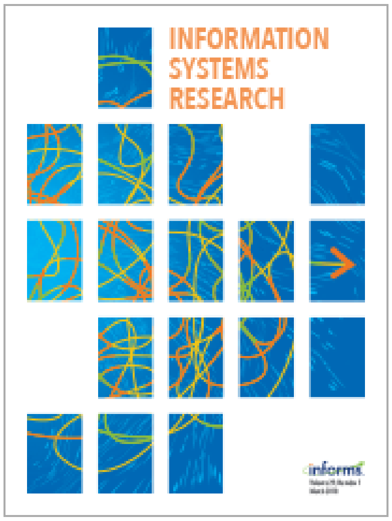

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How Does the Implementation of Enterprise Information Systems Affect a Professional's Mobility? An Empirical Study

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Abstract. Although significant research has examined the effect of enterprise information systems on the behavior and careers of employees, the majority of this work has been devoted to the study of blue- and gray-collar workers, with little attention paid to the transformative effect information technology may have on high-status professionals. In this paper, we begin to bridge this gap by examining how highly skilled professionals react to the increasing presence of enterprise systems within their organizations. Specifically, we investigate how the implementation of enterprise systems—in the form of electronic health records—affects the decision of physicians to continue practicing at their current hospital. Results suggest that when enterprise systems create complementarities for professionals, their duration of practice at the organization increases significantly. However, when technologies are disruptive and force professionals to alter their routines, there is a pronounced exodus from the organization. Interestingly, these effects are strongly moderated by individual and organizational characteristics, such as the degree of firm-specific human capital, local competition, and the prevalence of past disruptions, but are not associated with accelerated retirement or the strategic poaching of talent by competing organizations.

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Keywords: professional mobility • physicians • enterprise systems • technology adoption • electronic health records • logit hazard model

Introduction

Both the introduction of enterprise information systems and the digitization of organizational processes have had striking effects on the way firms leverage human capital. Indeed, a large body of research has identified intra- and interorganizational changes resulting from technology use. These include, but are not limited to, the effect of technology introduction on organizational learning (Argote 2013), the rise of globalization (Gopal et al. 2002), the metamorphic effect on the delivery of healthcare and social services (Agarwal et al. 2010b, Angst et al. 2012), and even the effect on workforce automation (Pinsonneault and Kraemer 1993, 1997). Yet, despite such rich literature, empirical work has primarily examined the effect of enterprise systems on un- or semiskilled labor, viz blue- and gray-collar workers, and paid less attention to the effect information technology (IT) may have on high-status professionals (e.g., engineers, physicians, and lawyers).[1] In this paper, we examine how highly skilled professionals react to the increasing presence of enterprise systems within their organizations. Specifically, we investigate whether the implementation of enterprise information systems affects professional turnover.

Theoretically, there are numerous reasons why extant knowledge of the relationship between labor and enterprise systems may not translate cleanly from other workers to high-status professionals. Highly skilled professionals often represent the most important asset possessed by the organization. It is therefore likely that the firm will make information technology (IT) investments that yield significant complements to this segment of its workforce (Karshenas and Stoneman 1993, Bresnahan et al. 2002). This is different from less-skilled labor, which may not be adding value beyond basic labors (Coase 1937). Further, there are significant differences in the agency and autonomy possessed by high-status professionals (Freidson 1988, Huckman and Pisano 2006). This level of agency makes it unlikely that the top management team would be able to strong-arm these professionals into adopting, because they might be able to do with a less-skilled workforce. This is notably true when highly skilled professionals occupy leadership positions in the organization, thereby giving them leverage over organizational strategic decision making. Finally, high-status professionals often face onerous educational requirements and licensing practices, which can significantly retard their availability (Sargen et al. 2011). As a result, high-status professionals can often move quickly across competing practices when dissatisfied with their current employer (Buchbinder et al. 2001), and there is often a limited excess labor pool for employers to dip into should professionals depart the organization.

Moreover, the a priori relationship between enterprise system implementations and high-status professional mobility is unclear. On the one hand, both the academic literature and the popular press provide evidence of the virtues of enterprise systems at both the individual and organizational levels (Gattiker and Goodhue 2005, McCullough et al. 2010, Aral et al. 2012). To the degree that formalizing and routinizing organizational processes bring with them cost reductions and quality increases (Nelson and Winter 1982) while simultaneously reducing the cognitive overhead on decision makers (Chase and Simon 1973), it follows that tools that increase performance would be treated as significant boons to organizations. Enterprise systems have been shown to produce quantifiable benefits in the form of reductions in errors, increased interoperability, and increased productivity (Hitt et al. 2002, Gardner et al. 2003, Metzger and Parasuraman 2005)—factors on which high-status professionals are often evaluated. Thus, it is plausible that enterprise systems may help the firm retain these key organizational resources by providing complementarities.

Conversely, the implementation of enterprise systems may also disturb the manner in which high-status professionals execute their duties, thereby disrupting personal routines and creating significant turmoil in the organization (Nelson and Winter 1982, Levitt and March 1988, Greenwood et al. 2013). Because enterprise systems such as enterprise resource plans, customer relationship management tools, and electronic health records (EHRs) lock users into procedural practices, it is plausible that the observed benefits that accrue to the organization (i.e., increased performance; Hitt and Tambe 2016, McCullough et al. 2016) come at significant cost to the professional (Robey et al. 2002, Gardner et al. 2003). For example, enterprise systems are known to have steep learning curves (Robey et al. 2002). This may be a function of poor training, technical challenges with user interfaces, bugs persisting into the live environment, and even the general degradation of organizational efficiency that occurs when routines are disrupted. Each can delay the accrual of benefits significantly. As a result, professionals may elect to exit the organization, or even the profession (Weiner and Biondich 2006, p. S36; Agarwal et al. 2010a, pp. 428–429), rather than deal with the disruptions and learning costs associated with new enterprise systems. Taken in sum, these accounts underscore the need for rigorous empirical examination of the effect of enterprise systems on the movement of high-status professionals. The intent of this paper is to resolve such disagreements by addressing the question of whether high-status employees are leaving their organizations (or staying longer) and, if so, under what circumstances.

To investigate this question, we leverage a unique empirical context, the movement of physicians between hospitals within the state of Florida. Data on employment come from the Florida Agency for Healthcare Administration (AHCA), which provides us with a census of bed-level admissions in Florida between 2000 and 2010. This allows us to track physician movement over the course of their career. Importantly, in the physician–hospital context in the U.S. healthcare system, it is not uncommon for physicians to practice at more than one hospital simultaneously, so departure from one hospital, because of the introduction of a new technology, is not implausible. Data regarding EHR adoption comes from the HIMSS Analytics data set. These data allow us to observe hospital-level adoption of both basic and advanced EHRs (as well as the composite modules that make up these systems). In doing so, we adopt the Dranove et al. (2014) classification of basic and advanced EHRs. We do so because prior research suggests there are differences in physician perceptions of these systems, particularly around workflow disruptions (Scott et al. 2005, Jha et al. 2009). Because of the endogenous relationship between hospital characteristics and technology adoption (Atasoy et al. 2014), we execute a logit hazard model (Singer and Willett 1993), which offers significant benefits over traditional proportional hazard models (e.g., Cox, Weibull, Efron's), such as the inclusion of time, hospital, and physician fixed effects to account for otherwise unobserved heterogeneity.

Results indicate three notable findings. First, the implementation of enterprise technologies that provide nontrivial complementarities (Scott et al. 2005, Jha et al. 2009) prolongs employee tenure at the organization (Bresnahan et al. 2002). However, the adoption of enterprise systems that significantly alter and disrupt routines overwhelms these benefits (Singh et al. 2011, Dranove et al. 2014) and accelerates professional departure from the organization (Nelson and Winter 1982, Levitt and March 1988). All else equal, this suggests that when enterprise systems create benefits at an individual level, without compromising personal routines (i.e., increasing efficiency and minimizing disruptions), the organization increases its ability to retain human capital. However, when technologies significantly alter and disrupt routines, despite the benefits that might be garnered by the worker in the long term, the organization may find highly skilled employees more difficult to retain.

Second, results suggest that there is considerable variation across professionals in terms of who departs. On the basis of tenure, we find that both younger (those practicing 10 years or less) and older (those practicing 30 years or more) professionals are far more likely to depart the organization when advanced and disruptive systems are implemented, with no simultaneous tenure increase from more basic enterprise systems. However, professionals in the prime of their careers (those with tenure between 10 and 30 years) are more likely to stay as a result of basic systems but not more likely to leave as a result of advanced systems. This suggests that these midcareer professionals may be attempting to generate IT-based human capital complementarities in the long term (Bresnahan et al. 2002, Agrawal and Tambe 2016). Furthermore, if we examine the effect across types of professionals (viz generalists and specialists), the results are greatly intensified. Whereas generalists are more likely to leave after the implementation of highly disruptive enterprise systems and less likely to leave after a less disruptive system is implemented, the effects are significantly attenuated for those who have specialized skills, indicating that practitioners possessing a greater degree of firm-specific human capital are affected less than their confederates (Huckman and Pisano 2006).

Finally, there is significant heterogeneity in the effect across organizational settings, inasmuch as notable differences are observed on the basis of local competition and the historical adoption of IT in the hospital. With regard to IT history, we find that the deleterious effects of implementing disruptive systems are greatly exacerbated as the number of previously installed enterprise systems increases (i.e., the effects are stronger if the organization has implemented many forms of IT in the past). This is striking because it suggests that instead of organizations becoming adept at dealing with organizational change and routines being in a constant state of flux (Feldman and Pentland 2003), highly trained professionals instead react more negatively with each disruption, thereby leading to a greater exodus. Further, we find the effects are greatly influenced by the level of local competition. More specifically, in the presence of heightened competition for talent, even enterprise systems providing complementarities to employees may accelerate their departure from the organization. Intuitively, this suggests that when professionals have outside options, in the form of alternate local employers, their sensitivity to disruptions within the organization is dramatically heightened.

Notable implications for theory and practice stem from this work. From the perspective of workforce digitization, we extend prior theory by considering the effect of technology introduction on highly trained professionals. Although extant research has highlighted the stalwart ability of technology to make workers more efficient (Brynjolfsson 1993, Brynjolfsson and Hitt 1996, Devaraj and Kohli 2003) and streamline the organization (Pinsonneault and Kraemer 1993, 1997, 2002), our results underscore the boundary condition of such an effect. Although the natural inclination of managers may be to downsize or marginalize labor to increase efficiency (i.e., machines replacing people), this is not feasible in highly professional contexts (e.g., medicine, law, engineering, academia). As a result, managers are compelled to work within the preferences of highly skilled professionals, who place a high value on autonomy in decision making (Freidson 1988) and controlling the conditions and content of their work (Ford et al. 2009).

Related Literature

To motivate the absence of a strong a priori expectation of the relationship between EHR adoption and physician workforce mobility, we draw on robust streams of literature in information systems, strategic management, and healthcare economics. The first stream relates to strategic human capital and talent migration. The second stream discusses the unique aspects of EHRs, as well as their value to the physician. We conclude by combining these literatures, theorizing as to how enterprise systems might affect mobility on the part of high-skill professionals, and considering the conditions under which departure or retention might occur.

Workforce Mobility

The literature on professional workforce mobility and strategic human capital (e.g., the movements of lawyers, entrepreneurs, scientists, and academics) has grown considerably in recent years (Agarwal et al. 2004, Campbell et al. 2012, Carnahan et al. 2012). Although a wide variety of factors that influence mobility have been investigated, ranging from compensation (Campbell et al. 2012, Carnahan et al. 2012) to new venture formation (Agarwal et al. 2004, Carnahan et al. 2012), to nonpecuniary benefits (Elfenbein et al. 2010, Agarwal and Ohyama 2013), to fit with the organization or senior management (Sheridan 1992, Klepper and Thompson 2010), to lack of necessary skills and training (Tambe et al. 2016), to the possession of unique skills (Chatterji et al. 2016), the impact of technology implementation on professional mobility has yet to be considered.

Research discussing workforce automation is equally sparse as it relates to professional mobility, inasmuch as it has primarily focused on the effect of information systems implementation on unskilled or semiskilled labor, with a few notable exceptions (Joseph et al. 2007, Tambe and Hitt 2013, Tambe 2014, Lu et al. 2017). Pinsonneault and Kraemer (1993), for example, examine the technology–labor substitution question for middle managers. Insofar as much of the role of middle management is information filtering and communication facilitation for the organization, the authors argue that these managers are obviated by the implementation of enterprise-level IT such as enterprise resource planning systems (ERPs). Others, such as Speier and Venkatesh (2002), examine sales force automation. Wilson and

Sangster (1992) examine accounts payable and other low-level accounting functions. Even Tambe and Hitt (2013), who investigate spillovers as a function of localized IT investment, focus to a greater degree on how innovation is disseminated by the introduction of technology within the organization, rather than how technology affects the retention of human capital. Yet, as discussed, what is notable regarding this corpus of research is that it has yet to directly address the question of how technology implementation affects the careers and working conditions of career professionals. In effect, these two literatures often talk past each other. Although the former (e.g., Agarwal et al. 2004, Campbell et al. 2012, Carnahan et al. 2012, Chatterji et al. 2016) discusses the movements of career professionals, the question of IT's impact is never breached. In the latter (e.g., Pinsonneault and Kraemer 1993, 1997, 2002; Speier and Venkatesh 2002), the effect of IT is often discussed but not the impact that it has on professionals.

