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

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This paper studies the impact of an electronic medical record (EMR) system on the productivity of physicians. Physicians influence a vast majority of treatment decisions and are central to the care delivery process; thus, it is important to understand how EMRs may impact the nature of their work. Our research builds on prior literature on physician productivity, IT productivity, and task–technology fit theory. We use a unique panel data set comprising 87 physicians specializing in internal medicine, pediatrics, and family practice, located in 12 primary care clinics of an academic healthcare system in the western United States. We employ the Arellano–Bond system generalized method of moments estimation technique on our data set, which contains 3,186 physician-month productivity observations collected over 39 months. We find that productivity drops sharply immediately after technology implementation and recovers partly over the next few months. The ultimate, longer-term impact depends on physician specialty. The net impact of the EMR system is more benign on internal medicine physicians than on pediatricians and family practitioners. We postulate that the fit provided by an EMR system to the task requirements of physicians of various specialties may be key to disentangling the productivity dynamics. Our research finds that on one hand, present-day EMR systems do not produce the kind of productivity gain that could lead to substantial savings in healthcare; at the same time, EMRs do not cause a major productivity loss on a sustained basis, as many physicians fear.

Keywords: Arellano–Bond GMM estimation; dynamic panel model; electronic medical records; EMR; EMR productivity; health informatics; IT productivity; physician learning; physician productivity; task–technology fit; work relative value units
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Introduction

Widespread and meaningful application of modern information technology (IT) in the healthcare industry is considered essential for the economic well-being of the United States. Central to this goal is the effort to digitize patient records and introduce electronic medical record (EMR) technologies into the practice of healthcare. EMRs are comprehensive records of patients' health-related information, created, gathered, and managed by clinicians and staff from a single care-providing organization. The application of EMRs is expected to play a fundamental role in the transformation of the healthcare industry in the United States because these technologies hold the promise to eliminate pathologies present in clinical processes and improve quality of care (Aron et al. 2011, Devaraj and Kohli 2003, Linder et al. 2012, McCullough et al. 2010, Menon and Kohli 2013, Zhou et al. 2009). By making information available at the point of care, EMRs can also streamline healthcare processes and enhance the efficiency of care delivery (Agarwal et al. 2010, Dranove et al. 2012, Goh et al. 2011, Furukawa et al. 2010, Housman et al. 2006, Lee et al. 2013). Not surprisingly, policy makers in the United States have made a significant push to increase the use of EMRs among physicians through promoting and publicizing both incentives and eventual penalties. As unprecedented investments are being made in the U.S. healthcare industry to implement EMRs, it is critical to understand the implications of such initiatives (Lee et al. 2013).

This paper examines the impact of EMRs on physician productivity, a measure of a physician's output weighed by input. Examining how EMRs impact physician productivity is vital for two reasons. First, physicians are typically the highest paid employees in healthcare organizations. They are also at the frontline of interactions with EMRs. Physicians perform not only knowledge work, such as making decisions and crafting treatment regimen based on patient information, but also data entry and system operation. This is a stark contrast with other industries such as financial services, manufacturing, and telecommunications, where top executives delegate data entry and system operation to less-expensive employees at lower levels, and perform only knowledge-intensive tasks. The post-EMR data entry burdens on physicians are exacerbated due to less efficient workflows engendered by currently available EMRs, such as the use of drop-down menus, free-text typing, and generic template-based data entry on multiple screens that are not customized for physicians. Thus, physicians have significant concerns about clinical documentation, efficiency in patient processing, and administration issues (Agarwal et al. 2010, Holden 2010). This study draws attention to these physician-centric issues, which are one of the critical determinants of EMR implementation success and systemwide impacts, yet have received relatively little attention in the past.

Second, EMRs' impact on physician productivity is also likely to affect whether or not the technology fulfills its potential to curtail the rise in healthcare expenditures in the United States. Physicians are at the front line of overall healthcare expenditures. They drive a majority of care decisions, and up to 21% of healthcare costs in the United States can be directly attributed to the services they provide (Hartman et al. 2009). EMRs hold the potential to improve physician workflows and productivity, and, consequently, contain healthcare costs. However, the purported, and much-publicized, benefits of EMRs are possible only when physicians use these technologies meaningfully in patient care (DeVore and Figlioli 2010, Holden 2010). The willingness of physicians to use EMRs is critical to their widespread diffusion in the healthcare industry (Goh et al. 2011).

Given this backdrop, and the national policy consensus toward digitizing patient data, it is vital to understand how the transition to EMRs will affect physician productivity. However, there is limited formal research on the nature and dynamics of productivity impacts of EMRs on physicians (Cheriff et al. 2010, Stevens 2010). Past empirical research in information systems (IS) has generally focused on other industries such as financial services, manufacturing, IT products, and retailing (Chiasson and Davidson 2005). Insights from these studies are not easily applicable in the context of EMR use by physicians because of fundamental differences in how the EMR technology is used by them in comparison to technology uses by the highly educated knowledge workers and top executives in other industries. Concurrently, research in health IT (HIT) has been largely clinically oriented and focused on correlations between variables, while paying insufficient attention to contextual factors of HIT use (Agarwal et al. 2010). Accordingly, researchers have suggested that an explicit focus on use context of various providers and the application of granular data are critical for advancing research on performance impacts of HIT (Agarwal et al. 2010, Athey and Stern 2002, Himmelstein et al. 2010).

This paper attempts to fill the gap in the literature by examining two important research questions: (1) How does physician productivity change over time as a result of EMR implementation? Does physician productivity differ in different time periods, such as immediately after EMR implementation, in the medium term as the physicians and other systems adapt to the new technology and during steady state after the learning period? (2) Does this impact differ for physicians of different specialties? If yes, what are some potential explanations for these differences? Examining these issues enables us to provide the context of EMR use for physicians of different specialties and to focus on how this context evolves temporally.

We define physician productivity as the total amount of production physicians generate each month, measured in work relative value units (WRVUs), per unit time. A WRVU is a measure of clinical work accomplished when seeing a patient, after accounting for multiple factors such as type and severity of the patient problem, and the diagnostic procedures used in treating the patient. Thus, an hour spent with a patient in the operating room, performing an oncological surgery, yields a different WRVU than the same amount of time spent counseling a patient in the office. Furthermore, WRVUs normalize the amount of production generated by physicians and facilitate cross-specialty and cross-disease comparisons (Miller et al. 2012), thereby addressing an important issue in the literature—how to measure and compare the performance of knowledge workers (Aral et al. 2012a, Chang and Gurbaxani 2012).

We suggest that the nature of interactions physicians have with EMRs can potentially play an important role in the performance and productivity discourse. These interactions can be classified into two broad categories—information review and information entry. The first category refers to physicians' use of EMRs to *retrieve, review, aggregate, and synthesize* information, which helps them learn about the patient's current and past health conditions and enables better and faster decision making. The second category involves using EMRs to *enter and document* patient conditions, diagnoses, treatments, and test results. It is generally understood that IT is powerful and efficient at the first task, and relatively less so at the second (O'Malley et al. 2009, Park et al. 2012, Vishwanath et al. 2010). Our research provides suggestive evidence that the time trade-offs inherent between the two types of EMR uses may differentially impact the productivity of physicians in different specialties, and calls for further and more formal investigations to obtain conclusive evidence.

The data for our study were collected at an academic medical center associated with a large public university in the western United States. We focused our study on primary care physicians (PCPs). PCPs are an important physician segment to study because they coordinate care for patients, and visits to them constitute more than 60% of total physician visits patients make in the United States (Sebelius et al. 2011). We collected pre- and postimplementation productivity data on 87 PCPs over a 39-month period, yielding 3,186 physician-month observations. These physicians—internal medicine specialists (IMs), pediatricians (Peds), and family practitioners (FPs)—were spread over 12 clinics at our study site. Additionally, we collected qualitative interview data from three top administrators, two of whom are also physicians, and survey data from 35 physicians to obtain insights into the context of EMR use at our study site. Our central finding is that the impact of EMRs on productivity varies significantly across physician specialty and time periods.

Related Literature and Theoretical Development

The conceptual foundations for our study draw upon research from three strands of work—physician productivity, IT-enabled productivity, and task–technology fit (TTF). The physician productivity literature provides us with insights on various productivity measures that have been used by researchers and helps us select a measure that affords a consistent meaning of productivity across physician specialties. Prior work on IT-enabled productivity sensitizes us to the importance of data and measurement issues and broad patterns of post-technology impacts on organizations. 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, whereas other forms do not deliver such gains. Next, we discuss extant literature and present our propositions.

Physician Productivity

In the healthcare industry, the conceptualization and measurement of physician input and output are central to revenue generation, physician compensation, and workforce planning (Newhouse and Sinaiko 2007–2008, Tufano et al. 1999). However, productivity of knowledge workers, such as physicians, defies simple measurement because their outputs, which include appropriate and inappropriate outcomes, as well as inputs, such as time, knowledge, and skills, are not directly comparable (Zaslove 2003). Some commonly used measures, including the number and type of patient encounters, time spent with patients, and revenues generated for the organization, are not robust. For instance, the revenue generated by a physician is directly dependent on the insurance carried by the patient and may not accurately reflect physician productivity.[1] 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).

The concept of work relative value units has evolved to address the above limitations in measuring physician productivity (Newhouse and Sinaiko 2007–2008). WRVUs are relative value units generated for clinical activities rather than administrative, teaching, training, or care coordination activities, to measure physician productivity (Coleman et al. 2003). WRVUs are determined by the Centers for Medicare and Medicaid Services (CMS), in consultation with a committee consisting of 23 representatives from major specialties, as well as delegates from the American Medical Association (AMA). The measure is independent of any dollar amount generated; thus, limitations associated with patient charges, collections, and insurance mix are excised away from WRVU calculations. Furthermore, as discussed, WRVUs account for the fact that patient encounters are different.

The conceptualization of WRVUs was shaped by the work of Hsiao et al. (1988). Their research led to the development of the resource-based relative value scale, which is used to assign a work relative value unit to every current procedure terminology (CPT) code (Maxwell and Zuckerman 2007–2008). Under the system developed, WRVUs are calculated from four resource 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. For instance, the CPT code 99203, used for outpatient visit of a new patient, generates 1.42 WRVUs; the CPT code 99213, used for an outpatient visit of an existing patient, generates 0.97 WRVUs; and the CPT code 99291, used for critical care first hour, generates 4.50 WRVUs. These WRVUs reflect the "resource costs" physicians incur to provide care to patients. Once the patient visit has been coded in CPTs and converted, the resultant metric, WRVU, is comparable across all specialties. Thus, the productivity of a family practitioner can be directly compared with that of a cardiologist, a pediatrician, and an oncologist, because the acuity and the number of the patients seen by them are already reflected in the total WRVUs they generate. Because of its grounding in the nature of physicians' work; its creation by domain experts such as physicians, statisticians, economists and measurement experts; and its support by the AMA, CMS, and other leading organizations, the WRVU has been widely adopted and is now the de facto physician productivity measure used in the industry. This measure has been applied extensively in the clinical literature to analyze physician productivity (Andreae and Freed 2002, Holcombe and

[1] Two doctors who are similar in every other aspect except one sees largely private insurance patients and the other sees largely Medicare and Medicaid patients will generate considerably different revenue streams.

