocorrelation	F(1,86) = 1.58; p=0.20		F(1,86) = 1.62; p=0.21		F(1,86) = 1.63; p=0.22	
N	3,186		3,186		3,186	

Note: Clinic AB, Specialty IM and Gender Male served as the bases

†:p<.1; *:p<.05; **:p<.01; ***:p<.001

Table 7: Relationship between Average Productivity by Clinic and EMR Implementation Sequence

	AB	AP	P	C	L	D	E	F	J	N	R	U
Average productivity	20.93	23.09	20.24	17.95	23.87	18.20	18.84	21.22	18.67	19.74	21.14	20.18
Implementation Month and year	September 2005	August 2005	April 2005	July 2005	July 2005	March 2005	May 2005	June 2004	August 2004	June 2005	October 2005	October 2004
The Order of Implementation	11	10	5	8	8	4	6	1	2	7	12	3
The Order of Average Productivity	5	2	6	12	1	11	9	3	10	8	4	7