Why might the introduction of technology into the organization yield fundamentally different effects for highly professionalized labor, as compared with blue- and gray-collar workers? Extant literature suggests at least two reasons, which are especially salient in the medical context. First, to the extent that highly skilled professionals, like physicians, represent the largest asset that the hospital possesses, it is likely that the firm will make investments in IT that yield significant complements to them (Karshenas and Stoneman 1993, Bresnahan et al. 2002). This stands in direct contrast to less-skilled labor, which may not be directing the means of production for the organization or adding value beyond basic labors (i.e., technology as a substitute for labor; Coase 1937). In other words, because technology often complements high-skill, nonroutinized, human capital activities (Autor et al. 2003), the organization is incentivized to make strategic investments in IT that yield complementarities for high-skilled labor. In contrast, less-skilled labor, whose work is often routine based and can often be automated, offers few incentives for strategic investment (Bresnahan et al. 2002, Autor et al. 2003). Examples of complements that stem from technological investments directed at highly skilled professionals are abundant. These include, but are not limited to, increases in firm knowledge management that stem from communication technologies (Aral et al. 2012), the ability to commercialize de novo technologies and protect intellectual property (Arora and Ceccagnoli 2006), and, in our context, the ability to provide superior patient care as a result of EHR systems (McCullough et al. 2016).

Further, technology introduction might differentially impact professionals as result of the agency and autonomy they possess (Freidson 1988, Huckman and Pisano 2006, Ford et al. 2009). This level of agency makes it unlikely that the top management team would be able to strong-arm professionals into adopting, as they might be able to do with a less-skilled workforce. Indeed, information systems scholars have highlighted the difficulties associated with user resistance to change for decades (Cooper and Zmud 1990), notably among individuals whose decision-making processes are disrupted (Jiang et al. 2000) and especially in the healthcare setting (Ford et al. 2010, Ajami and Bagheri-Tadi 2013). Moreover, and underscoring the degree of agency physicians possess, it should be noted that there is potentially an absence of readily available replacement labor in the medical context (Sargen et al. 2011), meaning that the firm (i.e., the hospital) may not have the option of dealing with resistant physicians by dipping into the excess labor pool. Indeed, a significant proportion of the health economics literature points to physician labor shortages as a nontrivial issue for policymakers (Cooper et al. 2002, Colwill et al. 2008). As of 2013, physician unemployment was less than 1% in the United States,[2] compared with 12% by non–high school graduates at the same time.[3] This suggests that the reaction of the medical community, specifically physicians, is likely to be different from that of un- or semiskilled workers. We next provide a brief overview of EHR literature and discuss the potential reaction of physicians to the implementation of these information systems.

Why Would the Introduction of Enterprise Information Systems Impact Mobility?

In the preceding section we argued that technology, in general, could alter the workforce in unintended ways. In this section we focus on how the introduction of enterprise systems might affect professional mobility.

On the one hand, if there are benefits that accrue to professionals after the implementation of an enterprise system, it would stand to reason that they would react positively to the existence of these systems. High-status professionals often are awarded discretionary bonuses based on their performance (Rosenthal and Dudley 2007, Frydman and Jenter 2010) or the amount of business they generate (Bok 2002). As a result, systems that provide significant complementarities, be they in the form of revenue generation (e.g., customer relationship management) or error avoidance (e.g., the identification of patient allergies in a medical context), should be attractive to highly skilled professionals (Bresnahan et al. 2002).

Digging further, extant research suggests that enterprise systems can yield critical organizational changes that provide complementarities to high-skilled professionals. First, enterprise systems increase data accessibility throughout the organization, thereby decentralizing decision making and allowing the professional greater autonomy in decision making (Brynjolfsson and Mendelson 1997, Bresnahan et al. 2002). Second, enterprise technologies facilitate information sharing as a coordinating mechanism across diverse sets of employees. Professionals have especially benefited from this capability, which has allowed the free flow of information across departmental and institutional barriers (Kanawattanachai and Yoo 2007). Anecdotal accounts, for example, suggest that the widespread dissemination of document management systems has had a transformative effect on the legal profession, greatly increasing the efficiency of legal talent by accelerating the process of legal discovery and document review, and facilitating the solicitation and coordination of outside counsel.[4]

On the other hand, evidence also exists to suggest that the implementation of enterprise systems may lead to deleterious changes to the organization, at least from the viewpoint of professionals. The introduction of enterprise systems may lead to the obsolescence of costly to acquire skills the professional already possesses. To the extent that professional skill sets must be significantly retooled to exploit the new technology, a process that imposes significant learning costs both in terms of time and effort (Nelson and Winter 1982, Edmondson et al. 2001), it is intuitive that the worker may want to avoid such costs. Further, training on the enterprise system may be firm and/or vendor specific, making such human capital acquisition not only costly but also potentially not portable across organizations (Bresnahan et al. 2002, Huckman and Pisano 2006). If this is the case, the worker's long-term mobility could be compromised by the existence of the system, notably if changing firms requires additional and costly retraining (and furthering user disinterest; Kim and Kankanhalli 2009).

Similarly, to the extent that enterprise systems are often developed as a standardized suite that can be implemented across organizations with minimal customization (Gattiker and Goodhue 2005), it is intuitive that misalignments may arise between the encoded routines of the system and the routines of the adopting organization. Although one might argue that such routine change would likely encode more efficient processes into the organization, the disruption still forces users to update their behavior and develop workarounds for any postimplementation discord that persists in the system (Soh and Sia 2004). Third, the systems may enforce routines that encroach on the agency historically possessed by the worker (Bala and Venkatesh 2013). Within the context of medicine, many physicians have argued that EHRs force them to look at their computer screens instead of at their patients, possibly hindering communication and lowering the quality of care provided (Toll 2012). Thus, the forced use of technology by professionals may be viewed as changing the basic ethos that characterizes their profession, making them resistant to the arrival of enterprise IT.[5]

In the context of healthcare delivery, no enterprise system is more widely discussed than the EHR (Park et al. 2017).[6] Not dissimilar from the broader enterprise information systems literature, extant research suggests mixed effects of these systems, such that some studies demonstrate beneficial aspects of EHRs, some show negative outcomes, and some find little to no effect. Although evaluating whether enterprise information systems add value to the organization is outside the scope of this research, it is of critical importance to establish that EHRs, at least during the time period under investigation, were not universally lauded. There was, and continues to be, consternation and disagreement among clinicians surrounding the value that EHRs provide. Moreover, to the extent that hospital administrators believe that there will be financial gains from EHRs, there is nontrivial institutional pressure for physicians to extensively use EHRs. Coupling institutional pressure with physicians who see varying degrees of value in EHRs, we contend that the presence of the technology will likely influence the physicians' stay or go decisions.

Further, specific EHR modules have been shown to introduce differing levels of disruption to a physician's routine. Advanced EHR modules often have steep learning curves and create greater workflow disruptions due to changes that physicians need to make to the process of documenting patient data (Singh et al. 2011, Dranove et al. 2014). Coupled with the fact that physicians often view their own sociotechnical autonomy as sacrosanct (Freidson 1988) and that their autonomy and identity as a caregiver (Mishra et al. 2012) could be threatened by the existence of a system that locks them into certain practice behaviors (Ford et al. 2009), there is evidence to suggest that physicians may resist the implementation of EHR systems and elect to practice elsewhere. More generally, extant literature has identified that IT impacts professional job roles by taxing the user with increased informational demands (Gardner et al. 2003), further challenging a physician's desired primary identity as a caregiver.

The presence of such conflicting evidence undermines the existence of a dominant a priori expectation of the effect of EHR introduction on physician behavior. If physicians believe that they can capture benefits that stem from the complementarities the technologies bring, they may stay at the hospital longer than in the absence of such technologies (Bresnahan et al. 2002). Alternately, if they believe that their autonomy is being threatened, which has been identified as a key determinant of departure (Elfenbein et al. 2010), and their long-term mobility is undermined, they may exit the hospital and continue their careers elsewhere. In the face of such conflicting evidence, we address the question empirically. In so doing, we examine the differential effects of both basic and advanced EHR systems. We also consider heterogeneity in the effect across physician, as moderated by tenure and degree of firm-specific human capital, and across hospital. Finally, conditional on departure from the organization, we consider where

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physicians depart to (i.e., the characteristics of the individual hospitals) and whether physicians are selecting out of the practice of medicine entirely (i.e., retiring), as some media accounts suggest (Gurley 2014, Krauthammer 2015).

Methodology

Data

To address how the implementation of enterprise systems influences mobility, we leverage a unique data set constructed from several widely used sources. Information on the mobility of physicians comes from the Hospital Inpatient Data set provided by the Florida AHCA. Used extensively in prior literature (Burke et al. 2007, Lu and Rui 2015, Greenwood and Agarwal 2016, Greenwood et al. 2017), these data provide detailed accounts of each patient (e.g., age, race, International Classification of Diseases, Ninth Revision codes, method of admittance) admitted to hospitals in the state of Florida. Moreover, and critical to examining our research question, these data provide information on where physicians have been treating patients during the course of the sample. Data regarding EHR implementation are retrieved from HIMSS Analytics, a nationwide survey of healthcare delivery organizations that has been used in numerous information system studies (Angst et al. 2011, Atasoy et al. 2014, Ganju et al. 2016). These data grant us access to information regarding hospital-level adoption of EHR systems at the module level, as well as organizational characteristics, such as for-profit status, teaching, specialties, vendor information, and size, at the year level.

When combined, these data give us information regarding physician employment and EHR implementation at the physician–hospital–year level between 2000 and 2010. We restrict our sample to after the year 2000 because EHR adoption is not tracked consistently by HIMSS Analytics before that time. We end our sample at the end of 2010 owing to data availability. However, because the passage of the Health Information Technology for Economic and Clinical Health (HITECH) Act occurred in 2009, essentially imposing a de facto mandate for the adoption of EHR systems, and our goal is to measure the movement of physicians across hospitals as well as potential exit from the profession, the discontinuation in 2010 is of little consequence to our goals.[7] We acknowledge that the HITECH Act may alter the internal calculus for the physician by eliminating the possibility that the physician could avoid EHR systems in the long term; hence our sample timeframe is optimal for the research question we investigate. Further, we consider only physicians who begin practicing at the focal hospital *before* the focal EHR module was adopted because entering a hospital after the module was implemented may elicit a different decision-making process. Finally, we include only physicians who have treated more than 100 patients over the course of their careers, to avoid consulting physicians.[8] The final data set comprises 144,317 physician–hospital–years covering 12,966 physicians across 304 hospitals in the state of Florida between 2000 and 2010.

Variable Definitions

The primary dependent variable, *Departure*, is a dichotomous indicator of whether physician i exits (i.e., does not continue treating patients) at hospital j in year t (summary statistics and a correlation matrix are in Table 1, and variable definitions are in Table 2). Consistent with research using survival models, this variable is coded as 1 if the physician exits the hospital (i.e., the total number of patients treated by i in jt is equal to zero when the total number treated by i in jt_{-1} is greater than zero). *Departure* is coded as 0 if the total number of patients treated by i in jt is greater than zero.

Table 1. Summary Statistics and Correlation Matrix

	Mean	Standard deviation	1	2	3	4	5	6	7	8	9	10	11	12
1 *Departure*	0.224	0.417	—	—	—	—	—	—	—	—	—	—	—	—
2 *Retirement*	0.074	0.262	0.543	—	—	—	—	—	—	—	—	—	—	—
3 *New hospital*	0.150	0.357	0.772	−0.114	—	—	—	—	—	—	—	—	—	—
4 *Basic*	0.769	0.421	0.028	0.047	−0.003	—	—	—	—	—	—	—	—	—
5 *Advanced*	0.154	0.361	0.102	0.119	0.031	0.093	—	—	—	—	—	—	—	—
6 *Executive IS*	0.693	0.461	0.019	0.009	0.016	0.000	0.064	—	—	—	—	—	—	—
7 *EDI*	0.427	0.495	0.077	0.090	0.023	0.033	0.162	−0.024	—	—	—	—	—	—
8 *General ledger*	0.921	0.270	0.053	0.049	0.025	0.156	0.131	0.297	0.197	—	—	—	—	—
9 *Tenure*	14.734	9.797	0.031	0.085	−0.028	0.034	0.069	−0.003	0.052	0.029	—	—	—	—
10 *Generalist*	0.421	0.494	−0.007	0.010	−0.015	0.009	0.005	−0.018	0.007	−0.003	−0.034	—	—	—
11 *Specialist*	0.579	0.494	0.007	−0.010	0.015	−0.009	−0.005	0.018	−0.007	0.003	0.034	−1.000	—	—
12 *DRG focus*	0.005	0.016	0.270	0.360	0.047	0.022	0.159	−0.017	0.138	0.043	0.059	0.010	−0.010	—
13 *Merger*	0.018	0.135	0.002	−0.006	0.006	0.049	0.043	0.099	−0.073	0.044	0.008	−0.034	0.034	−0.012

Table 2. Variable Definitions

Variable	Definition
Measures of physician departure	
Departure	Dichotomous indicator of whether physician i exits hospital j in year t
Retirement	Dichotomous indicator of whether physician i exits hospital j in year t and is not practicing at another hospital
New hospital	Dichotomous indicator of whether physician i exits hospital j in year t and is observed practicing at another hospital
Measures of EHR presence	
Basic	Adoption of any of these modules denotes the presence of a basic EHR (Dranove et al. 2014) • Clinical data repository (CDR): A centralized database that allows organizations to collect, store, access, and report on clinical, administrative, and financial information collected from various applications within or across the healthcare organization • Clinical decision support system (CDSS): An application that uses pre-established rules and guidelines, that can be created and edited by the healthcare organization, and integrates clinical data from several sources to generate alerts and treatment suggestions • Order entry (OE): An application that allows for entry of orders from multiple sites, including nursing stations, selected ancillary departments, and other service areas; allows viewing of single and composite results for each patient order
Advanced	Adoption of either of these modules denotes the presence of an advanced EHR (Dranove et al. 2014) • Computerized practitioner order entry (CPOE): An order entry application specifically designed to assist clinical practitioners in creating and managing medical orders for patient services or medications • Physician documentation (PD): This software enables capturing of structured medical data to utilize in the care of a patient
Instruments	
Executive IS	A database driven information system that supports senior executive information needs and decision making
EDI	Electronic data interchange is a standardized format that facilitates the transfer of data across heterogeneous systems in the hospital without human intervention
General ledger	A database-driven accounting information system that captures historical financial transactions and maintains an electronic log of assets, liabilities, and equity

Note. The EHR module definitions come from the HIMSS Analytics database.