Hollinger 2010, Miller et al. 2012). We use this measure in our study.[2]

IT-Enabled Productivity

Extant research on IT productivity is mature (Aral et al. 2012a, Brynjolfsson and Hitt 1996, Hitt et al. 2002, Lee et al. 2013, Menon et al. 2000, Tambe and Hitt 2012). Using more granular and extensive data and advanced econometric techniques, researchers have found convincing positive relationships between IT and productivity at firm (Aral et al. 2012b, Banker et al. 2002, Barua and Lee 1997, Brynjolfsson and Hitt 1996, Tambe and Hitt 2012, Tambe et al. 2012), industry (Jorgenson and Stiroh 2000), and country levels (Dewan and Kraemer 2000). Whereas this research has proven invaluable in laying the foundation for future studies, our work expands this influential line of research in two important ways.

First, extant IT productivity research is concentrated on manufacturing industries (Aral et al. 2012a). This lopsided focus on manufacturing is not reflective of the U.S. economy, which is primarily service oriented. Additionally, large improvements in productivity in the last decade can be attributed to those occurring in the services sector of the economy (Triplett and Bosworth 2004). Thus, ironically, although the service industry is the largest employer of workers and user of IT, researchers know less about productivity mechanisms and magnitude changes in the service industry than in the manufacturing industry. Relatedly, only a small number of studies have examined productivity implications of IT in the healthcare industry (e.g., Agha 2012, Dranove et al. 2012, Furukawa et al. 2010, Lee et al. 2013). Second, individual worker-level productivity studies are lacking in the IS literature (Aral et al. 2012a, Bulkley and Van Alstyne 2004). Research investigating the productivity of *knowledge workers* is particularly sparse in the literature. Measuring the productivity of these workers is markedly difficult because output they produce is not as concrete and tangible as that generated by other professions (Aral et al. 2012a), and gains or impediments in productivity are difficult to attribute to one person. These limitations have inhibited the research on productivity impacts of IT on knowledge workers, especially physicians.

Despite these limitations, extant research can inform investigation on productivity impacts of IT on knowledge workers. Cronin and Gudim (1986) suggest that information has the features of a hidden property good, so its contribution to processes is not fully realized in the short term. The nature of IT impacts evolves, and the immediate effects of IT may be significantly different from longer-term ones (Aral et al. 2006, Tambe et al. 2012). The introduction of a new technology triggers the disruption of existing work practices, routines, and information flows (Aral et al. 2012b, Pisano et al. 2001). Goh et al. (2011) suggest that HIT can significantly influence information flow routines by facilitating certain new functionalities, while simultaneously eliminating others possible with past routines. For instance, paper-based records enable easy and reliable communication between physicians, who use them to track the medical conditions of patients. The introduction of an EMR forces physicians to invest time to acquire specialized knowledge to use the new system. Such investments and learning needs are higher for interventions that require new forms of information processing and significant adjustments to workflows. As a result, the disruptions caused by new technologies can result in a short-term decline in productivity because of shocks to the existing work systems (Kemerer 1992, Pisano et al. 2001).

The initial drop is well documented in the literature for large-enterprise systems (Aral et al. 2006, 2012b; Bendoly and Cotteleer 2008; Brynjolfsson and Hitt 2000; Hitt et al. 2002). As users develop expertise with the new technology to more fully exploit its potential and integrate its functionalities in their workflows, their productivity begins to improve. Thus, a recovery ensues in productivity levels as workers become more familiar with the new system, and procedures become better aligned. Information can make 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 (Bulkley and Van Alstyne 2004). Once the technology has been absorbed—i.e., in a stable postlearning period—productivity gains plateau (Kemerer 1992), and any further variations in productivity should reflect the variation pattern prior to the deployment of the technology. Emphasizing this temporal impact of enterprise resource planning (ERP) systems, Hitt et al. (2002) argue for a more nuanced examination of the long-term productivity effects of IT. Similar to ERP systems, EMRs entail significant process modifications, as well as development of more complete and reliable patient data. Thus, we expect physician productivity levels to decline after an EMR implementation. However, as physicians acquire expertise and proficiency with the technology and integrate it in their workflows, we expect the productivity levels to improve. Finally, we expect productivity levels to plateau after the full absorption of the EMR technology. Thus, we propose the following:

Proposition 1. *Following the implementation of an EMR system, a physician's productivity is likely to undergo a period of decline. This is likely to be followed by a reversal in trend where physician productivity begins to recover and then plateaus.*

[2] The most current WRVUs and the corresponding CPTs can be obtained from the CMS website.

Task–Technology Fit

The central tenet of TTF theory is that the alignment between task needs and system functionalities drive task performance (Banker et al. 2002, Dennis et al. 2001, Goodhue 1995, Goodhue and Thompson 1995). The TTF theory suggests that it is important that the information processing features of the technology fit informational requirements of the task. For simple tasks, no information processing support may be required, but for tasks that entail decision making and judgment, of which clinical tasks are an apt example, information processing adds significant value (Dennis et al. 2001, Zigurs and Buckland 1998). Information processing support entails enabling users to evaluate, gather, and aggregate information as well as to organize and analyze information (Zigurs and Buckland 1998).

As discussed earlier, EMRs can potentially influence physician productivity through two possible effects, information review and information entry. Accordingly, the influence of EMRs on different groups of physicians may differ if the technology provides disparate impacts with respect to information review versus information entry and these groups diverge in the extent to which they employ information review versus information entry features. The first impact is dependent on how EMRs alter the way physicians access and record patient information during the care provision process. Information review functionalities of EMRs enable physicians to retrieve and synthesize information quickly and efficiently. Traditional, paper-based, patient records pose substantial challenges in the 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 voluminous health history. EMRs can speed up information retrieval and search. Moreover, EMR systems facilitate the combination, aggregation, and synthesis of multiple data elements for physicians. For instance, consider an IM physician interested in looking at time-series data on a particular test (C-reactive protein (CRP) levels) for a patient who has had a series of lab tests (e.g., WBC count, CRP levels, etc.). With the traditional paper record, the physician will need to extract this data, which might be scattered over several pages in the file, and collate the information. An EMR system, in contrast, makes such data easy to retrieve and, moreover, facilitates visual display of the test results as a longitudinal line graph. Thus, EMRs enhance the speed with which physicians can obtain additional information about disease conditions, search for more relevant information, and navigate the embedded knowledge base, resulting in improved information review, synthesis, and medical decision making (Bulkley and Van Alstyne 2004). In contrast, EMR technologies may actually make information entry less efficient. EMR technologies often change the way physicians enter information, such as documentation about a patient visit. Information entry with EMRs requires a higher level of technological skill, including typing sentences or paragraphs and navigating a hierarchy of forms and/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' records and privacy-related regulatory requirements, doctors can no longer rely on nurses to enter patient information. For many physicians, this new mode of data entry can consume a greater amount of time relative to scribbling notes, dictation, or checking yes/no boxes on a paper form.

It is likely that the net impact of an EMR system on productivity will depend on how physicians of different specialties interact with the technology, how their informational requirements differ, how information review and information entry impact their work processes, how much displacement they suffer from earlier information flows and routines, and how quickly they recover from the losses. The extent to which physicians receive a productivity boost or reduction is likely to depend on the relative significance of information review in their work. 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 conceivably enjoy relatively low benefits from information retrieval capabilities of EMRs. The negative effect is likely to be more pronounced for physicians whose routine work requires a considerable amount of documentation, and thus compromise their productivity. In contrast, physicians who do not have to adjust workflows to spend substantive amounts of time documenting will potentially suffer relatively less.

Synthesizing these observations, we posit that in the absence of customized interfaces and tailored workflow support, the fit between the information review and information entry needs of physicians and the features offered by EMRs is likely to differ. In fact, Park et al. (2012) argue that depending on the role of a physician in a hospital, his or her responsibility to electronically document patients' medical history, exam results, care plans, and also results and interpretations of lab tests, imaging, diagnoses, and handoff notes may differ significantly. More importantly, the burden of data entry tends to fall on upstream physicians, whereas the downstream physicians may benefit significantly from the information already entered (Lahiri and Seidmann 2012, Park et al. 2012). Thus, we propose the following:

Proposition 2. *The productivity impacts of EMRs on a physician are likely to vary depending on his or her specialty.*

Extant literature suggests that the ratio of information review to information entry is likely to vary by specialty. Despite broad similarity in the work practices of PCPs, which include tasks such as managing more than 500 new topics each year and responding to multiple medical conditions, there are considerable differences in their information needs (González-González et al. 2007, Shachak et al. 2009). Crosson et al. (2005) suggest that family medicine has some unique communication and workflow aspects, which should be investigated in detail. For instance, FPs are required to treat patients from multiple age groups, diagnose symptoms from many potentially unrelated conditions, and keep comprehensive records from multiple isolated sources (Loomis et al. 2002). Their generalist orientation suggests that patients approach them for a wider variety of medical conditions than others, which may lead to increased documentation requirements and reduced opportunities to exploit learning around EMR navigational structures associated with certain specific diseases.

Peds experience a distinct set of challenges, which may impact their informational needs. EMRs are typically designed for elder care. In contrast, medical needs of children tend to differ significantly. Peds are required to perform immunization, prescription and growth tracking, chart completion, and infant and adolescent dosage calculations (Barjaktarevic 2008). Children tend to experience many physiological changes, acquire infections, and, in general, fall sick frequently. As a result, children need to see Peds regularly for different disease conditions, thereby significantly increasing the data entry burden on Peds (Ferranti et al. 2011). In fact, children need to visit Peds regularly for well-care even when they are not sick, generating extensive documentation needs. Furthermore, the description of pediatric terms is rather involved in EMR systems. Peds need to expend a significant amount of time expanding standard terminology to include concepts that adequately represent these terms by describing historical findings, family details, social history, physical examination findings, developmental problems, behavioral issues, congenital syndromes, and diagnoses particular to pediatrics (Barjaktarevic 2008).