After a physician departs hospital j, the physician is no longer observed in the data set unless she begins practicing at a new hospital.

Prior research has established the importance of classifying EHR implementations into various categories based on the software modules installed, the types of ways the modules are used, and the complexity of the clinician interaction with the module (Jha et al. 2009, Adler-Milstein et al. 2014, Dranove et al. 2014). Although the earliest studies treated EHRs as a collection of modules rather than a single entity (e.g., Bower 2005), subsequent literature treated these modules as an instance of *basic* EHRs (Jha et al. 2009, Adler-Milstein et al. 2014, Dranove et al. 2014). As more modules were added to EHR suites, more functionalities were included, which ultimately led to increases in the complexity of the system—from both an implementation and a usage standpoint (Dranove et al. 2014, Adler-Milstein et al. 2014, Angst et al. 2017). These newer modules are identified as *advanced*[9] EHR systems. We use both of these classifications.

The first independent variable of interest, $Basic_{jt}$, is a dichotomous indicator, which designates that a basic EHR module has been implemented at hospital j during year t. Following extant literature (Dranove et al. 2014), a basic EHR includes the presence of a clinical data repository (CDR), a clinical decision support system (CDSS), or an order-entry (OE) module. This variable is coded as 1 if j is in possession of the module at time t and 0 otherwise. The second independent variable of interest is $Advanced_{jt}$. Much like the basic EHR indicator, this dichotomous variable indicates whether an advanced EHR module has been implemented in hospital j in year t. Again, in line with prior research, the presence of an advanced system is defined as the implementation of a computerized practitioner order-entry (CPOE) or physician documentation (PD) module. Note that although *Advanced* and *Basic* are coded as dichotomous indicators, results are generally consistent, transforming them into continuous values based on the number of modules adopted (see Appendix A, Table A.3). For a complete discussion of the definitions of *Advanced* and *Basic* systems, see Dranove et al. (2014).

Owing to the endogenous relationship between EHR adoption and physician departure, we condition the estimation on a robust set of controls. First, given the accelerating adoption of EHRs over time, we include year fixed effects. Second, because some hospitals may be more or less likely to adopt EHRs during the timeframe of our sample, on the basis of local competition, celebrity status, localized regulation, etc. (Miller and Tucker 2009, Angst et al. 2010, Atasoy et al. 2014), we include hospital fixed effects to account for time-invariant hospital heterogeneity, which might drive such a decision. Finally, owing to the fact that unobserved, time-invariant heterogeneity across physicians may cause differences in the reactions of the physicians to the arrival of this new technology, we include physician fixed effects.

Estimation Technique

Because the relationship we are estimating relates to the physician's departure from the focal hospital, we use a logit hazard model specification (Singer and Willett 1993). Extensively used in social science and management research for estimating survival relationships (Beck et al. 1998, McGinn and Milkman 2013, Greenwood and Agarwal 2016), this strategy offers several benefits over traditional continuous time survival models (e.g., Cox 1972), such as the ability to include fixed effects to account for otherwise ignored heterogeneity (recall that Cox models allow only for shared frailty, which is tantamount to the inclusion of a random effect). This reduces concerns of time-invariant omitted variable biases. Furthermore, methods like Cox, although making no assumptions about failure time distribution, do enforce proportional hazards across strata, which may be untenable. The use of the logit hazard model effectively ameliorates these issues. We therefore estimate the effect of EHR introduction on the mobility of physicians using the following equation:

$$P(y_{ijt} = 1|x) = \beta_1 \alpha_{j,t} + \tau_t + \delta_j + \gamma_i + \varepsilon, \qquad (1)$$

where α_{jt} is the dichotomous indicator of EHR possession. This is first defined as an indicator of basic EHR possession. The estimation is then replicated with α_{jt} defined as advanced EHR possession. Finally, both indicators are included simultaneously in the estimation. The vector of time fixed effects is τ, δ is the vector of hospital fixed effects, γ is the vector of physician fixed effects, and ε is the error term.[10] Results are in columns (1)–(3) of Table 3 and will be discussed below. Owing to the concern that the physician fixed effect will perfectly predict the dependent variable for any physician that does not change practice location during our sample, we replicate these estimations with a physician random effect. Results are in columns (4)–(6) of Table 3.

Before discussing our results, we first address several concerns that could threaten our basic claim of identification. Our first concern is the nature of the contracts between hospitals and physicians. To the extent that the heterogeneous presence of physician contracts over time, and across hospitals, may correlate with the willingness of hospital administrators to adopt enterprise technologies, an omitted variable bias may exist. Although the simplest resolution, in the absence of detailed longitudinal contract data, would be to use a hospital–physician fixed effect (thereby accounting for the idiosyncratic nature of the relationship between the physician and the hospital directly), such a control is infeasible because the overwhelming number of physicians i only leave a given hospital j a single time. Thus, to capture the idiosyncratic relationship between the hospital and the physician more robustly, we first replicate Equation (1) using a hospital–physician random effect. Results are in columns (7)–(9) of Table 3.

Next, to the degree that adoption of EHRs is nonrandom at the hospital level, we have included hospital fixed effects. However, dynamic conditions to which the hospital is potentially subject, such as adoption by competing hospitals, might influence the decision on the

Table 3. Logit Hazard Estimate of EHR Implementation on Physician Departure

	Departure								
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Basic	−0.0715***	—	−0.0897***	−0.119***	—	−0.132***	−0.168***	—	−0.177***
	(0.0247)	—	(0.0252)	(0.0192)	—	(0.0197)	(0.0172)	—	(0.0177)
Advanced	—	0.131***	0.0866***	—	0.0943***	0.0667**	—	0.0728***	0.0459*
	—	(0.0244)	(0.0320)	—	(0.0212)	(0.0274)	—	(0.0199)	(0.0254)
Constant	—	—	—	−1.690***	−1.739***	−1.683***	−1.474***	−1.588***	−1.470***
	—	—	—	(0.0258)	(0.0213)	(0.0259)	(0.0219)	(0.0188)	(0.0220)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hospital fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician fixed effects	Yes	Yes	Yes	No	No	No	No	No	No
Physician random effects	No	No	No	Yes	Yes	Yes	No	No	No
Physician–hospital random effects	No	No	No	No	No	No	Yes	Yes	Yes
Observations	112,461	143,567	112,161	113,355	144,317	113,055	112,877	143,448	112,577
No. of groups	10,262	12,429	10,245	10,907	12,966	10,890	10,907	12,966	10,890

Note. Standard errors in parentheses.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

part of the local hospital to adopt (Angst et al. 2010). This is especially problematic in the case of estimating nonrepeated events, such as ours, because the inclusion of other covariates, notably those that are monotonically increasing over time (Allison and Christakis 2006), creates issues with the estimation procedure. To resolve this concern, we take an instrumental variable approach.

An acceptable instrument for the adoption of an EHR must meet two criteria: it must be correlated with the adoption of EHR technology in the focal hospital, and it must be uncorrelated with the physician's decision to depart (Greene 2003), which creates multiple concerns. First, because of the exclusion restriction, instrumenting for the entire system of equations is inherently problematic (because two instruments are required, both of which are correlated with both advanced and basic EHR adoption). Second, because most of the instruments which are commonly used for EHR adoption are based on marketplace conditions (e.g., competitor behavior; Atasoy et al. 2014), they are unsuitable for our analysis. This is because access to technology resources could plausibly influence a physician's decision to relocate to a new organization (Tambe and Hitt 2013). We therefore instrument for EHR adoption using nonclinical IT, an approach used in prior EHR adoption studies (Hydari et al. 2019). More specifically, we instrument for *Basic* systems using the implementation of an *electronic data interchange* (EDI) and instrument for *Advanced* systems using the existence of an *executive information system* (Exec IS) within the hospital. Conceptually, the existence of these nonclinical forms of technology should be correlated with the willingness to adopt EHRs in the future because they allow hospital administrators to effectively monitor hospital operations, thereby signaling a core belief by hospital leadership that IT is an effective tool at their disposal. The existence of the EDI and Exec IS should be uncorrelated with physician turnover because neither influences routines, nor is it visible to physicians in their day-to-day activities. Formally, we model this in two stages using Equation (2):

$$\begin{aligned} P(\alpha_{ijt} = 1|x) &= \pi_0 + \pi_1 z_1 + \tau_t + \delta_j + \gamma_i + \varepsilon, \\ P(y_{ijt} = 1|x) &= \beta_0 + \beta_1 \hat{\alpha}_{jt} + \tau_t + \delta_j + \gamma_i + \varepsilon, \end{aligned} \tag{2}$$

where z_1 is the excluded instrument. All other indicators are consistent. Results are in Table 4.[11]

Table 4. Two-Stage Least Squares Survival Model

Stage	(1)	(2)
First stage		
Dependent variable	Basic	Advanced
EDI	0.0109***	—
	(0.0031)	—
Executive IS	—	0.0106***
	—	(0.0026)
Cragg-Donald F statistic	15.46	16.221
p-value	$p < 0.01$	$p < 0.01$
Second stage		
Dependent variable	Departure	Departure
Basic	−0.677*	—
	(0.400)	—
Advanced	—	1.518***
	—	(0.484)
Time fixed effects	Yes	Yes
Hospital fixed effects	Yes	Yes
Physician fixed effects	Yes	Yes
Observations	90,605	120,621
No. of groups	8,876	11,708

Note. Robust standard errors in parentheses.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

A third threat to our basic claim of identification is that it is possible there is time-varying heterogeneity in the unobservable characteristics of the hospitals and/or physicians. To the degree that this heterogeneity might be correlated with the adoption of either advanced or basic EHR systems, the comparability of the control group (nonadopting hospitals) to the treatment group (adopting hospitals) may be undermined. This could plausibly manifest in two ways. First, the turnover of physicians may be heterogeneous across the two groups before adoption, implicitly suggesting that hospitals that are adopting EHRs may be reacting to a hospital-specific idiosyncrasy during their adoption period. Conceptually, this is similar to a violation of the parallel trends assumption from difference-in-difference estimations (Bertrand et al. 2003), because the ex post change in behavior is actually attributable to an ex ante difference in behavior. Alternatively, there may be heterogeneity in characteristics of hospitals that end up adopting EHR systems. Again, insofar as we include hospital fixed effects to account for non-time-varying characteristics, we should be controlling for this concern. However, to the extent that an increase in the homogeneity between the treatment and control group increases the strength of any claim that our estimates are unbiased, it is important to minimize these differences.

To resolve concerns related to parallel trends, we examine the pretreatment trends associated with hospitals adopting EHRs. To execute this test, we modify Equation (1) to include two relative time indicators (i.e., 0/1 dummies) that are set to 1 during the periods before EHR adoption:

$$P(y_{ijt} = 1|x) = \beta_1 \alpha_{jt} + \beta_2 \alpha_{jt-1} + \beta_3 \alpha_{jt-2} + \tau_t + \delta_j + \gamma_i + \varepsilon. \tag{3}$$

We then regress the *Departure* of the physician from the focal hospital on these indicators. Thus, β_2 and β_3 capture differences in turnover before the implementation of EHR at the hospital j. Intuitively, what this approach allows us to do is determine whether there is significant

Table 5. Logit Hazard Model Examining Pre-Treatment Trends

	Departure					
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
Basic	−0.0715***	−0.102***	—	—	−0.0897***	−0.121***
	(0.0247)	(0.0274)	—	—	(0.0252)	(0.0287)
Basic$_{t-1}$	—	−0.0824	—	—	—	−0.0821
	—	(0.0706)	—	—	—	(0.0712)
Basic$_{t-2}$	—	−0.0669	—	—	—	−0.0680
	—	(0.0582)	—	—	—	(0.0587)
Advanced	—	—	0.131***	0.104***	0.0866***	0.0922***
	—	—	(0.0244)	(0.0256)	(0.0320)	(0.0339)
Advanced$_{t-1}$	—	—	—	−0.00239	—	0.0549
	—	—	—	(0.0409)	—	(0.0511)
Advanced$_{t-2}$	—	—	—	−0.0873***	—	−0.0266
	—	—	—	(0.0318)	—	(0.0394)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Hospital fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Physician fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	112,461	112,461	143,567	143,567	112,161	112,161
No. of groups	10,262	10,262	12,429	12,429	10,245	10,245

Note. Standard errors in parentheses.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

heterogeneity in the pretreatment (i.e., preadoption) turnover in hospitals adopting EHRs. Results are in Table 5.

To resolve the concern related to heterogeneity in adopting hospitals, we replicate our results using only hospitals that eventually adopt advanced EHRs, thereby omitting hospitals that never adopt an advanced EHR system. Conceptually, this test is similar to the look-ahead propensity score match proposed by Bapna et al. (2016). By omitting hospitals that do not adopt advanced EHRs over the course of the sample, we implicitly match on the latent propensity of the hospital to adopt EHRs. Removing nonadopters should therefore increase the homogeneity between the treatment and control groups. Results are in Table 6.

Results

Results in Table 3 provide a nuanced picture of how EHR implementation affects physician mobility. First, in columns (1) and (3) of Table 3, and consistent with work that suggests basic EHRs create complementarities for the physician (Bresnahan et al. 2002, McCullough et al. 2010, Miller and Tucker 2011), we observe a strong and significant *negative* effect of basic EHR adoption on the probability that the physician leaves the hospital. This suggests that after the implementation of basic EHRs, physicians are significantly less likely to exit the organization. Economically, this result translates to a 6.77% increase in the retention rate of physicians per year. However, when considering the effect of advanced EHR systems, the *opposite* effect emerges, that is, there is a significant *acceleration* of physician departure, to the tune of a 6.94% increase in the rate of physician departures per year,[12] suggesting that when more-advanced, complex modules are implemented, physicians are driven from the organization. These conflicting results indicate that the complexity of specific modules within the EHR system may be driving the strikingly different effects we see in physician departures.[13] Importantly, when we explore alternate operationalization of the base estimation, results remain consistent. In columns (4)–(6) of Table 3, where physician random effects are introduced to allow the capture of nondeparting physicians, findings are consistent in terms of magnitude and directionality. This is further observed in columns (7)–(9), inasmuch as results remain consistent in the presence of a physician–hospital random effect, which should capture the idiosyncratic relationship between the physician and the hospital (e.g., an employment contract).

Table 6. Logit Hazard Model Excluding Nonadopting Hospitals

	Departure		
Dependent variable	(1)	(2)	(3)
Basic	−0.0850**	—	−0.0984***
	(0.0350)	—	(0.0352)
Advanced	—	0.118***	0.0506
	—	(0.0260)	(0.0343)
Time fixed effects	Yes	Yes	Yes
Hospital fixed effects	Yes	Yes	Yes
Physician fixed effects	Yes	Yes	Yes
Observations	93,885	125,012	93,583
No. of groups	8,928	11,773	8,906

Note. Standard errors in parentheses.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

When considering the robustness and falsification checks, our results are largely corroborated. In Table 4, we report findings from the instrumented model. Diagnostics of the instrument in the first stage indicate that the presence of EDI (Exec IS) is strongly correlated with the adoption of basic (advanced) EHR. Further, we note that the Cragg–Donald F statistic (which diagnoses the strength of the instrument) is significant for both sets of estimations. In the second stage of analysis (see columns (1) and (2) of the lower panel of Table 4), the results are consistent with prior estimations. Whereas basic EHRs significantly slow physician departure from the organization, more complex, advanced EHR systems significantly accelerate it. Before discussing other robustness checks, we do make three cautionary notes. First, because two-stage least squares is a linear model, there is a concern of heteroscedasticity in this model. We implement robust standard errors to minimize this concern. Second, although the Cragg–Donald F statistic is significant, the instrument does not quite meet the Stock and Yogo (2005) strength requirements (each estimate meets the 15% maximal instrumental variable (IV) size). Third, and finally, we are unable to effectively compute Sargan values because the number of excluded instruments is equal to the number of endogenous variables. The raw correlation of 1% between turnover and Exec IS suggests that this is likely not a concern (7% for EDI), but it nevertheless bears mention. We address these last two concerns in Appendix B. Using additional instruments yields consistent results with insignificant Sargan values and meets the thresholds ascribed by Stock and Yogo (2005).

When considering the pretreatment trends and the heterogeneity across hospitals (i.e., Tables 5 and 6), the central finding that basic EHRs slow the departure of physicians from hospitals, whereas advanced EHRs accelerate it, remains consistent. In columns (2) and (6) of Table 5, we see no significant correlation between the pretreatment dummies and the departure rate of physicians. Yet, the indicator of basic EHR adoption remains negative and significant, lending support to prior findings. Further, there is no significant correlation between the advanced EHR pretreatment dummies and physician departure in column (6) of Table 5, whereas the advanced EHR indicator remains positive and strong. It should be noted that there is a difference between advanced adopting hospitals and nonadopting hospitals two years before adoption of an advanced EHR module in column (4). Yet, this indicator is negative (i.e., the opposite of the eventual effect), suggesting a slight conservatism in the estimation. Moreover, the effect disappears in the fully specified model (p = 0.67).

Turning to Table 6, the omission of nonadopting hospitals, results are once again supported. We first note that the omission of these hospitals removes a nontrivial portion of the sample (14.8%–19.8% of observations and ~15% of the physicians). Further, we note in columns (1) and (2) that the effect of basic and advanced EHR adoption is consistent. Interestingly, in the fully specified model (column (3)), the effect of advanced EHR systems slips from significance (p = 0.141) but retains a nontrivial economic size (3.53%).

Robustness Checks

Before discussing possible empirical extensions to these findings (i.e., basic EHRs assist hospitals in retaining physicians, and advanced EHRs accelerate physician turnover), we first discuss several concerns that could be biasing our results. In the interest of space, the statistical output of these estimations can be found in Appendix A. A summary of the threats to our identification, the executed tests, and findings is in Table 7.

First, our investigation occurs just as the HITECH Act takes effect. As discussed earlier, the de facto mandate imposed by the HITECH Act makes the time period after the law goes into effect potentially concerning as a sample timeframe, the reason being that de facto adoption mandates rarely occur organically (with the exception of superior performance). We thus remove the final two years of the sample, after the passage of the Act, and reestimate Equation (1). Results are in Appendix A (Table A.5) and remain consistent. This suggests results may be consistent during the HITECH era. However, we interpret this result cautiously.

Second, our results are constrained to the state of Florida and physicians licensed to practice within it. Given the stringency of physician licensure, this assumption is not unreasonable. As stated by Kocher (2014), "Although the basic standards for initial physician licensure are uniform across states, states impose a patchwork of requirements for acquiring and maintaining licenses. These requirements are varied and burdensome and deter doctors from obtaining the licenses required to practice across state lines." However, it is possible that physicians are taking positions outside the state and that this relocation is correlated with EHR implementation. To remedy this concern, we retrieve data on physician licensing data from the AHCA and exclude all physicians licensed to practice in states other than Florida (e.g., Georgia, New York). Intuitively, this should dramatically increase the switching costs associated with leaving the state. We then reestimate Equation (1), omitting these physicians. Results are in Appendix A (Table A.6) and remain consistent.

Third, our theorizing has thus far assumed that physicians are the individuals imbued with the agency to make the "stay or go" decision. Given the lack of available replacement labor in medicine, coupled with a stunted supply of physicians from medical schools

Table 7. Summary of Robustness Checks

Alternate explanation	Executed test	Results and location
HITECH Act changes physician decision making by imposing a de facto mandate	Replicate estimations excluding 2009 and 2010	Result remain consistent (Table A.5)
Physicians treating fewer than 100 patients or entering after EHR implementation exhibit different behavior	Replicate estimations without these exclusions	Results remain consistent (Table A.1 and A.2, respectively)
Implementation of basic and advanced EHR systems should be coded continuously	Replicate estimates using count of the number of active modules within basic and advanced	Results remain consistent (Table A.3)
Time-invariant factors are correlated with hospital adoption and physician movement	Instrument for EHR adoption using EDI and Exec IS adoption	Results remain consistent (Tables 4 and B.1)
	Examine pretreatment differences across in turnover adopting and nonadopting hospitals	No significant differences in turnover observed (Table 5)
Nonadopting hospitals are an inappropriate control group for adopting hospitals	Exclude all hospitals that do not adopt both EHR modules by the conclusion of the sample	Results remain consistent (Table 6)
Physicians are changing location of practice to outside the state of Florida	Replicate estimations excluding any physician licensed to practice outside Florida (e.g., NY)	Results remain consistent (Table A.6)
EHR adoption is correlated with structural changes at the hospital	Regress EHR adoption on DRG Focus and % of patients from each insurer pool	No observed correlation between changes in DRG Focus, changes in payer pool, and EHR adoption (Table A.7)
Hospital mergers are correlated with EHR adoption and forcing physicians out	Replicate analyses excluding all hospitals that experienced a merger during period sample	Results remain consistent (Table A.9)
Physicians are departing because physicians' professional management corporations are forcing the adoption of different EHR vendors	Replicate analyses excluding all hospitals where basic and advanced EHRs are from different vendors	Results remain consistent (Table A.10)
EHR adoption is correlated with the contracts of physicians currently used at the hospital	Replicate the base estimations with a hospital-physician random effect to capture contract status	Results remain consistent (Table 3)
	Examine whether the number of physicians more likely to resist enterprise IT (older physicians) and those more likely to move (freelancers) is correlated with EHR adoption	Changes in the number of older physicians and freelancers is uncorrelated with EHR adoption (Table A.7)
	Replicate analysis excluding all physicians who may be subject to restrictive employment covenants (noncompetes)	Results remain consistent using freelancers only (Table A.8)

(Cooper et al. 2002, Colwill et al. 2008), this assumption is reasonable. However, it is possible that structural changes at the hospital level (i.e., strategic decisions on the part of the organization correlated with EHR adoption) may be resulting in turnover. For example, a hospital may be changing the care providers it partners with, thereby selecting out of one plan and into another, or it may choose to no longer accept Medicaid. Further, hospitals often divest and acquire physician practice groups, which will bring new physicians into the organization or push practicing physicians out. Finally, hospital administrators may be making the adoption decision strategically as a result of the physicians practicing at the hospital and its inability to retain or dismiss them during an EHR implementation.[14]

To investigate whether these hospital-level changes (i.e., changes to the accepted forms of payment or divestiture/acquisition of a group) are correlated with the adoption of basic or advanced EHR systems, and therefore biasing our estimates, we replicate our analysis using EHR adoption as the dependent variable. The intuition behind this test is that it allows a direct examination of hospital level factors, which may correlate with adoption of EHRs, thereby biasing the primary estimates. Formally, this is done with Equation (4):

$$P(\alpha_{jt} = 1|x) = \beta_1 \rho_{jt} + \sigma'_{j\tau} + \tau_t + \delta_j + \gamma'_t + \varepsilon, \qquad (4)$$

where α_{jt} is the adoption of individual EHR modules at the hospital–year level. To capture the divestiture or acquisition of a group ρ_{jt}, we use the Herfindahl index of the Diagnosis Related Group (DRG) (Equation (5)):

$$DRG\ Focus_{jt} = \sum_i \left(\frac{Number\ of\ patients\ coded\ in\ DRG_{ijt}}{Total\ Patients_{jt}} \right)^2. \qquad (5)$$

Doing so allows us to measure the extent to which hospital resources are devoted to specific services (Huckman and Pisano 2006, Ding 2014). If a new physician group is acquired or divested, there will be a significant change in the number of patients from that specialty group seeking treatment (e.g., the divestiture of a nephrology practice will significantly decrease the number of nephrology patients). To capture change in payment partners, shown as vector $\sigma'_{j\tau}$, we include percent indicators of the number of patients using that form of insurance. If the hospital suddenly accepts, or no longer accepts a certain insurer, the percent change for commercial health maintenance organizations (HMOs), preferred provider organizations (PPOs), etc. would also change. Thus, if we do not see a significant correlation between DRG Focus or insurer and EHR adoption, we can be reasonably certain the aforementioned factors are not biasing the results.

Finally, the vector γ contains markers of two groups likely to influence a hospital administrator's decision to adopt an EHR. Intuitively, two pools of physicians might specifically affect this decision: older physicians and physicians subject to restrictive employment covenants. With regard to older physicians, research in technology adoption has widely suggested that as people age, their willingness to adopt de novo technologies decreases significantly (Venkatesh et al. 2003). It is therefore reasonable to believe that hospital administrators with many older physicians may be more apprehensive about adopting a disruptive system, the reasons being that the administrator may lack the ability to force such physicians out of the hospital and that older physicians may actively resist the implementation of the EHR. To capture these physicians, we create a new variable, *Number of Older Physicians*, which is defined as the number of physicians in the hospital who have been practicing for more than 30 years (as is consistent with later estimations of tenure).

With regard to contracts in the form of restrictive employment covenants (Starr et al. 2017) (i.e., noncompete agreements), it is also possible that the administrator may lack the ability to retain certain physicians if they are not subject to such agreements. Conceptually, this is the opposite problem to the one posed by older physicians. If many physicians in the hospital have not signed noncompete agreements, the administrator may be concerned that she will be unable to retain these physicians during or after an EHR implementation. To capture these physicians (i.e., those not subject to noncompete agreements), we create a new variable, *Freelancers*, which captures physicians practicing at multiple hospitals simultaneously (Huckman and Pisano 2006, Greenwood et al. 2017). Formally, this variable is set to 1 if physician i is observed at multiple hospitals j in the same time t. With such a measure, we can be assured that the physician is not subject to noncompete agreements because she is currently practicing across organizational bounds.

In columns (1) and (2) of Table A.7 (Appendix A), we execute a logit hazard model with time fixed effects. Because each hospital can only adopt each type of EHR once, these estimations are run with hospital random effects. In columns (3) and (4) of Table A.7, we execute a conditional logit model, regressing the presence or absence of the EHR system on the discussed covariates. Results indicate that changes in DRG Focus are not significantly correlated with presence of either system. This suggests a limited correlation between EHR adoption and the acquisition or divestiture of practice groups in the hospital. Further, there is a lack of consistent significance across the estimations in terms of insurance. For example, although we see that the percent of commercial HMO patients is negatively correlated with basic EHRs, it has limited effect on advanced adoption. This suggests that EHR adoptions have a limited association with structural changes at the hospital in terms of accepted payers.[15] Finally, we note that changes in the number of freelancers or older physicians within the hospital is uncorrelated with the adoption of either basic or advanced EHR systems. This suggests that although hospital administrators may be cognizant of the groups of physicians practicing within their organization, changes in their relative proportions over time do not seem to be significantly influencing adoption. This is further corroborated by the accelerated turnover of older physicians (discussed below) and the similar results from the estimation of Equation (1) while excluding all non-freelancers (i.e., including only those physicians not subject to restrictive employment covenants; Appendix A, Table A.8). Although we interpret these results cautiously, because the absence of evidence is not evidence of absence, they do, in sum, indicate little effect of changes in insurance, departments, or physician contracts on adoption.[16]

Taken as a whole, these results suggest that the implementation of basic EHR systems extends the amount of time a physician stays at the hospital, likely because they reduce complexity in the organization and create positive clinical spillovers for the clinician. However, the implementation of advanced EHR systems, which are significantly more complex and disruptive to both the physician and the organization, significantly reduces the amount of time a physician spends within the focal hospital.