IMs typically provide care to adult patients. Internists regularly serve as PCPs; however, they are different from FPs.[3] Their patients tend to have multiple well-defined chronic conditions. Often these conditions tend to be related. They are often asked to provide consultation to patients whom other doctors have already seen. To provide care to these patients, internists have to consider multiple sources of information and undertake involved diagnoses and decision making (McAlister et al. 1999). Their need for information review and synthesis tends to be significant.

Qualitative interviews with three top administrators, two of whom are physicians, and survey data collected from 35 PCPs from our study site also seem to suggest that there are substantial differences in the work practices of PCPs and their information needs.[4] Our analysis of the short survey data collected from 35 physicians provides further evidence, albeit not in a statistically significant way due to the small sample size split among three specialties, and that physicians' informational needs differ and they derive differential value from the implementation of EMRs (see the appendix for details). For instance, explaining the need for documentation, Dr. X informed us, "Patient complexity drives the value of EMRs." Dr. Y built on this idea and suggested, "Internists handle sicker, more complex patients. Their patients may be seen in more subspecialties; it is difficult for them to wrap their head around all the paper-generated information and make decisions. EMRs are more helpful for them." Our survey data support these judgments and deliberations. We find that in comparison to Peds and FPs, IMs believe that EMRs allow them to easily synthesize information from multiple sources and to make patient treatment decisions efficiently. This may enhance the value of EMRs to IMs in comparison to Peds and FPs. Additionally, the need for information documentation and information review among various specialties differs because the technology does not fit the workflows of all physician specialties equally. As Dr. X mentioned, "There are differences across specialties. The quantity of information doctors use, need and enter is different. Some document more and some review information more." Emphasizing this, Dr. Y stated, "The tool was not built keeping in mind the requirements of all physicians." Again, our survey data support these reflections. We find that FPs believe that EMRs interrupt their workflow and that they document useful information about patients that is used later by other physicians. Finally, discussing the potential impact of EMRs on different physicians, Dr. Y suggested, "Peds struggled with the EMR system even in the long run. They had issues with it. IMs benefitted." Ms. Z reiterated the sentiments of Dr. Y by saying, "EMR impact was different for different physician specialties. Pediatricians hurt from its implementation and did not benefit much. IMs benefitted more. Family physicians were in the middle."

[3] American College of Physicians, "About Internal Medicine." Last accessed June 20, 2014, http://www.acponline.org/patients_families/about_internal_medicine/.

[4] Three administrators we talked to are Dr. X, Dr. Y, and Ms. Z. Dr. X is the current EMR medical director. Dr. Y is the ex-medical director and current associate medical director. Ms. Z is an office manager. Dr. Y and Ms. Z were both involved with the EMR implementation in the 2004–2005 time period. Dr. Y had oversight across all physicians. Ms. Z is a registered nurse who led deployment across all clinics. The 35 physicians who returned our brief, one-page survey were divided as follows: 20 FPs, 12 Ims, and 3 Peds.

She also mentioned, "Computer systems are good for retrieval, not so much for entry." Drawing comparisons across different specialties, she said, "Internists are going to have more lab orders and prescriptions, for which EMRs are beneficial. On the other hand, Peds have more data entry responsibilities and do not benefit much from EMRs. She further mentioned, "IMs were quick to learn the system, but Peds struggled with it longer and did not benefit much." Our survey data reveal that Peds, by a large margin, do more information entry than synthesis and that EMRs increase their documentation time significantly.

In summary, arguments from TTF theory and our interview and survey data suggest that IMs are likely to benefit more from EMRs than Peds and FPs. Hence, we propose the following:

Proposition 3. *EMR implementation will have a more benign impact on the productivity of internal medicine physicians than on that of pediatricians and family practitioners.*

Empirical Framework

The Data

Our study was conducted in the context of outpatient visits in an academic healthcare system in the western United States. The system implemented a leading EMR system across all primary care clinics over a period of time. The use of the system was mandated on all the PCPs in these clinics. The deployment started in June 2004 and concluded in October 2005. Our data set includes monthly physician schedule and production data (days worked (*DAYS*) and *WRVUs*, respectively) from May 2003 to July 2006. Both counts represent clinical work and do not include administrative or teaching time or output.

A physician's monthly productivity is determined as the level of production per unit time, i.e., WRVUs divided by days worked that month on clinical tasks. As explained earlier, WRVU measurements are highly standardized, reliable, and comparable across specialties. At the system studied, productivity measures were derived from clinical records that served financial accounting and reimbursement. The use of productivity rather than production reduces the vulnerability of the metric to seasonal and other effects that may affect the nature of patient visits. For instance, the flu season may increase the number of patients seen, causing more production, but not necessarily the rate of production as the time spent on clinical work also increases correspondingly. In fact, clinics and physicians account for the estimated demand from patients in scheduling vacation days and leaves, so that more (fewer) work hours are scheduled when the expected demand is higher (lower).[5]

Table 1 **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	8	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	8	6	14	4	87

For each physician we have several months of data before and after EMR deployment. Each physician in the data set was associated with a unique clinic and specialty during the study period. This allowed us to control for extraneous effects that may obfuscate results if physicians shifted clinics or specialties. Our data set consisted of 3,189 observations covering 87 physicians across 12 clinics. Three observations were deleted because they suffered from typographical errors, leaving us with 3,186 observations. The numbers of physicians for each clinic–specialty pair are given in Table 1.

Exploratory Data Analysis

Our primary interest in this paper is to examine physician productivity differences before and after EMR implementation and to assess whether the nature of the physician's work, as defined by his or her specialty, has an effect on the direction and magnitude of influence. An exploration of the longitudinal data revealed possible temporal and specialty effects of EMR implementation. Table 2 provides mean productivity levels for IMs, FPs, Peds, and all specialties for both pre- and post-EMR-implementation durations. A T test comparing physician productivity means before and after EMR implementation (20.48 and 19.48, respectively) is significant at $p < 0.01$. This provides preliminary evidence of the temporal impact of the technology. To assess specialty effects, we first tested mean productivity levels of different physician groups prior to EMR implementation. T tests confirmed that the variation in mean productivity across specialties is not significant before EMR implementation ($p > 0.1$). The absence of specialty effect was also confirmed by running a random effects panel regression on the pre-EMR productivity data for all physicians. We did not find any specialty effects. However, T tests on post-EMR mean productivity levels indicate that IMs have higher post-EMR productivity than Peds or FPs ($p < 0.05$). The lack of variation by specialty in the pre-EMR regime, combined with the presence of such variation post-EMR, provides initial evidence that

[5] Our analysis controlled for seasonality using month dummies. All results are robust to these seasonal controls, which are omitted from the formal presentation for the sake of brevity.

Table 2 Comparison of Mean Productivity Levels by Specialty

Specialty	Pre-EMR	Post-EMR	% change	0–6 months post-EMR	% change	> 6 months post-EMR	% change
IM	20.80	20.31	−2.36	17.75	−14.66	21.02	1.06
FP	20.37	18.85	−7.46	17.33	−14.92	19.22	−5.64
Peds	20.25	19.50	−3.7	18.29	−9.67	19.74	−2.51
All specialties	20.48	19.48	−4.88	17.71	−13.53	20.17	−1.51

Note. Percentage changes reflect comparisons with the pre-EMR period.

specialty may play a significant role on the impacts of EMR.

Nonmonotonic Temporal Effect of EMR Implementation

The analysis thus far imputes a uniform treatment to the entire post-EMR duration without differentiating between the period right after implementation and the steady state. As with most large-scale process-oriented IT, introduction of EMRs is a major shock to the system. The shock causes a substantial decline in productivity immediately after technology implementation. Subsequently, a phase of learning and recovery ensues, during which productivity starts marching toward the pretechnology norms (albeit with some volatility). Finally, after the shock is fully absorbed, the system achieves a steady state, which might be above or below the level prior to technology implementation. Figure 1 illustrates this point across the three different physician specialties. The productivity of physicians of all specialties goes down in month 0 (when the implementation takes place) and month 1; shows improvements in months 2, 3, and 4, where it begins to stabilize; and reaches a steady state, a "new normal" level, in month 6. To illustrate this point further, we note that the mean productivity level across months 1 to 5, for all specialties combined, is 17.65, a drop of 13.84% from the pre-EMR period, whereas the mean productivity level for months 6 and later is 19.95, a decrease of 2.59%. The two means are statistically different from each other at $p < 0.01$.

We notice that the temporal aspects of EMRs on productivity are neither uniform across time nor monotonic in the duration since implementation. Because of this nonmonotonicity, the post-EMR drop in mean productivity mentioned earlier may be a red herring; that is, the drop might reflect the sharp, and temporary, decline in productivity immediately after EMR implementation. Indeed, a "steady-state" post-EMR phase offers a more meaningful comparison with pre-EMR productivity. To explore this, we split the post-EMR-implementation period into two parts: (i) the initial shock and learning period of zero to six months and (ii) a longer-term period of more than six months. Table 2 shows mean productivity levels for the three physician specialties in the pre-EMR and two post-EMR time segments (see the fifth through eighth columns). Comparing pre-EMR productivities with those beyond 6 months after implementation, we find that whereas there is a significant productivity drop for Peds and FPs ($p < 0.05$), IMs are better off ($p < 0.1$). Productivity levels for IMs are also distinct from the other two specialties ($p < 0.01$) in the steady state. The difference between FPs and Peds is statistically insignificant ($p > 0.1$). The evidence

Figure 1 Productivity Variation Before and After EMR Implementation, for Each Specialty

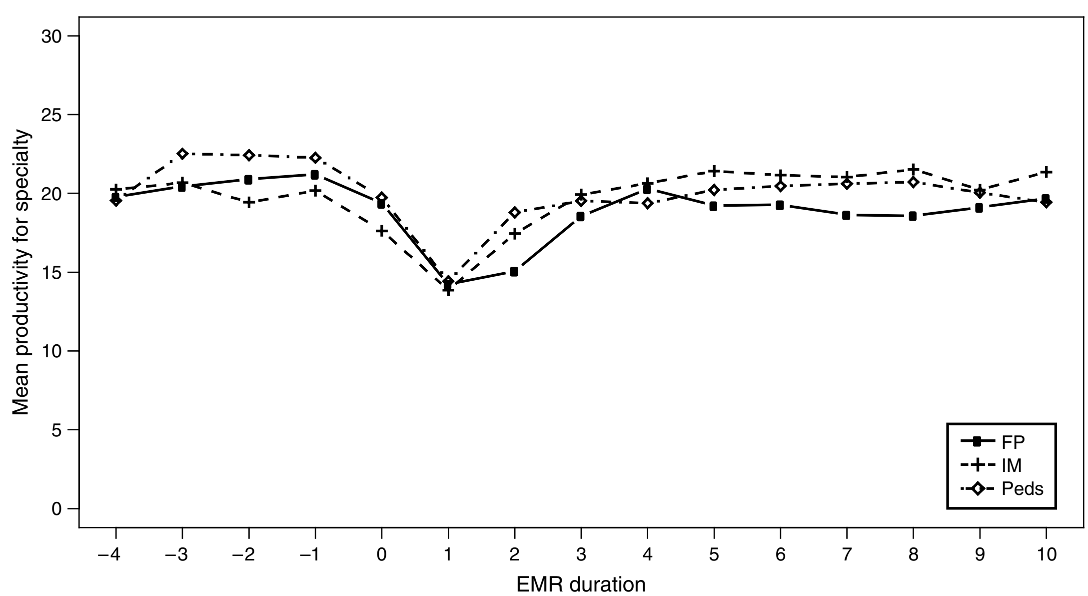


Table 3 Post-EMR-Implementation Physician Learning: Asymptotic Regression Estimation

			95% confidence interval	
Parameter	Estimate	Std. error	Lower bound	Upper bound
*b*1	19.961	0.128	19.711	20.212
*b*2	−9.264	1.684	−12.567	−5.962
*b*3	−0.290	0.070	−0.428	−0.153

presented collectively provides support for the argument that there are specialty-specific and temporal differences in how EMRs impact physician productivity.

Figure 1 shows that the nadir of the productivity for each physician is reached in the first two months following EMR implementation, after which the learning and recovery process starts. The second and third components can be modeled via an asymptotic regression on the post-EMR productivity data to estimate the learning period. Few studies in extant literature have focused specifically on learning curve effects to examine post-HIT-implementation physician productivity (Vishwanath et al. 2010). Most researchers use arbitrary cutoffs, ranging from 3 to 12 months after EMR implementation. In light of the lack of any concrete guidance, we estimated the learning period empirically. We modeled the learning process using the asymptotic regression function: $Productivity = b1 + b2 * \exp(b3 * (Duration + Duration^2))$, where duration is the number of months since EMR implementation.[6] Here, $b1$ represents the upper asymptote, $b2$ is the difference between the value of productivity when $Duration = 0$ and the upper asymptote, and $b3$ is the negative of the slope between two "well-separated" points. Our parameter estimates and the resultant learning curve are shown in Table 3 and Figure 2.

The parameters obtained from the asymptotic regression model are used to calculate predicted values, which we have graphed in Figure 2. The left and right panels in Figure 2 show the decline, learning, and recovery patterns for all specialties combined and separated out, respectively. The figure confirms that after the steep decline in the months 0 and 1, the productivity starts to improve. The productivity begins to stabilize four months after implementation and converges asymptotically at the level where it is six months after implementation.[7] IMs, although indistinct from FPs and Peds in the pre-EMR regime, have a visibly distinct recovery and steady-state pattern after EMR implementation. During the declining stage, Peds and FPs also experience drops, but their fall is not as dramatic as that of IMs. Furthermore, although IMs suffer a greater productivity loss initially, they rebound quickly, and once the recovery phase is complete, they demonstrate higher productivity in the long run than FPs and Peds. Another notable observation is that after the initial steep decline, the length of the recovery period until the emergence of a relatively stable "new normal" is the same, six months, for all three specialties when the productivity becomes asymptotically stable. We further analyze our data using econometric techniques.

Notation and Symbols

We model the productivity impact of EMR implementation by considering three distinct phases: the pre-EMR phase; the learning phase, which encompasses both shock and recovery; and a stable post-EMR phase. The notation 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

- $WRVU(i, t) =$ WRVUs for physician i in month t
- $DAYS(i, t) =$ Number of days worked on clinical tasks 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 Time Variables

- $emrGoLive(c) =$ Calendar month–year of EMR implementation at clinic c
- $emrDuration(c, t) = (t - emrGoLive(c))$, the number of months between calendar month t and $emrGoLive(c)$
- $Learning\ Phase(c, t) = 0$ if $emrDuration(c, t) \leq 0$; 1 if $1 \leq emrDuration(c, t) \leq 6$; 0 if $emrDuration(c, t) > 6$
- $Stable\ Phase(c, t) = 0$ if $emrDuration(c, t) \leq 6$; 1 if $emrDuration(c, t) > 6$

It is important to note that physicians are affiliated with the same clinic for the duration of the study; thus, time and implementation variables are the same for a physician and the clinic where he or she is employed.

Data Analysis and Results

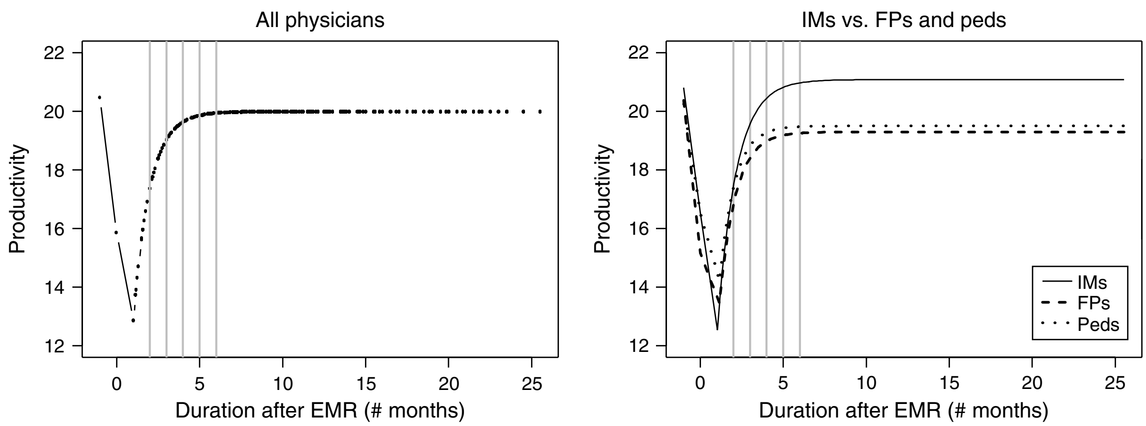
Estimation Strategy and the Econometric Model

To analyze the effect of EMR implementation on physician productivity, we considered and employed a number of panel data analysis techniques. These models were estimated using a panel data set with $N = 87$ and $T = 39$. We had unbalanced panel because different

[6] This functional form was suggested to us by Reviewer R1.

[7] As a measure of robustness, the learning time period stays the same when the *emrMonth* square term is deleted from the asymptotic regression model. Another functional form that is used to estimate asymptotic regression is $Productivity = b1 + b2 * (1 - \exp(-\exp(b3) * Duration))$. This functional form also suggests that the productivity starts to stabilize after four months and converges asymptotically at the level where it is six months after implementation. Starting values for $b1$, $b2$, and $b3$ were seeded based on the asymptotic regression guidelines.

Figure 2 Post-EMR-Implementation Learning Curve



clinics within the hospital started EMR implementation and data collection at different points in time.

The productivity of 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 the number of months, at month t, that EMR technology has been available at the clinic. Thus, it is important to account for these effects in our empirical model. Additionally, extant research suggests that the gender and experience of a physician can have a significant impact on his or her productivity (Conrad et al. 2002); hence, we should control for physician gender and experience in our study.[8] As our exploratory analyses indicate, the impacts of EMRs are likely to be different for physicians in different specialties, and this impact may vary temporally. Accordingly, our model must examine productivity variations by specialty and over time. Finally, we also allow for the possibility that clinics may impact physician productivity during the learning and stable phases. We begin our model estimation starting with the following econometric model:

$$\begin{aligned}
&\mathit{Productivity}(i,t)\\
&\quad= \beta_0 + \beta_1 * \mathit{Clinic}(c) + \beta_2 * \mathit{Specialty}(s) + \beta_3 * \mathit{Gender}(i)\\
&\qquad + \beta_4 * \mathit{Experience}(i,t) + \beta_5 * \mathit{Learning\ Phase}(c,t)\\
&\qquad + \beta_6 * \mathit{Stable\ Phase}(c,t) + \sum \beta_{7\text{–}8} * \mathit{Specialty}(s)\\
&\qquad * \mathit{Learning\ Phase}(c,t) + \sum \beta_{9\text{–}10} * \mathit{Specialty}(s)\\
&\qquad * \mathit{Stable\ Phase}(c,t) + \sum \beta_{11\text{–}21} * \mathit{Clinic}(c)\\
&\qquad * \mathit{Learning\ Phase}(c,t) + \sum \beta_{22\text{–}32} * \mathit{Clinic}(c)\\
&\qquad * \mathit{Stable\ Phase}(c,t) + \alpha_i + \varepsilon_{it}. \qquad (1)
\end{aligned}$$

[8] We had access to all the data elements except physician experience. We obtained physician experience data from http://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.

Endogeneity and Identification Strategy

The EMR was implemented at the 12 primary care clinics in different months, starting in June 2004 and concluding in October 2005. To estimate the causal effect of EMR implementation on physician productivity, we need to address several potential econometric concerns, including selection effect, reverse causality, measurement errors, and omitted variables or unobserved physician heterogeneity (Angrist and Pischke 2009, Wooldridge 2002).

First, recall that EMR implementation decisions are made for clinics. The EMR was implemented in clinics at different points in time. Our data show that average productivity in clinics differs significantly. Thus, there could be a selection effect where clinics with higher or lower productivity can implement EMRs early or late systematically; hence, it is possible that EMR implementation time is not exogenous. Additionally, it is possible that EMRs were not implemented at all the clinics or made available to physicians with different specialties in a strategic order. The exact reason for choosing the order of implementation of EMRs was not revealed to us. However, every primary care clinic and every primary care physician was involved in this effort. Additionally, there is no selection effect with respect to specialties. When a clinic implemented the EMR, all physicians had to move to the electronic platform simultaneously as EMR use was mandated. To examine any selection effect at the clinic level, we estimated the Heckman selection model. We found that there is no evidence of selection bias at the clinic level.[9]

[9] We calculated clinic-level productivity data by averaging the productivities of all the physicians in the clinic. In total, we have 39 time periods, 12 panels, and 467 observations for this analysis. We also calculated the average experience of physicians in each clinic in each month by taking a simple average of experience of each physician within that clinic. In the choice model, we included two variables: the number of physicians in the clinic and the average experience. In the outcome model, we included average experience and dummies for learning phase and stable phase. We included the

Second, physicians' specialties, the clinics where they worked, and their gender were time invariant in our study, and can be assumed to be exogenous. These variables are not determined within the context of our study of EMR productivity. In addition, we can assume that physician experience is exogenous because each physician graduated several years before EMR implementation at our study site. It is important to note here that we do not believe that physicians' productivity can causally influence EMR implementation month in a clinic. Our analysis indicates that there is no discernible pattern between physician productivity in a clinic and the EMR implementation time at that clinic. Furthermore, our data provide evidence that there is no significant productivity difference among physicians of different specialties during the pre-EMR-implementation stage. We conclude that reverse causality and simultaneity are not significant concerns in our study.