Empirical Extensions

Which Physicians Move?

Although our work considers whether physicians move, we have not yet considered which physicians are more or less likely to move. We address this question along two dimensions: (1) duration of tenure and (2) degree of firm-specific human capital, each of which have significant theoretical importance.

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Tenure. Investigations of tenure in the medical profession have a rich tradition. Yet, what is often striking about their findings is the mixed results that manifest between a physician's duration of practice and their ability to incorporate new information into their routines and behavior (Pisano et al. 2001, Choudhry et al. 2005, KC et al. 2013). Greenwood et al. (2013), for example, find that greater tenure is uncorrelated with a physician's ability to incorporate new information into his/her decision making, instead arguing that actions of deliberate practice produce a far greater effect (Ericsson et al. 1993). Conversely, both KC et al. (2013) and Pisano et al. (2001) find, in the context of cardiac surgery, that learning by doing (i.e., longer and greater practice) greatly expands the physician's absorptive capacity, thereby elevating clinical care outcomes, a finding echoed by McManus et al. (1998). In yet a third stream, scholars have argued that there is a curvilinear relationship between duration of practice and quality of care (Choudhry et al. 2005), whereby physicians initially benefit a great deal from hands-on practice but eventually become resistant to change as their routines reify. We therefore next consider how tenure moderates the reaction to EHR implementations.

To execute these estimations, we trichotomize the physician population into three categories: those practicing less than 10 years, those practicing between 10 and 30 years, and those practicing for 30 years or more. We opt to trichotomize our dependent variable, as opposed to using an interaction, owing to the difficulties inherent in interpreting interaction terms in logit models (Hoetker 2007). Duration of practice (i.e., tenure) is calculated according to data provided by the AHCA and is defined as the difference between the current year and the year the physician was initially licensed to practice medicine. We then replicate our estimation of Equation (1) using physicians in these three groups.

Results in Table 8 add interesting nuance to previous findings and broadly support the claims of Choudhry et al. (2005). Although younger physicians (those with less than 10 years of experience) and older physicians (those with more than 30 years of experience) seem to be pushed out by the appearance of advanced EHR systems, no such effect manifests for physicians in the prime of their careers (i.e., those practicing between 10 and 30 years). Even more striking, when considering the effect of basic EHRs, the findings reverse. Not only are basic EHRs efficacious in retaining physicians of moderate tenure, they exhibit limited correlation with the propensity to depart for younger or older physicians. These results offer two key takeaways. First, the fact that older physicians have been observed to suffer from reified routines underscores our prior findings: when physicians are forced to update behavior, they are more likely to leave. This also corroborates work in technology adoption (Venkatesh et al. 2003), which has implicated age as a key barrier. Second, the fact that younger physicians are more likely to exit the hospital has direct implications for the liability of newness (Freeman et al. 1983). To the degree that these practitioners may lack the absorptive capacity to respond to organization change, our work stresses the findings of prior scholars that have argued for training early on in a physician's career to ameliorate such concerns.

The heterogeneity in the effect relating to physician tenure subsequently raises another possibility: retirement. As discussed previously, one hotly contested issue in the popular press (Krauthammer 2015), and a subject of increasing interest to work in healthcare economics, is the possibility that physicians are not simply exiting the organization but are departing the profession entirely rather than dealing with disruptions to their routines and threats to their autonomy (Weiner and Biondich 2006, Agarwal et al. 2010a). To investigate this possibility, we next examine how the implementation of EHR in hospitals affects the percentage of physicians retiring, as opposed to continuing practice elsewhere:

$$\varphi_{jt} = \beta_1 \alpha_{jt} + \tau_t + \delta_j + \varepsilon. \tag{6}$$

Table 8. Logit Hazard Model of Departure Based on Physician Tenure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sample (years practiced)	Less than 10	Less than 10	Less than 10	10–30	10–30	10–30	>30	>30	>30
Dependent variable	Departure	Departure	Departure	Departure	Departure	Departure	Departure	Departure	Departure
Basic	−0.0559	—	−0.0760*	−0.151***	—	−0.163***	−0.0257		−0.120
	(0.0392)	—	(0.0399)	(0.0355)	—	(0.0361)	(0.140)		(0.148)
Advanced	—	0.200***	0.0866	—	0.0402	0.0655		0.170**	0.258**
	—	(0.0391)	(0.0635)	—	(0.0385)	(0.0444)		(0.0797)	(0.117)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hospital fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	32,356	53,559	32,153	59,089	65,542	59,035	7,100	9,910	7,071
No. of groups	3,767	5,409	3,752	6,175	6,716	6,172	1,253	1,565	1,251

Note. Standard errors in parentheses.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

In this estimation, φ_{jt} is the percentage of physicians who retire from practice at hospital j in time t. Time and hospital fixed effects are then included. Therefore, β_1 captures the difference in the differences across adopting and nonadopting hospitals. We take this approach for several reasons. Although, conceptually, a fixed effect multinomial logit (with the dependent variable as [0-stay, 1-change hospital, 2-retire]) could also be leveraged, current instantiations of such estimators (Pforr 2014) have yet to be optimized to a sufficient degree to be implemented on a large scale. Further, a direct estimation of the fixed effects would lead to an incidental parameters issue. The same is true of a fixed effect nested logit. Results of this analysis are in columns (1)–(3) of Table 9. Interestingly, we see no significant correlation between the implementation of either basic or advanced EHRs and retirement despite recent claims and anecdotal evidence (Agarwal et al. 2010a, Gurley 2014, Krauthammer 2015). Owing to concerns that physicians of younger tenure may be less likely to retire and the possibility that this might be masking a significant effect for longer-tenured physicians, we next replicate these estimations using the same groups as the tenure analysis (i.e., less than 10 years, 10–30 years, and more than 30 years).[17] Results are in columns (4)–(12) of Table 9. As can be seen, results remain consistent, with no significant correlation between EHR and retirement. Intuitively, these results call into question media reports suggesting physicians are retiring at an increased rate as a result of EHR implementation.[18]

Firm-Specific Human Capital. Our next question relates to the degree of firm-specific human capital the physician likely possesses. Recall, in the context of cardiac surgery, that Huckman and Pisano (2006) find that the degree of firm-specific human capital possessed by physicians yields little correlation with the physician's performance across organizations. In the context of departure due to technology implementation, this presents an interesting theoretical puzzle. On the one hand, clinicians with high firm-specific human capital might be affected to a lesser degree because the physician already faces significant disruption of their routines when transferring across hospitals, viz. because their performance may change significantly. Thus, the marginal change in disruption may be of little consequence owing to the existing scale of overall disruption. On the other hand, physicians with a high degree of firm-specific human capital may be impacted to a much greater degree. Given that their long-term mobility is already undermined by the extent to which their human capital is hospital specific, these physicians may be apprehensive about weakening their already tenuous mobility and locking themselves in to an even greater extent.

Table 9. Hospital–Year Difference in Difference Model of Proportion of Physician Retirement

	Sample											
	(1) All physicians	(2) All physicians	(3) All physicians	(4) <10 years	(5) <10 years	(6) <10 years	(7) 10–30 years	(8) 10–30 years	(9) 10–30 years	(10) >30 years	(11) >30 years	(12) >30 years
Dependent variable	% Retirement	% Retirement	% Retirement	% Retirement	% Retirement	% Retirement	% Retirement	% Retirement	% Retirement	% Retirement	% Retirement	% Retirement
Basic	−0.00226	—	0.000295	−0.00442	—	−0.00571	−0.00270	—	0.00197	0.0612	—	0.0574
	(0.0129)	—	(0.0132)	(0.0161)	—	(0.0163)	(0.0168)	—	(0.0171)	(0.0640)	—	(0.0643)
Advanced	—	−0.0135	−0.0135	—	0.00601	0.00689	—	−0.0254	−0.0257	—	0.0181	0.0159
	—	(0.0121)	(0.0123)	—	(0.0146)	(0.0149)	—	(0.0154)	(0.0157)	—	(0.0257)	(0.0258)
Constant	0.522***	0.523***	0.523***	0.537***	0.536***	0.536***	0.494***	0.496***	0.496***	0.865***	0.868***	0.861***
	(0.0475)	(0.0475)	(0.0475)	(0.0563)	(0.0563)	(0.0563)	(0.0586)	(0.0585)	(0.0586)	(0.189)	(0.189)	(0.189)
Hospital fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,013	4,013	4,013	3,782	3,782	3,782	3,749	3,749	3,749	1,362	1,362	1,362
R^2	0.465	0.465	0.465	0.398	0.398	0.398	0.407	0.407	0.407	0.381	0.380	0.381

Note. Standard errors in parentheses.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

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To examine the degree to which firm specificity in human capital impacts physician reactions to the introduction of enterprise technology, we split our sample into two groups, specialists and generalists, and replicate Equation (1). Generalists are composed of internists, family medicine practitioners, and pediatricians. Specialists are composed of other physicians who focus on a medical specialty (e.g., cardiology, neurology, gynecology, etc.). Following Huckman and Pisano (2006), these specialist physicians should have a much greater degree of firm specific human capital. We then replicate our estimations across these two groups.

Results are in Table 10. Interestingly, these estimations indicate that specialist status strongly *attenuates* the effect of both basic *and* advanced EHR systems on physician mobility. This is notable because it suggests that although generalists can capture far greater complementarities from the basic EHR systems, as compared with their specialist counterparts, they are also far more sensitive to routine disruption. However, unlike the specialists, they are able to seamlessly exit the organization when this occurs.

Destination of Continued Practice

Although our initial estimates give us some confidence in the fact that basic EHRs assist the hospital in retaining strategic human capital, whereas advanced EHRs often expedite its departure, it is also worth considering secondary questions that stem from these observations. Namely, given the limited evidence that physicians are selecting out of practice, but the substantive evidence that some physicians are departing the firm after the adoption of advanced EHRs, where are these clinicians departing to? Some possible destinations exist. It is plausible that physicians who leave the organization are electing to practice at hospitals that have not yet implemented an EHR, thereby allowing them to preserve their routines to some degree. A second option is that physicians are leaving the state of Florida entirely, in which case they would no longer appear in our data set (see the above discussion of this possibility in the "Robustness Checks" section). Finally, it is plausible that physicians are allowing the hospital to subsidize the acquisition of their EHR skills and then moving to a different hospital, which will soon adopt EHRs.

We first consider the selected location of practice for physicians who depart the organization but do not retire. More specifically, are physicians selecting their destination hospitals on the basis of the EHR modules that are currently implemented at the focal hospital? If our prior theory and findings hold, our a priori expectation would be that physicians departing after a basic EHR implementation would be relatively agnostic about the existence of a system of that type, owing to the complementarities they are able to garner. However, after advanced EHR implementations, we would expect physicians to depart to hospitals without advanced EHR systems, notably if they are departing to retain what remains of their routines.

Owing to the increasingly stringent restrictions such an estimation places on our data, we present these results in the form of cross-tabulations, as opposed to a direct estimation in which multiple outcomes are possible (recall the above discussion regarding multinomial logits). When doing so, we break the total physician departures (66,344) down by basic versus advanced EHR implementations and then further by module (CDR, CDSS, and so forth). We do so to ensure that within-type moves, viz basic or advanced, do not significantly bias the results. When considering the destination hospital, we code three possibilities: (1) departure to a hospital without the focal module, (2) departure to a hospital with the focal module made by that same vendor, and (3) departure to a hospital with the focal module but a different vendor. We include the breakdown by vendor to retain another proxy of routine disruption.

Table 10. Logit Hazard Model of Generalist vs. Specialist Departure

	Sample					
	Generalists			Specialist		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Departure	Departure	Departure	Departure	Departure	Departure
Basic	−0.0958**	—	−0.121***	−0.0552*	—	−0.0682**
	(0.0378)	—	(0.0387)	(0.0326)	—	(0.0332)
Advanced	—	0.174***	0.133***	—	0.0985***	0.0527
	—	(0.0377)	(0.0503)	—	(0.0320)	(0.0415)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Hospital fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Physician fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	47,190	60,477	47,058	65,271	83,090	65,103
No. of groups	4,135	4,983	4,127	6,127	7,446	6,118

Note. Standard errors in parentheses.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Results in Table 11 yield several interesting insights. First, there are far more departures associated with the basic EHR modules than compared with the advanced EHR modules (discussed further below). Recall that although basic modules slow departure, many more hospitals have adopted basic EHRs than advanced, so there are many more of them (192 basic implementations versus 145 advanced) over a longer period of time. Second, consistent with previous findings, physicians who depart after basic EHR implementations seem to be ambivalent about the presence of such modules in their new locations (>50% of physicians end up in hospitals with these modules). Further, they seem to be ambivalent about the vendor of the module at the destination hospital, with new vendors appearing at between 44% and 51% of destination hospitals. This stands in stark contrast to advanced EHR departures, in which more than 70% of the time physicians are fleeing to hospitals without an established module of the same type.

It is worth noting that one concern with this approach is the imbalance in the number of hospitals without any basic EHR module and without any advanced EHR module. Put simply, if a physician wishes to avoid basic EHRs near the end of the sample, their options are more limited (192 of the 304 hospitals having implemented some form of basic EHR, compared with only 134 of the 304 having implemented some form of advanced EHR). This suggests that a comparison of the crosstabs may not be valid. To remedy this, we back our sample of departures to 2005 and 2003, respectively, and replicate our calculations of the crosstabs. The intuition behind this decision is to increase the comparability of the two choice sets for the physician by limiting the installed base of basic EHRs in the state of Florida. Results are in Appendix A (Table A.11). As can be seen, the proportion of physicians departing to hospitals without basic EHRs does increase, yet it never approaches the approximately 80% preference by physicians faced with advanced EHR.