Third, the learning and stable phases are derived from the calendar month in which EMR was implemented in a clinic. Physician experience was calculated from the graduating year information available on http://www.healthgrades.com. The WRVU data and *DAYS* were obtained from daily work logs and financial and reimbursement data files. The hospital strived to maintain correct data on these metrics. According to Wooldridge (2002), when measurement error occurs in the dependent variable, the estimates are still unbiased and consistent, albeit inefficient, and there is no endogeneity problem. Measurement errors in experience and the two phases, which are uncorrelated with their true values, can lead to attenuation bias. We believe that any such bias will be small because of the following: (1) To the extent that healthgrades.com captured physician graduating year information correctly, our data will not suffer from measurement error in experience. Furthermore, both the statistical and economic impact of physician experience on productivity are rather small and insignificant. (2) As discussed earlier, we derived the learning period using a number of asymptotic regression specifications with similar results. Additionally, in a number of models estimated with learning period $\geq$4 months, we found our main results to be stable.

Finally, unobserved physician heterogeneity, such as ability or propensity to use technology, could be related to productivity. To the extent that such heterogeneity is not systematically related to physician specialty or changes systematically after EMR implementation, we expect the impacts of such heterogeneity to be small. For econometric robustness, we use dynamic panel data models of productivity as our main analysis technique, which use lags of differences and lags of levels as instruments in a system of simultaneous equations of differences and levels of productivity. The rationale is that the internal instrumental variables obtained through lagging are uncorrelated with the error terms. First differencing of variables further reduces any potential bias from omitted variables.

Our focus in this research is to examine how the productivity of physicians in multiple specialties evolves after EMR implementation. Thus, our foremost concern is to understand the interaction effects between specialty and learning and stable phases shown in Equation (1). Our identification strategy revolves around time. We exploit the fact that the implementation of EMR takes place in different months in different clinics. Hence, the month dummies created, and the resultant phase dummies—pre-EMR, learning, and stable—provide the variation that is used to identify the measured effect on physician productivity. Thus, identification comes from time series variation in implementation across various clinics, and as discussed earlier, the timing is not endogenous to physician productivity.

Model Estimation and Results

When used with panel data, standard applications of ordinary least squares (OLS) regression generate biased and inefficient parameter estimates as well as inaccurate standard errors. Thus, the use of OLS on panel data may result in heterogeneity bias (Baltagi 2005). Furthermore, unobserved characteristics, which may be correlated with physician productivity and our included covariates, can bias OLS results. We assessed the suitability of the OLS model by evaluating our data for poolability. We estimated a fixed effects model and found that we can reject the null hypothesis of no individual-level heterogeneity ($p < 0.001$). Thus, we can excise away the pooled regression model from further consideration.

To investigate the effect of EMR implementation within the panel model framework, we began our analysis with a difference-in-differences strategy. This analysis allows us to examine physician productivity before and after EMR implementation, after controlling for many fixed effects. Clinic AB, specialty IM, gender male, and pre-EMR phase, respectively, served as bases for the clinic, specialty, gender, and phase of EMR implementation. These variables also serve as bases for all subsequent panel analyses. We also added clinic and phase and specialty and phase interactions in the model. The results from the difference-in-differences analysis are shown in Table 4. We next analyzed our data

number of physicians in the choice model and not in the outcome model because size is a reliable indicator of innovation in most contexts, and hence number of physicians, a good proxy for practice size, is likely to be related to EMR adoption by the clinic. However, the relationship of firm size and productivity is not straightforward. Our results indicate that the likelihood ratio test of independence is insignificant ($\chi^2(1) = 0.7479$). This suggests that there is no significant selection effect. This result is available from the authors.

Table 4 Temporal and Specialty-Specific Physician Productivity Variation: Difference-in-Differences and Random Effects Models

	Difference-in-differences model		Random effects model	
Variables	Coefficient	Std. error	Coefficient	Std. error
Physician Experience	−0.001	0.008	0.01	0.03
Learning Duration	0.75	1.19	0.64	0.81
Stable Duration	0.89	1.47	−0.39	1.02
Pediatrics (*Peds*)	−1.11**	0.41	−1.57	1.13
Family Practice (*FP*)	−0.19	0.37	−0.01	0.97
Physician Gender	−0.2	0.16	0.29	0.62
Clinic AP	2.31**	0.79	2.36	2.61
Clinic P	−0.34	0.6	−0.59	1.80
Clinic C	−2.81***	0.51	−2.80*	1.48
Clinic L	2.54*	1.03	2.58	3.67
Clinic D	−3.56***	0.53	−3.94*	1.50
Clinic E	−2.43***	0.54	−2.62	1.66
Clinic F	1.41*	0.60	0.86	1.43
Clinic J	−4.03***	0.59	−3.93**	1.64
Clinic N	−0.72	0.67	−1.56	1.99
Clinic R	−0.11	0.46	0.45	1.44
Clinic U	−0.87	0.66	−0.34	2.02
Peds ∗ Learning Duration	**−1.98***	**0.96**	**−1.59***	**0.70**
Peds ∗ Stable Duration	**−1.86****	**0.69**	**−1.62**†	**0.89**
FP ∗ Learning Duration	**−1.42**†	**0.81**	**−1.57****	**0.6**
FP ∗ Stable Duration	**−2.03****	**0.61**	**−1.35***	**0.51**
Constant	21.98***	0.54	21.75***	1.65
Model fit statistics	$F(43, 3{,}142) = 16.11$		Wald $\chi^2(43) = 295.66$	
	Prob > $F = 0.000$		Prob> $\chi^2 = 0.000$	
	R-squared	0.17	BPLM test	$\chi^2(1) = 5{,}133.2$; $p < 0.000$
			Test for heteroskedasticity	$\chi^2(85) = 676.3$; $p < 0.000$
N	3,186		3,186	

Notes. Clinic AB, specialty IM, preimplementation phase, and gender male served as the bases. In the interest of clarity and space, clinic and duration interaction variables are not shown in this table. Key results shown in bold. BPLM, Breusch-Pagan Lagrange multiplier.
†Significant at $p < 0.1$; *significant at $p < 0.05$; **significant at $p < 0.01$; ***significant at $p < 0.001$.

within the static panel model framework. We evaluated the choice between fixed effects and random effects models by conducting the Hausman test. We found that Hausman test statistic is insignificant with p-value > 0.1, suggesting that the random effects model is the appropriate choice in our context. The results from the random effects model are also shown in Table 4. Results from both these analyses suggest that IMs outperform FPs and Peds.

Finally, we examined our data within the dynamic panel model framework (Menon and Kohli 2013). Static panel models do not incorporate any temporal dependency (lags) of the dependent variable. Dynamic panel models use lags of the dependent variable as explanatory variables. These models utilize the time dimension of the panel to provide internal instruments (Arellano and Bond 1991, Tambe and Hitt 2012). Consistent estimations of these models generally require longer panels than have historically been used in the IS literature (Tambe and Hitt 2012). Dynamic panel models are a standard tool in many subfields of economics. Recently a few studies in information systems have also used these methods (Aral et al. 2012a, Ghose and Han 2011, Menon and Kohli 2013, Tambe and Hitt 2012). In this study, we use Arellano–Bond system generalized method of moments (GMM) estimation that uses lagged differences as instruments to account for endogenous regressors and was developed specifically with productivity measurement in mind (Arellano and Bond 1991, Blundell and Bond 2000). Our panel data includes 39 time periods and 87 physicians, which is well-suited for dynamic panel models.

We created lagged values of physician productivity. Lags beyond two time periods were found insignificant; hence, we included only two lags of physician productivity. Additionally, we first-differenced the variables in the model. The resultant model is as follows:

$$\begin{aligned}
&\Delta Productivity(i,t)\\
&= \beta_1 * \Delta Productivity(i,t-1) + \beta_2 * \Delta Productivity(i,t-2)\\
&\quad + \beta_3 * \Delta Experience(i,t) + \beta_4 * \Delta Learning\ Phase(c,t)\\
&\quad + \beta_5 * \Delta Stable\ Phase(c,t) + \sum \beta_{6\text{–}7} * \Delta(Specialty(s)\\
&\quad * Learning\ Phase(c,t)) + \sum \beta_{8\text{–}9} * \Delta(Specialty(s)\\
&\quad * Stable\ Phase(c,t)) + \sum \beta_{10\text{–}20} * \Delta(Clinic(c)\\
&\quad * Learning\ Phase(c,t)) + \sum \beta_{21\text{–}31} * \Delta(Clinic(c)\\
&\quad * Stable\ Phase(c,t)) + \Delta\varepsilon_{it}. \qquad (2)
\end{aligned}$$

As discussed earlier, the system GMM estimation eliminates bias from unobserved heterogeneity by first-differencing and from endogeneity by using instrumental variables of available lags and levels (Aral et al. 2012a). Also notice that first differencing eliminated clinic, gender, and specialty dummy variables from the estimation equation (Cameron and Trivedi 2010).

Arellano–Bond system GMM estimation allows us to have some variables in the equation that are endogenous. We adopt a more conservative specification and assume that the learning phase, the stable phase, and all the associated interactions are endogenous. Two conditions must be met for the Arellano–Bond GMM estimation to be valid (Arellano and Bond 1991). The first is a Hansen test of overidentifying restrictions. It tests the overall validity of the instruments by analyzing the sample analog of the moment conditions used in the estimation process. The second test examines the hypothesis that the error term $\Delta\varepsilon_{it}$ is not serially correlated. The test entails examining whether the differenced error term is second-order serially correlated. The differenced error term is likely to be first-order serially correlated even if the original error term is not. Failure to reject the null hypotheses of both tests provides support to the model. We fail to reject the null hypothesis that overidentifying restrictions are valid ($\chi^2(324) = 73.47$; $p = 0.96$). Furthermore, we find that although the first-order serial correlation for the differenced error term is significant ($z = -6.21$; $p < 0.001$), the second-order serial correlation is insignificant ($z = -0.10$; $p = 0.92$). Thus, we also fail to reject the second hypothesis. These specification tests demonstrate that the Arellano–Bond system GMM estimator is apt for our data and will provide unbiased estimates. The Wald test for heteroskedasticity suggests that our data are heteroskedastic; thus, we estimate standard robust errors using Windmeijer (2005) correction.

Our results are shown in Table 5. We report results from three models estimated with the Arellano–Bond GMM estimator. The first model is the base model, which has two lagged productivity variables. To this model we add the three main effects—two duration variables and physician experience. Finally, in the third model we add interactions between specialty and EMR implementations phases and between clinics and EMR implementations phases. The stepwise approach enables us to assess the incremental impacts of adding additional variables to the base model. All the 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 rejected and that the estimated models are significant.

Our main interest is in the temporal and specialty-specific impacts of EMRs on physician productivity. Our results from Model 3 indicate that FPs and Peds are less productive in the stable phase in comparison to IMs. Thus, we find that the net impact of EMR is more benign on IMs than on Peds and FPs. Because such differences did not exist in the pre-EMR period, their existence in the post-EMR period demonstrates that specialty plays a significant role on the impact of EMR technology on physician productivity. To examine how Peds and FPs perform in comparison to each other after EMR implementation, we conduct a chi-squared

Table 5 Temporal and Specialty-Specific Physician Productivity Variation: Arellano–Bond Dynamic GMM System Estimation

	Model 1: Base model with two lagged productivity terms		Model 2: Experience and phase variables added		Model 3: Clinic and specialty interactions with phase added	
Variables	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error
Physician Experience	—	—	0.176***	0.041	0.09	0.22
Learning Duration	—	—	−2.009***	0.17	27.55***	8.39
Stable Duration	—	—	−1.37***	0.089	26.18**	10.44
Peds ∗ Learning Duration	—	—	—	—	**−37.12*** **	**7.63**
Peds ∗ Stable Duration	—	—	—	—	**−39.32*** **	**11.31**
FP ∗ Learning Duration	—	—	—	—	**−34.47*** **	**8.43**
FP ∗ Stable Duration	—	—	—	—	**−35.48*** **	**11.66**
Productivity ($t-1$)	0.186***	0.013	0.066***	0.01	0.064**	0.02
Productivity ($t-2$)	0.114***	0.01	0.037***	0.003	0.026*	0.013
Constant	13.99***	0.48	15.68***	0.717	16.85***	3.95
Model fit statistics	Wald $\chi^2(2) = 207.85$ Prob $> \chi^2 = 0.000$		Wald $\chi^2(5) = 1{,}859.34$ Prob $> \chi^2 = 0.000$		Wald $\chi^2(31) = 1{,}763.71$ Prob $> \chi^2 = 0.000$	
AR(1) test	-6.46; $p < 0.001$		-6.16; $p < 0.001$		-6.21; $p < 0.001$	
AR(2) test	-1.41; $p = 0.16$		-0.34; $p = 0.73$		-0.10; $p = 0.92$	
Hansen test	$\chi^2(700) = 85.22$; $p = 0.92$		$\chi^2(162) = 82.27$; $p = 0.98$		$\chi^2(324) = 73.47$; $p = 0.96$	
N	3,186		3,186		3,186	

Notes. Clinic AB, specialty IM, preimplementation phase, and gender male served as the bases. First-differencing eliminates clinic, specialty, and gender dummies from the system GMM estimation. In the interest of clarity and space, clinic and duration interaction variables are not shown in this table. Key results shown in bold.

*Significant at $p < 0.05$; **significant at $p < 0.01$; ***significant at $p < 0.001$.

test of the coefficients obtained. We cannot reject the hypothesis of equality ($p > 0.1$), suggesting that the post-EMR-implementation steady-state productivity of FPs and Peds are not statistically different from each other. Results from the static random effects model (see Table 4) indicate that physician gender is not significantly related to productivity. Our finding is in contrast to those of other researchers (e.g., Conrad et al. 2002). Additionally, our findings indicate that physician experience is not significantly related to productivity (see Table 4).

We also find that FPs and Peds experience a decrease in productivity compared to IMs in the learning phase. At first glance, this result seems surprising, because in the initial months after the implementation of the EMRs, IMs experience a larger initial drop in productivity than others. However, given that the learning phase is six months, and IMs recover quickly and surpass the productivity levels of FPs and Peds three months after implementation, it is possible that for the entire learning duration, IMs perform better.

Our results suggest that it is useful to consider the usage context, such as physician specialty and temporal dynamics, to unpack the impact of EMRs on physician productivity. Such emphasis on context is critical because it informs when IT can have a consequential impact. Without underscoring the usage context, it is possible that the real nature of the impact of EMRs on physicians will remain masked. For instance, a recent National Research Council report stated that clinicians spend more time entering data than using it, which might suggest that the information entry aspects of EMRs can dominate the overall effect on productivity (Stead and Lin 2009). Additionally, these researchers claim that although EMRs make audits, research, and billing more efficient, they may render the clinical work to be less efficient for a temporary period. A few other notable studies, such as a Medical Group Management Association (MGMA) study funded by the U.S. government (Gans 2005), have cautioned that EMRs may reduce overall physician productivity. In contrast, our research indicates that such statistics and observations should be examined at a finer-grained level that accounts for workflow differences due to systematic differences such as physician specialty, and assessed over a period of time using longitudinal data. Such an approach has the potential to highlight nuances that may have a significant impact on the way IT impacts physicians work practices.

Discussion

Physicians believe that the most appropriate use of their skills is in direct patient care, rather than spending valuable time entering patient information using technologies that may not be intuitive or customized to their specific needs, thereby compromising their productivity (Goh et al. 2011, Holden 2010). Concurrently, physicians realize significant value in being able to use existing information to diagnose patients and make patient care decisions. These trade-offs, and the resulting productivity considerations, are critical to many physicians. However, the actual effects of EMR implementation on physician productivity have been understudied in the literature (Agarwal et al. 2010, Cheriff et al. 2010, Goh et al. 2011). Much of the academic and policy discussion is centered around system-level goals such as cost reductions, readmission rates, quality of care, patient satisfaction, and privacy implications. The lack of insight on physician-level impacts of EMR, particularly those incorporating contextual factors, such as physician specialty, tends to prejudice doctors who are skeptical of how technologies apply specifically to them.

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 analysis suggests that the three physician specialties differ significantly in terms of how they absorb EMR technology and how EMRs impact their productivity in the long run. The post-EMR productivity levels for IMs settled slightly above the pre-EMR levels, despite there being a substantial productivity drop in the months immediately after EMR implementation. Compared with Peds and FPs, IMs experience greater productivity gains in the long run. Our results suggest that generic EMRs may not be suited equally for all the physician specialties.

Why might the different categories of primary care physicians exhibit differences in how they absorb EMRs and in the overall impact of EMRs on their productivity? To understand this, we return to the two ways in which EMRs can affect physician workflow and examine whether differences in work patterns and in the use of information, across specialties, can potentially account for the observed differences in productivity impacts. First, consider information review tasks. IMs, relative to Peds and FPs, are likely to do less data entry and more data synthesis and decision making. IMs see the most "new patients," whereas FPs and Peds tend to be more familiar with their patients because of their frequent interactions with them. Additionally, IMs are more likely to see patients whom other doctors may have examined previously and perhaps generated substantial data on regarding their health history. IMs also have greater use of health history and statistics in treating patients. Internists may not be as familiar as pediatricians and family practitioners tend to be with their patients. Moreover, because IMs tend to specialize in certain disease conditions, they become proficient in using EMRs to access and synthesize information about those conditions. In such cases, the EMR's replacement of the old paper health record is substantially and positively impactful once the new technology is integrated into physicians' daily operations.

Second, consider information entry tasks. Patients see FPs for a variety of reasons, necessitating information entry on widely different medical conditions. According to the National Ambulatory Medical Care survey, FPs accounted for 224 million out of 956 million visits in 2008 (Centers for Disease Control and Prevention 2008), the highest number reported by any physician specialty. Furthermore, although information entry requirements are high for FPs, their numbers have been plunging since the 1990s, making a bad situation much worse. Pediatricians spend substantial time in activities that do not require considerable review of past patient data, potentially lowering their benefits from the superior IT capabilities for data retrieval, review, and visualization. On the other hand, they are required to make substantial documentation for infants, children, and adolescents after each visit, facing a significant data entry burden.

Our results and arguments and insights provided by top administrators at our study site provide preliminary indications that impacts of EMRs may be most beneficial for IMs in the long-term because of the fit that technology provides to their workflows. What, then, explains the precipitous drop that IMs experience in the months following the EMR implementation? Medical information review, synthesis, and decision making 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. In the initial months, IMs may need to modify their information review, synthesis, and decision-making routines, schema, and workflows significantly because of the cognitive burdens, which may be more consequential at the beginning than those for information entry.

Recall that we do not find any significant impact of physician gender or experience, which can also 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. Whereas Conrad et al. (2002) use the annual cost and physician compensation and production surveys reported by the MGMA for the year 1997, we believe that the availability of a longer and granular panel data set 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 because 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.

Limitations of the Research

This study has several limitations that provide opportunities for further research. First, some may wonder about the generalizability of our findings, because we studied productivity implications of one EMR system on physicians associated with one university health system. To the extent that workflow and informational needs of FPs, Peds, and IMs at our study site are likely to be similar to those in other organizational settings, and to the extent that other EMR systems are likely to provide different levels of fit to physicians of different specialties, we would expect our results to be applicable in multiple settings. However, our findings raise the need for other researchers to further investigate productivity impacts of EMRs across a large number of specialties and in multiple health provider settings with varying levels of ownership, academic status (academic or community), and profit focus (for or not for profit).

Second, caution should be exercised in interpreting our results, because we do not have conclusive evidence that the fit of the physicians' tasks with the technological features of the implemented EMR determines the productivity of the physicians of various specialties. We do not have irrefutable evidence that the ratio of information review to information entry is the key mechanism through which EMRs impact physician productivity. In other words, we provide suggestive and not conclusive evidence of the fit between task characteristics and technology features. An ideal experiment would randomize the ratio of information review to entry across physicians. Teasing out the mechanism through which EMRs impact physician productivity and other outcomes can be a fruitful avenue for future research.

Third, 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. CMS as well as private insurance companies use WRVUs to measure physician productivity, yet it may be appealing to compare the productivity impacts of EMRs on multiple measures. We hope that future research will gather data on these measures and provide a comparison across them. Additionally, we recognize that productivity does not fully capture performance and value in a clinical setting; other measures such as revenues generated, costs saved, and patient satisfaction may be equally, if not more, important.

Finally, because of the lack of data, we are unable to examine the temporal and specialty-specific impact of EMR implementation on physician-level quality. Physician-level quality data were not available at our study site for the study period. Even now, such data are not available publicly for a majority of physicians in the Unites States.[10] The federal government has started an initiative called Physician Compare, through which quality data may become available in the future.[11] Additional physician-level quality data may also become available after stage-three meaningful use requirements have been completed. Examining temporal and specialty-specific impact of EMRs on productivity and quality simultaneously will provide more complete assessment of how technology influences physicians. Extant research has examined the implications of EMR and HIT implementation on quality and found systematic positive impact (Buntin et al. 2011, Lee et al. 2013), little or no significant impact (Agha 2012, Parente and McCullough 2009), and adverse impact (Ash et al. 2004, Nebeker et al. 2005). However, because of the lack of easily available, Verified, and standardized physician-level quality information, prior research has examined quality predominantly at the hospital or facility level. This represents an opportunity area for researchers to investigate the impact of HIT on physician-level quality.