To determine whether poaching is occurring in the market for physicians after EHR implementation, we make several changes to Equation (1). First, we condition on physicians who have departed a hospital in our sample. This allows us to compare physicians who are departing a hospital with the focal EHR module with the control group of those who are departing a hospital without the module. We then regress the *adoption* of the EHR module in the new hospital on a binary indicator of whether the physician had experience with the EHR module at their previous hospital. Conceptually, what this test allows us to do is determine whether physicians departing hospitals with EHRs are arriving at hospitals that are likely to adopt new EHR systems sooner. A positive and significant correlation between these indicators would suggest poaching is a potential driver of physician mobility. Results in Table 12 suggest little evidence of poaching. In columns (1) and (2) we see that the physician having previous experience with either a basic or advanced EHR module is correlated with a significant increase in the time it will take the focal hospital to adopt one of those modules. It should be noted that the model with both basic and advanced experience included concurrently could not be run, because the dependent variables are different across the specifications (i.e., basic and advanced adoption).

Hospital-Level Heterogeneity

Although our theoretical development of this work, as well as the empirical approach we have taken, have largely centered on the physician, it is equally compelling to consider organizational-level heterogeneity that might attenuate or exacerbate the observed relationships. As has been observed by many scholars, organizational characteristics of hospitals have been shown to be key determinants of adoption decisions (Damanpour 1991, Angst et al. 2010, Greenwood et al. 2017). We next consider two possible organizational moderators of the

Table 11. Cross-Tabulation of Destination Hospitals (Total 66,344 Physician Departures)

Basic EHR implementations				Advanced EHR implementations			
Module	Destination	No. of departures	% of departures	Module	Destination	No. of departures	% of departures
CDR	To no CDR	8,104	33.4	PD	To no PD	4,529	72.3
	To same CDR vendor	4,652	19.2		To same PD vendor	631	10.1
	To different CDR vendor	11,517	47.4		To different PD vendor	1,102	17.6
	Total	24,273	100.0		Total	6,262	100.0
CDSS	To no CDSS	8,685	39.8	CPOE	To no CPOE	2,283	79.6
	To same CDSS vendor	3,510	16.1		To same CPOE vendor	284	9.9
	To different CDSS vendor	9,628	44.1		To different CPOE vendor	301	10.5
	Total	21,823	100.0		Total	2,868	100.0
OE	To no OE	6,725	27.6				
	To same OE vendor	5,103	21.0				
	To different OE vendor	12,516	51.4				
	Total	24,344	100.0				

Table 12. Logit Hazard Model of Poaching Behavior

Dependent variable	(1) Basic adoption	(2) Advanced adoption
Was at *basic*	−1.157***	—
	(0.0819)	—
Was at *advanced*	—	−2.369***
	—	(0.0541)
Hospital fixed effects	Yes	Yes
Physician fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
N	33,195	78,366
No. of physicians	4,821	6,156

observed effect: hospital-level competition and technological intensity.

With regard to hospital-level competition, extant research offers a rather murky picture of how the presence of competitor hospitals might influence the behavior of physicians. Conceptually, heightened hospital competition should reduce the switching costs for physicians, because they can continue to practice in the same city or county and not uproot their personal lives when changing employers. Given that research on EHR adoption has attested to the increased benefits that physicians may observe over time (Parente and McCullough 2009, McCullough et al. 2016), it is reasonable to conclude that EHRs may become recruitment tools for hospitals. Thus, in the presence of heightened hospital competition, it is possible that jobs at the adopting hospital will become more coveted, making physicians practicing at the hospital less likely to select out and physicians practicing at competitors more likely to select in. By contrast, low switching costs may be a double-edged sword. Although it is plausible that it is easier to attract physicians who are practicing at local competitors, it is also worth noting that the switching costs for physicians practicing at the focal hospital are also lower. Thus, insofar as EHRs have also been shown to be disruptive to the individual's routine, it is equally plausible that physicians practicing in hospital markets characterized by high competition may be more likely to depart the organization, as compared with physicians practicing at lower-competition hospitals.

To empirically examine this possibility, we execute a subsample analysis comparing the physicians in high-competition areas with physicians in low-competition areas. Hospital competition is defined by the number of hospitals concurrently operating in the same county as the focal hospital. We then split the sample at the mean level of hospital competition and replicate Equation (1). Results are in Table 13. Strikingly, results suggest that when hospitals face stiffer competition (columns (4)–(6)), even basic EHRs significantly increase the exodus of physicians from the organization. Intuitively, this suggests that as the physician's switching costs become lower, her sensitivity to having her routines disrupted significantly increases. Alternately, administrators facing limited competition, in terms of local area hospitals, need not concern themselves with these issues given the limited number of options their physicians possess. A replication of these estimations proxying competition with Rural Urban Commuting Average (i.e., average commute) are consistent and available in Appendix A (Table A.12).

When considering technological intensity (i.e., the degree to which the hospital has historically utilized IT), the literature once again paints an unclear picture of the potential effect. To the extent that continual technological upgrades will increase the flexibility of organizational routines (Feldman and Pentland 2003), it is plausible that there is a diminishing effect for hospitals that have made many upgrades in the past, because the organization is undergoing change in perpetuity (Brown and Eisenhardt 1997). Thus, the organization, and the individuals within it, will have habituated the ability to adapt and adjust routines. By contrast, to the degree that routines are inherently fragile (Butler and Gray 2006), it is plausible that professionals within a continually disrupted organization will find each successive disruption more and more of an irritant. In such a situation,

Table 13. Subsample Logit Hazard Model of High-Competition vs. Low-Competition Hospitals

	Less competition			More competition		
Sample	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Departure	Departure	Departure	Departure	Departure	Departure
Basic	−0.0507	—	−0.0460	0.0926***	—	0.0632*
	(0.0415)	—	(0.0426)	(0.0352)	—	(0.0357)
Advanced	—	0.0827**	−0.0348	—	0.220***	0.204***
	—	(0.0340)	(0.0464)	—	(0.0380)	(0.0475)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Hospital fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Physician fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	59,158	77,829	59,063	52,990	65,391	52,785
No. of groups	6,246	8,112	6,233	5,032	6,018	5,024

Note. Standard errors in parentheses.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

the physician may be incentivized to depart to a greater degree, notably if her performance is perpetually hampered by the inability to establish basic routines of operation (Nelson and Winter 1982).

To empirically capture the degree of organizational IT intensity, we execute another subsample analysis, comparing the mobility decisions of physicians from organizations with high IT intensity with the behavior of physicians in hospitals with low IT intensity. We define IT intensity by the number of clinical IT implementations that the hospital has undergone, according to the HIMSS Analytics, to date. Intuitively, such a measure should capture the number of times the physician has needed to update their routines as a result of enterprise IT. Following the performance analysis, we split the sample at the mean intensity and replicate Equation (1). Results are in Table 14. Interestingly, results suggest that the effect of EHR on physician mobility is strongly moderated by IT intensity. In columns (1)–(3) of Table 14, estimations suggest that when fewer IT implementations have occurred, physicians are less likely to depart the organization, regardless of the EHR module implemented. This is in direct contrast to hospitals where more IT has been implemented (columns (4)–(6)), where the punitive effects of advanced EHRs quickly manifest. Intuitively, this suggests that administrators should be cautious when making implementation decisions, because each successive disruption will accelerate departure. A replication of this analysis using the Saidin Index of the hospital, a measure for how innovative the hospital's IT profile is, can be found in Table A.13. Once again, results suggest that the punitive effects are stronger in hospitals where many novel IT implementations have taken place.

Discussion and Conclusion

In this paper, we investigated how the implementation of enterprise-level information systems influences the mobility of career professionals. We conducted this investigation in the context of EHR systems and their subsequent effect on physician mobility. Although the implementation of EHRs has had wide-ranging effects on the provision of healthcare, there has been limited research examining how the adoption of these systems affects the career decisions of its users. On one hand, because of the potential gains enterprise systems offer, high-status professionals may be more likely to stay with the organization and obtain benefits that accrue (such as better clinical care outcomes). On the other hand, enterprise systems require users to learn new routines, meaning that such benefits are often delayed, if they manifest at all. As a result, there may be minimal incentives for professionals to disrupt their routines and acquire the necessary skills to use these systems.

Analysis of a unique data set containing a census of physicians in the state of Florida between 2000 and 2010 yielded five key results. First, there are heterogeneous effects of the introduction of EHRs on physician mobility. Whereas basic EHR systems led to an increased duration of stay of physicians, advanced EHR systems that require the physicians to alter and update their routines accelerate physician departure from the organization. In an effort to better understand this distinction between basic and advanced EHRs, we interviewed several physicians and asked about their perceptions of the disruptions each might create. Anecdotal results echoed prior work (Jha et al. 2009) and were best summed up by an interventional radiologist who said, "decision support [a basic EHR module] makes my life easier, [physician] documentation [an advanced EHR module] makes my life harder. [CDSS] gives me dropdown menus and takes the thinking out of it. With documentation, I need to think ... and write ... a lot." Conceptually, this underscores the punitive effects disruptive systems may have on the organization

Table 14. Subsample Logit Hazard Model of High vs. Low History of IT Implementation

	Fewer IT implementations			More IT implementations		
Sample	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Departure	Departure	Departure	Departure	Departure	Departure
Basic	−0.202***	—	−0.208***	−1.596***	—	−1.753***
	(0.0329)	—	(0.0330)	(0.0859)	—	(0.113)
Advanced	—	0.0331	−0.0782*	—	−0.326***	0.201**
	—	(0.0362)	(0.0472)	—	(0.0525)	(0.0981)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Hospital fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Physician fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	73,949	96,578	73,741	27,473	34,420	27,391
No. of groups	7,670	9,712	7,663	5,264	6,562	5,251

Note. Standard errors in parentheses.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

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and the care with which enterprise information system implementations must be managed.

Second, contrary to reports in the popular press and preliminary scholarly work, we found no correlation between the adoption of EHR systems and physician retirement, suggesting that these systems are not causing physicians to select out of medicine. Instead, presumably owing to labor market shortages and a skill set that is not specific to one particular institution, physicians were able to exercise sufficient agency to switch affiliations. This stands in direct contrast to studies examining blue- and gray-collar workers, who are unlikely to have such luxuries after the implementation of enterprise level systems.

Third, there is striking heterogeneity across physicians in terms of departure. Whereas physicians who are newer to the profession, as well as those who have practiced for many years, are universally pushed out of the organization by the adoption of enterprise level technology, physicians in the prime of their careers seem to be less affected by disruptions, instead embracing them. Moreover, there is a considerable attenuating effect on the basis of how portable a physician's skills are across organizational boundaries.

Fourth, when considering where physicians go when they depart, two potential destinations exist. Cross-tabulations of departure destination, conditional on nonretirement, indicate that physicians are relatively agnostic to the presence or absence of a basic EHR system in their destination hospital. However, an overwhelming majority of those who leave select into hospitals that do not have an advanced EHR system in place. This further supports our conjecture that they flee to avoid significant learning costs and disruptions to their routines.

Finally, there are interesting moderating effects across the organizations that adopt these systems. Results suggest that when switching costs are lower owing to geospatial competition, departures accelerate dramatically. Further, successive disruptions of the worker's routines, in the form of additional IT implementations, may also accelerate departure. These findings highlight the degree to which administrators must consider their environment before making any adoption decision.

From a theoretical perspective, this work makes several important advancements. We are able to demonstrate an important boundary condition of the ability of IT to increase worker productivity (Brynjolfsson 1993, Brynjolfsson and Hitt 1996, Devaraj and Kohli 2003) and streamline the organization (Pinsonneault and Kraemer 1993, 1997, 2002). Whereas the effect of enterprise systems on labor has been investigated rigorously in blue- and gray-collar contexts, its effect on career professionals has been largely neglected. This is particularly concerning when the relative degrees of autonomy and agency that white-collar professionals possess are considered. Second, this work provides insights into heterogeneities that manifest in the effect, not only across IT systems but across professionals. This highlights the care that must be taken by administrators when implementing such systems (i.e., not casting all systems or professionals as monoliths).

From a policy perspective, there are also important implications. Because the HITECH Act has now created a de facto mandate for hospitals to adopt and use EHR systems, policymakers must understand the potential negative ramifications of such an imposition, from a multistakeholder perspective (Kohli and Tan 2016). On the one hand, hospitals need to better understand best practices associated with training and implementation, to minimize the disruption to physician routines, so they can effectively use these systems in a meaningful manner. Failure to do so may result in a departure of physicians from the hospital. At the same time, assuming that benefits do exist, it is important to inform the public of the value proposition so issues such as concerns about privacy do not encumber uptake. For the full complement of benefits to be realized, it is critical to connect EHRs across organizational boundaries such that health information flows more freely, allowing for more complete medical information at the point of care (Kohli and Tan 2016).

Finally, our work has important practical implications for the state of medical regulation. To the degree that EHR implementation was a cornerstone of the HITECH Act of 2009, and perceived as central to the success of the Patient Protection and Affordable Care act of 2010 (Obama 2009, 2016), our results emphasize that any mass exodus on the part of physicians from practice (Keckley et al. 2013, Krauthammer 2015) is unlikely a result of EHR implementations, particularly given the low number of advanced EHRs currently implemented (Adler-Milstein et al. 2014). Even so, the fact that advanced EHR implementation is correlated with an increased departure does highlight the care that needs to be taken when implementing technologies that disrupt physician routines (because it may have significant ramifications for the organization).

Despite the fact that we uncover no significant correlation between EHR implementation and retirement, it is also incumbent upon both administrators and policymakers to identify groups vulnerable to departure during the implementation process and provide them additional consideration, to minimize personnel-based disruptions within the organization. Our results underscore the care administrators need to use when implementing each successive generation of healthcare technology. As automation and artificial intelligence will make both traditional and medical jobs redundant, policymakers and managers must be aware that the effects of information systems will not be limited to unskilled workers (Brynjolfsson and McAfee 2014).