Research Contributions and Implications

Effective implementation of EMRs in healthcare will depend significantly on physician acceptance of these technologies and their impact on physician productivity. Focusing on these critical issues, this paper makes several contributions to extant literature. First, to the best of our knowledge, this study is the first in the IS literature to offer a rigorous examination of physician-level productivity impacts of EMR implementation. Past research on this topic has provided predominantly anecdotal evidence to suggest that these technologies enhance or hurt physician productivity. Concurrently, the IT productivity literature has lamented the absence of individual-level productivity studies in the services sector, especially for knowledge workers (Aral et al. 2012a). Our study extends the research in both health informatics and IT productivity literatures. Second, our results provide informed indications that the nature, direction, and magnitude of impacts induced by technological innovations, such as EMRs, are contingent on the work performed by the knowledge workers (e.g., physicians) and vary systematically over time. The key insight from our study is that such temporal impacts vary across physician specialties. In fact, some physicians may be better off whereas others may be worse off, after EMR implementation. Third, this study makes a case for a more specific and thorough investigation of the concept of the information retrieval to information entry ratio. Although we cannot conclusively establish the mechanism through which EMRs impact physician productivity, our discussions with senior administrators and practicing physicians suggest that information retrieval to information entry is important for explaining productivity differences across different physician specialties.

Our research provides a rigorously derived dynamic pattern for describing the productivity impact of EMRs over time: a substantial productivity drop results from the initial shock, followed by a period of recovery and then an ultimate steady state pattern after the technology shock is absorbed. We observed productivity drops larger than 20% for all specialties and a six-month recovery period. This pattern underlines the need for health system managers to prepare for the productivity loss, and to not abandon the system merely based on short-term loss. If users do not take the time to learn the new system, and persevere during the period when they are experiencing productivity declines, they may not acquire enough expertise with it to benefit later. This lack of learning may inhibit physicians from discovering advanced features, including decision-making routines, which facilitate large productivity and quality enhancements in subsequent months.

Our findings, demonstrating divergence in EMR impact across specialties, require further investigation and are of consequence to both health IT vendors and users. In many EMR implementations, such as at our study site, every physician uses the same interface to interact with the EMR system. This standard design may not be an effective replacement for all physicians. It further fails to leverage IT's capability for customization. Some physicians may be more productive with voice-activated search and analysis feature, and others may find voice-enabled data input into EMRs more helpful. It is evident that one size does not fit all in this context. One physician summarized it well: "Wholesale redesign of the system may not be necessary, but customization of the system is key." An administrator suggested that for longer notes, vendors provide extensive dictation and speech recognition help in the software. The key managerial insight we propose here is that although integrated EMRs are valuable for data integration and exchange, and collaboration among health providers, it is vital to provide multiple input and output options so that physicians can assess fit with their respective workflows rather than be forced to use the preset options. Although back-end integration may be crucial for system-level impacts, vendors should examine customized front-end user interfaces that match physician workflows and patient data input/output requirements. We suggest that EMR designers and vendors recognize that these systems

[10] Agency for Healthcare Research and Quality, "Part I. Introduction to Performance Data." Last accessed June 20, 2014, http://www.ahrq.gov/qual/perfmeasguide/perfmeaspt1.htm.

[11] Medicare.gov, "Find & Compare Doctors, Plans, Providers." Last accessed June 20, 2014, http://www.medicare.gov/quality-care-finder/#physician-compare.

are decision-making tools for physicians, and the data input/output features are means to that end. Finally, managers must be cognizant about the disproportionate impact of the EMRs on physicians and indeed examine whether some physicians benefit from it at the expense of others.

This study can be extended in several possible ways. First, whereas we examined EMR implementation in the ambulatory primary care setting, future research can enhance the scope of study by contrasting EMR implementations in multiple settings such as in-patient settings, 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 EMRs. 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). Future research can examine how task traits may differ for different physicians working in diverse conditions and how these traits may influence the fit of health information technologies for different physician specialties. 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. Third, the concept of the information review to information entry ratio can also be extended to other contexts such as management and IT consulting and applied in various individual-level IT productivity studies, as also in studies that draw upon TTF theory. Finally, our arguments and results provide a strong foundation for future researchers to apply TTF theory, and contingency theories in general, in the study of HIT application in the healthcare industry.

We contribute to policy and practice discussions by emphasizing granular productivity analyses, the temporal nature of productivity, and physician specialty-specific workflows. Our results show, with remarkable consistency across many 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, before climbing back up. Thus, although the benefits of EMR technologies may be far from certain, our study suggests that the continued deep decline in productivity feared by physicians may not materialize. The healthcare industry is beginning a long and transformative journey, facilitated by standard-based clinical information technologies. We hope that this paper stimulates further research in HIT, contributing to our understanding of how IT impacts individual-level productivity among knowledge workers, and provides guidelines to vendors to design technologies that enhance the productivity of physicians.

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Appendix. Survey Questionnaire and Summary Statistics

Researchers at University ABC and University XYZ request you to participate in a short study. This study contains questions about your usage of the DEF electronic medical record (EMR) implemented at the PQR Medical Center. These questions will help PQR Medical Center to determine your initial and continued EMR training needs. Thank you very much for your help![12]

Please indicate the extent of your agreement with the following statements on a scale of 1 to 5, where 1 indicates *strong disagreement* and 5 indicates *strong agreement*. For comparison, please think about the time when you used paper documents predominantly to maintain patient information.

Survey question	Average for IMs	Average for FPs	Average for Peds
EMR allows me to easily synthesize information from multiple sources.	4.08	3.95	4.0
EMR allows me to make patient treatment decisions efficiently.	4.0	3.87	3.5
EMR interrupts my workflow.	2.58	3.07	3.0
I enter a lot of information about patients, which can be helpful to other physicians.	4.16	4.24	4.0
On the balance, I do more information entry than information synthesis using EMR.	3.67	3.75	4.5
EMR has increased my documentation time significantly. ________%	58.3	65.5	112.5

[12] The identifying information is withheld to safeguard the privacy of the respondents. The survey was kept very short at the request of the study site. Primary care physicians responded to this survey at the conclusion of an already-scheduled meeting. The researchers were not allowed to brief the physicians on the study or the purpose of these questions. The surveys were returned to the researchers at the conclusion of the meeting.

I am: a family practitioner/an internist/a pediatrician/other.[13]

My two most critical *current* training needs are:[14]

1.____

2.____

I believe that within the next 6–12 months, I will need training on:

____

____

References

Agarwal R, Gao G, DesRoches C, Jha A (2010) The digital transformation of healthcare: Current status and the road ahead. *Inform. Systems Res.* 21(4):796–809.

Agha L (2012) The effects of health information technology on the costs and quality of medical care. Working paper, Massachusetts Institute of Technology, Cambridge. http://economics.mit.edu/files/6216.

Andreae MC, Freed GL (2002) Using a productivity-based compensation program at an academic health center: A case study. *Acad. Medicine* 77(9):894–899.

Angrist JD, Pischke J-S (2009) *Mostly Harmless Econometrics an Empiricist's Companion* (Princeton University Press, Princeton, NJ).

Aral S, Brynjolfsson E, Van Alstyne M (2012a) Information, technology and information worker productivity. *Inform. Systems Res.* 23(3):849–867.

Aral S, Brynjolfsson E, Wu DJ (2006) Which came first, IT or productivity? The virtuous cycle of investment and use in enterprise systems. *Proc. 27th Annual Internat. Conf. Inform. Systems, Milwaukee*.

Aral S, Brynjolfsson E, Wu L (2012b) Three-way complementarities: Performance pay, human resource analytics, and information technology. *Management Sci.* 58(5):913–931.

Arellano M, Bond S (1991) Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Rev. Econom. Stud.* 58(2):277–297.

Aron R, Dutta S, Janakiraman R, Pathak PA (2011) The impact of automation of systems on medical errors: Evidence from field research. *Inform. Systems Res.* 22(3):429–446.

Ash J, Berg M, Coira E (2004) Some unintended consequences of information technology in health care: The nature of patient care information system-related errors. *J. Amer. Medical Inform. Assoc.* 11(2):104–112.

Athey S, Stern S (2002) The impact of information technology on emergency health care outcomes. *RAND J. Econom.* 33(3):399–432.

Baltagi B (2005) *Econometric Analysis of Panel Data*, 3rd ed. (John Wiley & Sons, Chichester, UK).

Banker R, Chang H, Kao Y (2002) Impact of information technology on public accounting firm productivity. *J. Inform. Systems* 16(2):209–222.

Barjaktarevic A (2008) Specific implementation of electronic medical record in pediatrics practice. *Acta Informatica Medica* 16(3):172–175.

Barua A, Lee B (1997) The information technology productivity paradox revisited: A theoretical and empirical investigation in the manufacturing sector. *Internat. J. Flexible Manufacturing Systems* 9(2):145–166.

[13] The sample includes 20 FPs, 12 Ims, and 3 Peds.

[14] The study site was keen on finding out the current and future training needs of its physicians. This is why training questions were included in the survey despite their lack of direct relevance to our study.

Bendoly E, Cotteleer M (2008) Understanding behavioral sources of process variation following enterprise system deployment. *J. Oper. Management* 26(1):23–44.

Blundell R, Bond S (2000) GMM estimation with persistent panel data: An application to production functions. *Econometric Rev.* 19(3):321–340.

Brynjolfsson E, Hitt L (1996) Paradox lost? Firm-level evidence on the returns to information systems. *Management Sci.* 42(4):541–558.

Brynjolfsson E, Hitt L (2000) Beyond computation: Information technology, organizational transformation and business performance. *J. Econom. Perspect.* 14(4):23–48.

Bulkley N, Van Alstyne M (2004) Why information should influence productivity. Working Paper 4680-08, Massachusetts Institute of Technology, Cambridge.

Buntin M, Burke M, Hoaglin M, Blumenthal D (2011) The benefits of health information technology: A review of the recent literature shows predominantly positive results. *Health Affairs* 30(3):464–471.

Cameron AC, Trivedi PK (2010) *Microeconometrics Using Stata* (Stata Press, College Station, TX).

Centers for Disease Control and Prevention (2008) National ambulatory medical care survey: 2008 summary tables. Last accessed June 20, 2014, http://www.cdc.gov/nchs/data/ahcd/names_summary/2008_names_web_tables.pdf.

Chang YB, Gurbaxani V (2012) The impact of IT-related spillovers on long-run productivity: An empirical analysis. *Inform. Systems Res.* 23(3):868–886.

Cheriff AD, Kapur AG, Qiu M, Cole CL (2010) Physician productivity and the ambulatory EHR in a large academic multi-specialty physician group. *Internat. J. Medical Inform.* 49(7):492–500.

Chiasson MW, Davidson E (2005) Taking industry seriously in information systems research. *MIS Quart.* 29(4):599–606.

Coleman D, Moran E, Serfilippi D, Mulinski P, Rosenthal R, Gordon B, Mogielnicki PR (2003) Measuring physicians' productivity in veteran affairs medical center. *Acad. Medicine* 78(7):682–689.

Conrad DA, Sales A, Liang SY, Chaudhuri A, Maynard C, Pieper L, Weinstein L, Gans D, Piland N (2002) The impact of financial incentives on physician productivity in medical groups. *Health Services Res.* 37(4):885–906.

Cronin B, Gudim M (1986) Information and productivity: A review of research. *Internat. J. Inform. Management* 6(2):85–101.

Crosson JC, Stroebel C, Scott JG, Stello B, Crabtree BF (2005) Implementing an electronic medical record in a family medicine practice: Communication, decision making, and conflict. *Ann. Family Medicine* 3(4):307–311.

Dennis AR, Wixom B, Vandenberg RJ (2001) Understanding fit and appropriation effects in group support systems via meta-analysis. *MIS Quart.* 25(2):167–193.

Devaraj S, Kohli R (2003) Performance impacts of information technology: Is actual usage the missing link? *Management Sci.* 49(3):273–289.

DeVore SD, Figlioli K (2010) Lessons premier hospitals learned about implementing electronic health records. *Health Affairs* 29(4):664–667.

Dewan S, Kraemer K (2000) Information technology and productivity: Evidence from country-level data. *Management Sci.* 46(4):548–562.

Dranove D, Forman C, Goldfarb A, Greenstein S (2012) The trillion dollar conundrum: Complementarities and health information technology. NBER Working Paper w18281, National Bureau of Economic Research, Cambridge, MA.

Ferranti JM, Horvath MH, Jansen J, Schellenberger P, Brown T, DeRienzo CM, Ahmad A (2011) Using a computerized provider order entry system to meet the unique prescribing needs of children: Description of an advanced dosing model. *BMC Medical Inform. Decision Making* 11:14, http://www.biomedcentral.com/1472-6947/11/14/prepub.

Furukawa M, Raghu TS, Shao BM (2010) Electronic medical records and cost efficiency in hospital medical-surgical units. *Inquiry* 47(2):110–123.

Gans DN (2005) Impact of electronic health records on the financial performance of medical group practices. Study, Medical Group Management Association, Englewood, CO. Last accessed June 20, 2014, http://www.ahrq.gov/about/annualmtg08/090908slides/Gans.htm.

Ghose A, Han SP (2011) An empirical analysis of user content generation and usage behavior on the mobile Internet. *Management Sci.* 57(9):1671–1691.

Goh JM, Gao G, Agarwal R (2011) Evolving work routines: Adaptive routinization of information technology in healthcare. *Inform. Systems Res.* 22(3):565–585.

González-González AI, Dawes M, Sánchez-Mateos J, Riesgo-Fuertes R, Escortell-Mayor E, Sanz-Cuesta T, Hernández-Fernández T (2007) Information needs and information-seeking behavior of primary care physicians. *Ann. Family Medicine* 5(4):345–352.

Goodhue DL (1995) Understanding user evaluations of information systems. *Management Sci.* 41(12):1827–1844.

Goodhue DL, Thompson RL (1995) Task-technology fit and individual performance. *MIS Quart.* 19(2):213–236.

Hartman M, Martin A, McDonnell P, Catlin A (2009) National health spending in 2007: Slower drug spending contributes to lowest rate of overall growth since 1998. *Health Affairs* 28(1):246–261.

Himmelstein DU, Wright A, Woolhandler S (2010) Hospital computing and the costs and quality of care: A national study. *Amer. J. Medicine* 123(1):40–46.

Hitt LM, Wu DJ, Zhou X (2002) ERP investment: Business impact and productivity measures. *J. Management Inform. Systems* 19(1):71–98.

Holcombe RF, Hollinger KJ (2010) Mission-focused, productivity-based model for sustainable support of academic hematology/oncology. *J. Oncology Practice* 6(2):74–79.

Holden RJ (2010) Physicians' beliefs about using EMR and CPOE: In pursuit of a contextualized understanding of health IT use behavior. *Internat. J. Medical Inform.* 79(2):71–80.

Housman MG, Hitt LM, Elo K, Beard N (2006) The effect of IT capital on hospital efficiency. *Workshop Inform. Systems Econom.* http://digital.mit.edu/wise2006/papers/5B-3_WISE%202006%20Abstract.pdf.

Hsiao WC, Braun P, Dunn D, Becker ER (1988) Resource-based relative values: An overview. *J. Amer. Medical Assoc.* 260(16):2347–2353.

Johnson SE, Newton WP (2002) Resource-based relative value units: A primer for academic family physicians. *Family Medicine* 34(3):172–176.

Jorgenson DW, Stiroh KJ (2000) Raising the speed limit: U.S. economic growth in the information age. *Brookings Papers Econom. Activity* 1:125–211.

Kemerer C (1992) How the learning curve affects computer aided software engineering (CASE) tools adoption. *IEEE Software* 9(3):23–28.

Lahiri A, Seidmann A (2012) Information hang-overs in healthcare service systems. *Manufacturing Services Oper. Management* 14(4):634–653.

Lee J, McCullough JS, Town RJ (2013) The impact of health information technology on hospital productivity. *RAND J. Econom.* 44(3):546–569.

Linder JA, Schnipper JL, Middleton B (2012) Method of electronic health record documentation and quality of primary care. *J. Amer. Medical Inform. Assoc.* 19(6):1019–1024.

Loomis GA, Ries JS, Saywell RM, Thakker NR (2002) If electronic medical records are so great, why aren't family physicians using them? *J. Family Practice* 51(7):636–641.

Maxwell S, Zuckerman S (2007–2008) Impact of resource-based practice expense on the Medicare physician volume. *Health Care Financing Rev.* 29(2):65–79.

McAlister FA, Graham I, Karr GW, Laupacis A (1999) Evidence-based medicine and the practicing clinician. *J. General Internal Medicine* 14(4):236–242.

McCullough JS, Casey M, Moscovice I, Prasad S (2010) The effect of health information technology on quality in US hospitals. *Health Affairs* 29(4):647–654.

Menon N, Kohli R (2013) Blunting Damocles' sword: A longitudinal model of healthcare IT impact on malpractice insurance premium and quality of patient care. *Inform. Systems Res.* 24(2):918–932.

Menon N, Lee B, Eldenburg L (2000) Productivity of information systems in the healthcare industry. *Inform. Systems Res.* 11(1):83–92.

Miller PR, Wildman EA, Chang MC, Meredith JW (2012) Acute care surgery: Impact on practice and economics of elective surgeons. *J. Amer. College of Surgeons* 214(4):531–535.

Nebeker J, Hoffman J, Weir C, Bennett C, Hurdle J (2005) High rates of adverse drug events in a highly computerized hospital. *Archives of Internal Medicine* 165(10):1111–1116.

Newhouse JP, Sinaiko AD (2007–2008) Estimates of physician productivity: An evaluation. *Health Care Financing Rev.* 29(2):33–39.

O'Malley AS, Grossman JM, Cohen GR, Kemper NM, Pham HH (2009) Are electronic medical records helpful for care coordination? Experiences of physician practices. *J. General Internal Medicine* 25(3):177–185.

Parente S, McCullough J (2009) Health information technology and patient safety: Evidence from panel data. *Health Affairs* 28(2):357–360.

Park SY, Lee SY, Chen Y (2012) The effects of EMR deployment on doctors' work practices: A qualitative study in the emergency department of a teaching hospital. *Internat. J. Medical Inform.* 81(3):204–217.

Pisano GP, Bohmer R, Edmondson AC (2001) Organizational differences in rates of learning: Evidence from the adoption of minimally invasive cardiac surgery. *Management Sci.* 47(6):652–768.

Sebelius K, Frieden TR, Sondik EJ (2011) Health, United States, 2010: With special feature on death and dying. Report, National Center for Health Statistics, Hyattsville, MD.

Shachak A, Hadas-Dayagi M, Ziv A, Reis S (2009) Primary care physicians' use of an electronic medical record system: A cognitive task analysis. *J. General Internal Medicine* 24(3):341–348.

Stead W, Lin H (2009) *Computational Technology for Effective Health Care: Immediate Steps and Strategic Directions* (National Academies Press, Washington, DC).

Stevens M (2010) Implementing EMRs: How to push physician productivity. *Clinical Innovation + Tech.* (January 4), http://www.clinical-innovation.com/topics/ehr-emr/implementing-emrs-how-push-physician-productivity.

Tambe P, Hitt L (2012) The productivity of information technology investments: New evidence from IT labor data. *Inform. Systems Res.* 23(3):599–617.

Tambe P, Hitt L, Brynjolfsson E (2012) The extroverted firm: How external information practices affect innovation and productivity. *Management Sci.* 58(5):843–859.

Triplett JE, Bosworth BP (2004) *Services Productivity in the United States: New Sources of Economic Growth* (Brookings Institution Press, Washington, DC).

Tufano JA, Conrad DA, Liang S-Y (1999) Addressing physician compensation and practice productivity. *J. Ambulatory Care Management* 22(3):47–57.

Vishwanath A, Singh SR, Winklestein P (2010) The impact of electronic medical record systems on outpatient workflows: A longitudinal evaluation of its workflow effects. *Internat. J. Medical Inform.* 79(11):778–791.

Windmeijer F (2005) A finite sample correction for the variance of linear efficient two-step GMM estimators. *J. Econometrics* 126(1):25–51.

Wooldridge J (2002) *Econometric Analysis of Cross Section and Panel Data* (MIT Press, Cambridge, MA).

Zaslove MO (2003) *The Successful Physician: A Productivity Handbook for Practitioners* (Jones & Bartlett Publishers, Sudbury, MA).

Zhou L, Soran CS, Jenter CA, Volk LA, Orav EJ, Bates DW, Simon SR (2009) The relationship between electronic health record use and quality of care over time. *J. Amer. Medical Inform. Assoc.* 16(4):457–464.

Zigurs I, Buckland BK (1998) A theory of task/technology fit and group support systems effectiveness. *MIS Quart.* 22(3): 313–334.