Examples of such de novo technologies are not difficult to find, and include narrow artificial intelligence for the diagnosis of patients, the emergence of genomic editing, and competitors to da Vinci surgical robots. Each of these technologies will likely not have an adoption mandate but will impose learning costs and disrupt professional and organizational routines. Thus, it is critical for administrators and policymakers to be cognizant of the fact that certain sets of professionals may choose, volitionally, to leave their place of employment rather than modify their behavior to incorporate de novo enterprise technologies. Importantly, these results are likely to not be limited to physicians. High-skilled professionals of all stripes, ranging from engineering to law to academia, are noting the increased presence of technology within the organization, and managers of such firms should take equal care when implementing enterprise IT.

Although these results broaden our understanding of the impact of the adoption of EHR systems on the provision of healthcare, the study is not without limitations. First, we analyze the effect of the adoption of EHR systems before the passing of the HITECH Act. During this period, the adoption of EHR systems by hospitals was volitional. Hence, physicians could choose to transfer to a hospital that did not have advanced EHR systems. However, after HITECH implementation in 2009, this de facto technology mandate made it increasingly difficult for physicians to select hospitals that did not have advanced EHR systems and thus significantly changed the physician's decision-making calculus. This does not limit the generalizability of our findings, however, because the U.S. healthcare market, as well as numerous other industries, is quite dynamic, with new policies and technology mandates being adopted on a regular basis. Importantly, our study is not meant to be generalizable across all timeframes, but it is intended to show that when IT is implemented, professionals may react in unanticipated ways. Although we cannot predict what new policy will be implemented or when it will be enacted, we can be quite certain that new (and likely disruptive) innovations (e.g., artificial intelligence in the diagnostic process, automated robotic surgery and nursing, remote patient monitoring, etc.) will be introduced into organizations where high-status professionals are employed, and our study shows the dramatic effects that can result.

A second limitation is that the Florida AHCA data set does not contain explicit information about physician movement, and HIMSS Analytics data do not explicitly account for use. As such, we are forced to impute mobility through the treatment of patients (i.e., a physician must appear as a "treating physician" for her to show up in our data set) and assume disruption through use on the part of physicians who are practicing at an adopting hospital. However, this is not of great concern because physicians who are not treating patients (e.g., researchers and administrators) are unlikely to be interacting with clinical IT. Third, our data are limited to physicians of a single state, Florida. Although Florida is a large and diverse state and has significant prior precedence as a context (Burke et al. 2007, Lu and Rui 2015, Greenwood and Agarwal 2016, Greenwood et al. 2017), it nevertheless bears note. Clearly, longer panels of movement over a larger geographic area will be required to ensure that the findings are generalizable. Finally, we must note the extent to which EHR adoption should not be considered random. Although we have taken care to rule out as many alternate explanations as possible, the lack of exogeneity in such a design should stress the caution that must be taken when interpreting our findings. We hope this research serves as a broader call for similar investigations, which further our understanding of the dynamics of enterprise technology and labor in organizations.

Appendix A. Statistical Appendix

Table A.1. Logit Hazard Model of Physician Departure with No Minimum Patient Restriction

	Departure		
Dependent variable	(1)	(2)	(3)
Basic	–0.0344*	—	–0.0485**
	(0.0187)	—	(0.0190)
Advanced	—	0.121***	0.0579**
	—	(0.0179)	(0.0240)
Time fixed effects	Yes	Yes	Yes
Hospital fixed effects	Yes	Yes	Yes
Physician fixed effects	Yes	Yes	Yes
Observations	201,962	268,089	201,371
No. of groups	21,194	28,271	21,139

Note. Standard errors in parentheses.
***p < 0.01; **p < 0.05; *p < 0.1.

Table A.2. Logit Hazard Model of Physician Departure with No Physician Arrival Restriction

	Departure		
Dependent variable	(1)	(2)	(3)
Basic	–0.135***	—	–0.149***
	(0.0208)	—	(0.0213)
Advanced	—	0.0408*	0.0740***
	—	(0.0227)	(0.0231)
Time fixed effects	Yes	Yes	Yes
Hospital fixed effects	Yes	Yes	Yes
Physician fixed effects	Yes	Yes	Yes
Observations	150,226	150,226	150,226
No. of groups	12,846	12,846	12,846

Note. Standard errors in parentheses.
***p < 0.01; **p < 0.05; *p < 0.1.

Table A.3. Logit Hazard Model of Physician Departure with Modules Measured as Count Variables

	Departure		
Dependent variable	(1)	(2)	(3)
Basic count	–0.0171*	—	–0.0221**
	(0.00939)	—	(0.00969)
Advanced count	—	0.0985***	0.0406
	—	(0.0211)	(0.0278)
Time fixed effects	Yes	Yes	Yes
Hospital fixed effects	Yes	Yes	Yes
Physician fixed effects	Yes	Yes	Yes
Observations	112,461	143,567	112,161
No. of groups	10,262	12,429	10,245

Note. Standard errors in parentheses.
***p < 0.01, **p < 0.05, *p < 0.1

Table A.4. Linear Probability Model Hazard Model of Physician Departure

	Departure		
Dependent variable	(1)	(2)	(3)
Basic	–0.0106***	—	–0.0122***
	(0.00312)	—	(0.00318)
Advanced	—	0.0165***	0.00658*
	—	(0.00335)	(0.00400)
Constant	0.0655***	0.0627***	0.0663***
	(0.00335)	(0.00279)	(0.00336)
Time fixed effects	Yes	Yes	Yes
Hospital fixed effects	Yes	Yes	Yes
Physician fixed effects	Yes	Yes	Yes
Observations	113,355	144,317	113,055
R^2	0.222	0.223	0.222
No. of groups	10,907	12,966	10,890

Note. Standard errors in parentheses.
***p < 0.01; **p < 0.05; *p < 0.1.

Table A.5. Logit Hazard Model of Physician Departure Omitting HITECH Years

	Departure		
Dependent variable	(1)	(2)	(3)
Basic	–0.0861***	—	–0.104***
	(0.0249)	—	(0.0254)
Advanced	—	0.129***	0.0901***
	—	(0.0252)	(0.0328)
Time fixed effects	Yes	Yes	Yes
Hospital fixed effects	Yes	Yes	Yes
Physician fixed effects	Yes	Yes	Yes
Observations	93,855	120,817	93,620
No. of groups	8,739	10,491	8,726

Note. Standard errors in parentheses.
***p < 0.01; **p < 0.05; *p < 0.1.

Table A.6. Logit Hazard Model of Physician Departure (Excludes Physicians Licensed to Practice Outside Florida)

	Departure		
Dependent variable	(1)	(2)	(3)
Basic	–0.113***	—	–0.129***
	(0.0301)	—	(0.0307)
Advanced	—	0.120***	0.0832**
	—	(0.0319)	(0.0393)
Time fixed effects	Yes	Yes	Yes
Hospital fixed effects	Yes	Yes	Yes
Physician fixed effects	Yes	Yes	Yes
Observations	64,851	78,992	64,717
No. of groups	5,854	6,722	5,847

Note. Standard errors in parentheses.
***p < 0.01; **p < 0.05; *p < 0.1.

Table A.7. Logit Hazard Model of Hospital Changes on EHR Adoption

	Method			
	Logit hazard		Logit	
	(1)	(2)	(3)	(4)
Dependent variable	Basic	Advanced	Basic	Advanced
DRG Focus	−2.518	12.69	−12.59	−8.078
	(22.39)	(11.56)	(17.06)	(10.22)
% Medicaid	−0.000170	0.000141	2.94e-05	7.89e-05
	(0.000146)	(9.32e-05)	(0.000374)	(0.000183)
% Medicaid HMO	0.000259	−0.000143	0.00114*	0.000477
	(0.000436)	(0.000247)	(0.000672)	(0.000382)
% Commercial insurance	−0.000940***	−8.09e-05	−0.000856	−0.000266
	(0.000259)	(0.000168)	(0.000543)	(0.000294)
% Commercial insurance (HMO)	−0.000745***	−0.000158	−0.000711*	−2.38e-06
	(0.000138)	(0.000108)	(0.000374)	(0.000213)
% Commercial insurance (PPO)	−0.000483***	−0.000239*	−5.22e-05	0.000963***
	(0.000185)	(0.000124)	(0.000472)	(0.000260)
% Worker's compensation	−0.00165	0.00373**	0.00544	0.00349
	(0.00209)	(0.00175)	(0.00510)	(0.00256)
% CHAMPUS	0.00116	0.000358	−0.00753	0.00101
	(0.00125)	(0.000574)	(0.00584)	(0.000840)
% Veterans Administration	−0.00579	0.00265*	−0.00849	0.00446
	(0.00594)	(0.00160)	(0.00533)	(0.00280)
% State medical assistance	−0.000752	−0.00137**	−0.000642	0.00196**
	(0.000977)	(0.000559)	(0.00127)	(0.000913)
% Self-pay	−0.000309	−0.000217	0.000110	−0.000250
	(0.000321)	(0.000198)	(0.000732)	(0.000364)
% Other	−0.000743	0.000569	−0.00117	0.000711
	(0.00148)	(0.000898)	(0.00141)	(0.00138)
% Charity	−0.001000***	−0.000471**	0.000375	0.000413
	(0.000250)	(0.000230)	(0.000471)	(0.000397)
% Kid care	−0.00786	−0.00243	0.0150	−0.00503
	(0.0123)	(0.00272)	(0.0125)	(0.00405)
Total patients	0.000439***	8.34e-05**	−6.48e-05	−0.000271**
	(7.04e-05)	(4.13e-05)	(0.000217)	(0.000115)
No. of freelancers	0.000294	0.00132	0.00221	0.00515
	(0.00168)	(0.00236)	(0.00410)	(0.00336)
No. of older physicians	0.00488	0.00805	0.0114	0.0164
	(0.0192)	(0.0104)	(0.0185)	(0.0158)
Constant	−0.705***	−4.062***	—	—
	(0.215)	(0.490)	—	—
Hospital fixed effects	No	No	Yes	Yes
Hospital random effects	Yes	Yes	No	No
Time fixed effects	Yes	Yes	Yes	Yes
Observations	949	1,562	572	1,225

Note. Standard errors in parentheses.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Table A.8. Logit Hazard Model of Physician Departure Using Freelance Physicians

	Sample: Freelancers		
	(1)	(2)	(3)
Dependent variable	Departure	Departure	Departure
Basic	−0.137***	—	−0.152***
	(0.0264)	—	(0.0270)
Advanced	—	0.0902***	0.0807**
	—	(0.0291)	(0.0387)
Time fixed effects	Yes	Yes	Yes
Hospital fixed effects	Yes	Yes	Yes
Physician fixed effects	Yes	Yes	Yes
Observations	77,289	99,813	77,078
No. of groups	6,655	8,003	6,642

Note. Standard errors in parentheses.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table A.9. Logit Hazard Model of Physician Departure (Excludes Hospitals with Different EHR Vendors)

	Sample: Consistent vendors		
	(1)	(2)	(3)
Dependent variable	Departure	Departure	Departure
Basic	−0.138***	—	−0.154***
	(0.0388)	—	(0.0390)
Advanced	—	0.153***	0.0953***
	—	(0.0284)	(0.0368)
Time fixed effects	Yes	Yes	Yes
Hospital fixed effects	Yes	Yes	Yes
Physician fixed effects	Yes	Yes	Yes
Observations	78,157	102,152	77,855
No. of groups	7,836	10,329	7,808

Note. Standard errors in parentheses.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table A.10. Logit Hazard Model of Physician Departure (Excludes Hospitals Experiencing Merger During Sample)

	Sample: Mergers excluded		
	(1)	(2)	(3)
Dependent variable	Departure	Departure	Departure
Basic	−0.0714***	—	−0.0894***
	(0.0249)	—	(0.0255)
Advanced	—	0.130***	0.0849***
	—	(0.0248)	(0.0326)
Time fixed effects	Yes	Yes	Yes
Hospital fixed effects	Yes	Yes	Yes
Physician fixed effects	Yes	Yes	Yes
Observations	110,387	140,885	110,087
No. of groups	10,189	12,337	10,172

Note. Standard errors in parentheses.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table A.11. Replication of Cross-Tab of Destination Hospitals Using Constrained Time Windows

	Basic EHR implementations					
	2000–2005: 47,435 physician departures			2000–2003: 39,839 physician departures		
Module	Destination	No. of departures	% of departures	Destination	No. of departures	% of departures
CDR	To no CDR	4,292	38.6	To no CDR	3,043	48.0
	To same CDR vendor	1,823	16.4	To same CDR vendor	899	14.2
	To different CDR vendor	4,618	41.5	To different CDR vendor	2,396	37.8
	Total	11,133	96.4	Total	6,338	100.0
CDSS	To no CDSS	4,996	50.6	To no CDSS	3,169	54.1
	To same CDSS vendor	1,325	13.4	To same CDSS vendor	745	12.7
	To different CDSS vendor	3,550	36.0	To different CDSS vendor	1,942	33.2
	Total	9,871	100.0	Total	5,856	100.0
OE	To no OE	3,958	40.2	To no OE	2,464	45.2
	To same OE vendor	1,741	17.7	To same OE vendor	939	17.2
	To different OE vendor	4,148	42.1	To different OE vendor	2,050	37.6
	Total	9,847	100.0	Total	5,453	100.0

Table A.12. Subsample Logit Hazard Model of High-Competition vs. Low-Competition Hospitals (Defined By Rural Urban Commuting Average)

	Sample					
	Urban commute			More commute		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Departure	Departure	Departure	Departure	Departure	Departure
Basic	0.0759***	—	0.0575*	–0.228**	—	–0.268***
	(0.0290)	—	(0.0295)	(0.0946)	—	(0.0968)
Advanced	—	0.164***	0.0833**	—	0.0817	0.228**
	—	(0.0265)	(0.0349)	—	(0.0862)	(0.112)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Hospital fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Physician fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	95,275	122,766	94,975	16,802	20,415	16,802
No. of groups	8,927	11,104	8,905	2,608	3,156	2,608

Note. Standard errors in parentheses.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table A.13. Subsample Logit Hazard Model of High vs Low Innovation IT Profiles (Innovation Captured by Saidin Index)

	Sample					
	Less innovative			More innovative		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Departure	Departure	Departure	Departure	Departure	Departure
Basic	–0.297***	—	–0.299***	–0.147***	—	–0.203***
	(0.0477)	—	(0.0479)	(0.0358)	—	(0.0371)
Advanced	—	0.107**	0.00757	—	0.188***	0.235***
	—	(0.0419)	(0.0586)	—	(0.0365)	(0.0469)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Hospital fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Physician fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	48,518	67,133	48,435	52,331	63,160	52,171
No. of groups	6,639	9,101	6,625	6,854	8,024	6,839

Note. Standard errors in parentheses.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Appendix B. Additional Instrumentation

Table B.1. Two-Stage Least Squares Survival Model with Additional Instruments

Stage	(1)	(2)
First stage		
Dependent variable	Basic	Advanced
Executive IS	–0.0048	0.0083***
	(0.0032)	(0.0027)
EDI	0.0105***	—
	(0.0031)	—
General ledger	—	0.0135***
	—	(0.0028)
Cragg–Donald F statistic	9.28	13.147
p-value	$p < 0.01$	$p < 0.01$
Second stage		
Dependent variable	Departure	Departure
Basic	–0.966**	—
	(0.405)	—
Advanced	—	1.202***
	—	(0.292)
Time fixed effects	Yes	Yes
Hospital fixed effects	Yes	Yes
Physician fixed effects	Yes	Yes
Hansen's J	0.1021	0.208
Observations	88,550	120,621
No. of groups	8,874	11,708

Note. Robust standard errors in parentheses.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Although our initial instrumentation in Table 4 presents relatively compelling evidence that the observed effects are unbiased, notably when considered in conjunction with the other corpus of other evidence, it is important to highlight several shortcomings of these estimations. The first concern is that, because Table 4 uses only a single instrument, we are unable to effectively compute a Sargan or Hansen's J statistic. Although the limited correlation between the implementation of an Executive IS (EDI) and employee turnover suggests that this likely is not a concern (approximately 1% and approximately 7%), it nevertheless bears note. It is therefore incumbent on us to search for additional instruments. The second, and arguably more pressing, concern is that although the implementation of an EDI is strongly correlated with the implementation of a basic EHR system (column (1) of Table 4, first stage), the resulting Cragg–Donald F statistic does not quite meet the strength requirements ascribed by Stock and Yogo (2005) (the strength of the instrument meets the 15% maximal IV threshold). Again, this underscores the need to search out additional instrumental regressors (to meet the additional needs of both strength as well as superseding the exclusion criterion).

Following Hydari et al. (2019), we continue to instrument for the adoption of basic and advanced EHR systems using nonclinical IT. Yet, in practice, this creates nontrivial concerns. Because Hydari and his colleagues were concerned with the adoption of a single EHR system, the CPOE, they were able to consider the correlation of instruments with the focal independent and dependent variables "in a vacuum." However, because our investigation leverages multiple independent variables of interest, we must find instruments that meet the diagnostic requirements of both the basic *and* advanced EHR instrumentations independently. Unfortunately, instruments of this type are rare. For example, a plethora of possible nonclinical IT meet the strength requirements (e.g. accounting software in the form of payroll, billing, and benefits) yet fail the Sargan test. Others meet the test of noncorrelation with the error term, and by extension a lack of correlation with physician turnover, yet fail the strength requirements (e.g., supply chain management IT in the form of ERP and materials management).

As a result, we are compelled to continue using different instrument pools for both the basic and advanced EHR systems. For each, we continue to use our instruments from Table 4. However, we additionally instrument for the adoption of basic systems with Executive IS and for advanced systems with general ledger software.[19] Although this does not allow us to create a complete system of equations (in which both independent variables are concomitantly estimated), it does allow for strength testing and the calculation of Hansen's J. Results are in Table B.1 and remain consistent. Although basic systems reduce the propensity for physician departure, advanced systems accelerate departure from the focal hospital. Further, in each case the Cragg–Donald F statistics continue to exceed the Stock and Yogo (2005) 15% maximal IV size requirement, the Hansen's J tests indicate that the first stage is not significantly correlate with the error terms (and by extension the dependent variable), and the Kleibergen–Paap LM statistic indicates that the equations are not underidentified.

Appendix C. Extant EHR Literature

Table C.1. Overview of Extant EHR Literature

	Authors	Findings	Sample
Adoption/ implementation	Miller and Sim (2004)	Key barriers to EHR use are high initial costs with uncertain benefits, physician resistance to training and change, poor support for extracting complementarities, poor EDI, and lack of incentives.	Qualitative study of physicians
	Bower (2005)	EHR adoption has been slow as a result of poor coordination standards, poor quality measurement, and a lack of complementary technology investments.	Survey of literature and physicians
	Jha et al. (2006)	Adoption rates differ significantly based on size but the technology is poorly defined at present.	Survey of practices
	Kazley and Ozcan (2007)	Environmental factors (e.g., competition, local wealth, employment) and organizational factors (size+, ownership, system affiliation) affect adoption.	HIMSS cross-sectional adoption data (2004)
	Simon et al. (2007)	Organizational factors (e.g., size, ownership, location) and market factors (e.g., managed care penetration, rurality, and incentives) affect adoption.	Survey of physicians adopting CPOE/ CDSS
	Jha et al. (2009)	Defined basic and comprehensive EHR functionality. Observed that hospital characteristics (e.g., size, urban/rural) often influence adoption.	Cross-section of basic and advanced adoption
	Miller and Tucker (2009)	HSA level network effects and state privacy laws affect adoption.	National panel
	Ford et al. (2010)	Best of suite approaches increase the probability of complete adoption over best of breed and single vendor options.	AHA annual IT survey
	Adler-Milstein et al. (2015)	Small and rural hospitals lag in EHR adoption, a result of up-front and ongoing costs, physician resistance to change, and meaningful use criteria confusion.	AHA annual IT survey
Financial implications	Menon and Kohli (2013)	Health IT expenditure is negatively correlated malpractices insurance premiums for hospitals.	Panel of 66 Washington hospitals
	Kohli et al. (2012)	Healthcare IT spending can significantly increase firm value but does not affect ROA or operating income.	Cross-sectional study of 497 hospitals
	Agha (2014)	EHRs increase medication costs with no impact on quality of care.	Claims data
	Atasoy et al. (2014)	Although EHR increases costs at adopting hospitals, it can reduce regional costs when the sharing of patient information is common.	Panel of Medicare cost data with HIMSS
	Bhargava and Mishra (2014)	Productivity drops sharply after EHR is implemented. This drop attenuates over time, but speed of recovery is dependent on specialty.	Individual panel of 87 specialists
	Dranove et al. (2014)	EHR adoption is associated with initial cost increases that attenuate over time. Hospitals outside IT-intensive locations do not realize cost savings.	Panel based on Medicare cost reports
	Li (2014)	EHR presence increases the probability of patients being assigned to higher paying DRGs.	Multistate discharge data
	Ganju et al. (2016)	CPOE systems result in DRG upcoding. This is most prevalent at for profit hospitals and can be attenuated by auditing programs.	Medicare discharge data

Table C.1. (Continued)

	Authors	Findings	Sample
	Hitt and Tambe (2016)	After EHR implementation, hospitals observed higher productivity and greater efficiency, but at higher costs and with no change in quality care outcomes.	Merged CMS and Survey data in NY
	Ransbotham et al. (2016)	EHR implementation significantly reduces claims resolution times and the legal costs associated with them by expediting legal discovery.	Panel of Florida legal claims
Quality implications	Teich et al. (2000)	EHR with CPOE significantly improves prescribing practices through the adherence to recommended drug utilization levels.	Time series analysis at an urban AMC
	Han et al. (2005)	Short-term increases in child mortality were observed after CPOE implementations a result of learning curves and system integration issues.	Single hospital pre/post examination
	Mahoney et al. (2007)	EHR with CDSS capabilities and a pharmacy IS decreased drug-allergy errors, excess doses, and unclear orders.	Serial cross-section at three hospitals
	Friedberg et al. (2009)	Multifunctional EHR increases adherence to recommended care standards.	Survey with cross-sectional data
	Parente and McCullough (2009)	EHR increases patient safety at both leading academic institutions and more traditional care settings, but investment in evaluation metrics is needed.	Panel of Medicare inpatient data
	Devine et al. (2010)	EHR with limited CDSS significantly reduced errors (but not ADEs).	Pre/post examination
	Kaushal et al. (2010)	EHR with CDSS significantly decreased prescribing errors based in illegible handwriting, duration errors, rule violations, and others.	E-prescribing in an ambulatory setting
	McCullough et al. (2010)	EHR with CPOE led to middling increases in quality of care adherence for large hospitals.	Panel of 3,401 acute care hospitals
	Miller and Tucker (2011)	EHR reduced infant mortality. Effects stronger for low income and low education populations. Effect increased with additional EHR functionality.	12-year panel
	Kennebeck et al. (2012)	Length of stay and time to treatment increased after EHR implementation.	ED patients
	Leung et al. (2012)	EHR decreases preventable ADEs but increases potential and overall ADEs.	Panel of five hospitals
	Kern et al. (2013)	EHR with CDSS improves most process quality measures of care.	Ambulatory care setting
	McCullough et al. (2016)	Mortality reduction was observed for the most complex patients. These included those with cross-specialty needs and extensive clinical data.	Panel of Medicaid admissions

Note. ADE, adverse drug event; AHA, American Heart Association; AMC, academic medical center; ED, emergency department; HSA, health service area; IS, information system; ROA, return on assets.

Endnotes

[1] There are several studies that investigate turnover of IT professionals (Joseph et al. 2007), and others examine the effect of spillovers from IT and IT skills' investments on workforce mobility (Tambe 2014). However, because software development and IT professionals' careers typically do not require postgraduate education and are not subject to professional licensure (as is the case with physicians, lawyers, and professional engineers), these studies fall outside the scope of this investigation. We further acknowledge the extensive work on managers of the firm (Pinsonneault and Kraemer 1993, 1997). However, the purpose of our investigation is to examine the effect on professional labor mobility, as opposed to the effect on the managers of the firm. The health informatics literature provides numerous examples that investigate the effect of IT on physician work practices; however, we are not aware of any studies that consider physicians from the perspective of human capital and mobility.

[2] http://money.cnn.com/2013/01/04/news/economy/jobs-lowest-unemployment/index.html.

[3] https://www.bls.gov/opub/ted/2014/ted_20141112.htm.

[4] https://www.npr.org/sections/alltechconsidered/2017/11/07/561631927/from-post-it-notes-to-algorithms-how-automation-is-changing-legal-work.

[5] There is one final situation to consider because it relates enterprise systems and mobility. Prior literature suggests that some

professionals may stay at a firm just long enough to acquire specific skills, with the intent of departing if and when the conditions are suitable (Chatterji et al. 2016). Thus, it is possible that some professionals may choose to depart not to escape the enterprise system but instead to leverage their new skills at a different firm. Although externally this could be perceived as a professional fleeing a disruptive system, the opposite is actually occurring. Importantly, our analysis is able to isolate these opposing effects.

[6] In the interest of space, we have not provided an expansive review of EHR literature (see Table C.1 in Appendix C for a focused overview).

[7] Results omitting the final two years of the sample, after the passage of the HITECH Act, are consistent (Table A.5).

[8] Results are consistent when this restriction is removed (i.e., physician entry after EHR adoption). Further, results are consistent when the patient restriction is removed. Results are available in Appendix A (Tables A.1 and A.2).

[9] Adler-Milstein et al. (2014) and Jha et al. (2009) call the advanced EHR a "comprehensive" EHR.

[10] Others, such as HIMSS Analytics (2013), established a proprietary eight-stage model that measures the adoption and utilization of EHR functions. These data are not currently available for research purposes. Note that the inclusion of a hospital–physician fixed effect, arguably the most stringent possible set of controls, yields significant convergence issues using a time series logit estimator.

[11] Additional instrumentation and diagnostics, with multiple instruments per adopted technology, are available in Appendix A. They are omitted here in the interest of space. It should be noted that the *Exec IS* statistically qualifies as an instrument for *Basic* systems (but is negatively correlated in the first stage). We thank the anonymous reviewer for raising this concern.

[12] Marginal effects are calculated using the margins command in Stata 12.1.

[13] Results are consistent using a linear probability model–based hazard model (see Appendix A, Table A.4).

[14] We thank the anonymous reviewers for bringing these possibilities to our attention.

[15] Note that the creation of a "focus" index for Payers, similar to DRGs, yields consistent results.

[16] Further robustness checks examining the ownership structure of hospitals were also conducted, specifically to rule out the possibility that physician practice management companies and hospital mergers were not biasing the results. Details of these tests are available in Table 7 and indicate that neither factor unduly biases the results. Results in Table A.9 and A.10, respectively.

[17] We thank the anonymous reviewer for suggesting this test.

[18] Estimations using a logit hazard model of retirement and conditioning on departure, or twin logit hazard models capturing the stay/go versus stay/retire decision, yield generally consistent results and are available on request.

[19] It must be emphasized that although EDI is an effective instrument for basic systems and the General Ledger is an effective instrument for advanced systems, these instruments are not interchangeable. In other words, instrumenting for advanced systems using EDI or basic systems using the General Ledger does not pass diagnostic requirements.

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