Organizational Innovation in Health Care

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Abstract

This dissertation investigates whether differences in organizational innovation amongst health care providers can explain the huge variation in costs and outcomes. I specifically consider two facets of organizational innovation: the deployment of information technology and the relationships between hospitals and physicians.

In the first chapter, I investigate IT adoption in a service setting by considering the impact of electronic medical records (EMRs) on the length of stay and clinical outcomes of patients in US hospitals. To uncover the distinct impacts of EMRs on operational efficiency and care coordination, I present evidence of heterogeneous effects by patient complexity. I find that EMRs have the largest impact for relatively less complex patients. Admission to a hospital with an EMR is associated with a 2% reduction in length of stay and a 9% reduction in thirty-day mortality for such patients. In contrast, there is no statistically significant benefit for more complex patients. However, I present three additional results for complex cases. First, patients returning to the same hospital benefit relative to those who previously went to a different hospital, which could be due to easier access to past electronic records. Second, computerized order entry is associated with higher billed charges. Finally, hospitals that have a high share of publicly insured patients, and hence a bigger incentive to curb resource use, achieve a greater reduction in length of stay for complex patients after EMR adoption.

In the second chapter, co-authored with Robert Huckman, I investigate the role of process specialists in guiding customers through such complex service transactions by considering the management of patients admitted to U.S hospitals. Traditionally, a patient's primary care physician has been in charge of his or her hospital admission. Over the past decade, however, there has been a steady rise in the use of hospitalists - physicians who spend all their professional time at the

hospital - in managing inpatient care. Using data from the American Hospital Association and the Agency for Healthcare Research and Quality's Nationwide Inpatient Sample (NIS) database, we find that hospitals with hospitalist programs achieve reductions in the risk-adjusted length of stay of inpatients over the time period 2003 to 2010. The effect is strongest for complex patients who have a higher number of comorbidities. Our findings support the view that process specialists such as hospitalists are particularly beneficial for complex transactions that entail a greater degree of coordination.

In the final chapter, I document the positive relationship between consolidation in the health care industry and technology adoption. I propose several mechanisms that could explain the association between the adoption of electronic medical records and greater hospital-physician integration. I show that the positive correlation between technology adoption and hospital consolidation has been increasing over time. I show that hospitals located in concentrated markets are more likely to adopt electronic medical records and to use hospitalists. Moreover, for a limited set of hospitals, the quality of management is positively associated with the adoption of electronic medical records and the use of hospitalists.

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Chapter 1

Technological Innovation and Productivity in Service Delivery: Evidence from the Adoption of Electronic Medical Records

1.1 Introduction

Economists have long been interested in the link between technological innovation and productivity growth (Solow, 1957; Griliches, 1979). Recently, many have attributed the productivity surge at the end of the 20th century to the widespread adoption of information technology (IT) and the subsequent reorganization of business practices (Brynjolfsson and Saunders, 2010).[1] When investment in IT accelerated in the 1990s, it transformed many service industries such as retail, travel and banking, by reducing the costs of processing information and coordinating production (Brynjolfsson and Hitt, 2003; Stiroh, 2002).

Relative to the rest of the service sector, the health care industry has lagged behind in IT adoption and productivity growth. But that may be changing. The HITECH Act, which was

[1] US labor productivity growth, which averaged just 1.4% per year between 1973 and 1995, increased to 2.6% per year in 1996-2000, and rose even further to 3.6% in 2001-2003.

passed as part of the stimulus package in 2009, provided up to $30 billion in subsidies to eligible hospitals and physicians for the meaningful use of certified electronic medical records (EMRs). Hospital adoption of EMRs has increased more than five-fold since 2008, and the majority of US hospitals now have EMRs.[2] In this paper, I investigate how the rapid diffusion of IT has affected productivity in the health care sector.

IT can have several distinct effects on productivity. First, it helps to expedite many tasks, which leads to greater operational efficiency. This channel is especially important for simple transactions consisting mainly of routine, rules-based tasks that can be easily done by computers (Autor *et al.*, 2003). Second, IT increases the amount of information that is available to a worker, which can either help with decision-making or increase the cognitive burden on the worker.[3] This channel is especially important for complex transactions that involve a large volume of information. Finally, IT helps to coordinate complex transactions by lowering communication costs (Bloom *et al.*, 2009). There are two aspects to such coordination: coordination at a point in time between different service providers and coordination over time by virtue of storing data from previous encounters.[4] These channels suggest that IT could have different effects on different types of patients in a health care setting.

To understand how IT affects productivity in hospitals empirically, I consider heterogeneous impacts by patient complexity. The bulk of this paper is an empirical analysis of how EMRs have affected patient outcomes in US hospitals. I merge detailed patient-level data from Medicare beneficiaries with a new dataset on the adoption of EMRs, the American Hospital Association Health IT Supplement, that is closely tied to the meaningful use criteria proposed in the HITECH Act. Taking advantage of the rapid uptake of EMRs following the HITECH Act, I employ a difference-in-difference research design to explore the impact of EMRs on patient-level outcomes for four diseases typically studied in the literature: pneumonia, congestive heart failure (CHF), heart attack, and hip fracture. I measure complexity in two different ways: whether patients have a high number of secondary diagnoses, and whether they have been admitted to a hospital in the

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[2] <http://www.healthit.gov/sites/default/files/oncdatabrief16.pdf >

[3] Kesselheim *et al.* (2011); Singh *et al.* (2013); Gino (2013)

[4] In addition to these permanent effects of IT, there might also be a temporary productivity loss from learning how to use new IT, which should become smaller over time.

year preceding their current admission.

I find that EMRs have the largest impact on less complex patients. For pneumonia or CHF patients with a low number of secondary diagnoses, going to a hospital with an EMR is associated with a 2% reduction in length of stay and a 9% reduction in mortality. This result fits the notion that computers can help with routine tasks. In hospitals, all transactions involve some routine tasks such as ordering medications or transferring lab results from one department to another. However, improving the efficiency of these tasks is more likely to have a marginal impact on productivity for less complex patients. In contrast to my results for less complex patients, I find that more complex cases do not appear to benefit from EMR adoption. There are several potential explanations for this result. A purely logistical barrier, such as delays or errors in ordering medications, is less likely to be the bottleneck in such cases; there is a greater need for customization and workarounds; and there is a higher scope for information overload for clinicians. It is possible that as more EMRs become interoperable across hospitals and physician practices over the next few years, the benefits to more complex patients will increase.

Due to the various mechanisms via which EMRs might affect outcomes for more complex patients, I investigate such cases in more detail through an additional set of empirical tests. With regard to coordination over time, I find that EMRs are associated with lower lengths of stay and improved quality outcomes for patients who had been admitted to the same hospital in the twelve months preceding the current admission. Information about these patients is likely to be stored in the hospital's electronic system, which clinicians can access during the current visit. I also show that EMR systems that include computerized order entry (CPOE) lead to higher billed charges at the hospital for more complex patients. CPOE reduces the cost of ordering additional lab and radiology tests, and therefore doctors are more likely to order such tests. However, this effect is diminished for patients who have been to the same hospital before, possibly because some important information is already stored in their EMR. I also find that hospitals that have a high share of publicly insured patients achieve a greater reduction in length of stay for more complex patients when they have IT systems. Such hospitals have a bigger incentive to leverage EMRs for curbing resource use because public insurance programs pay relatively low rates to hospitals. Moreover, the HITECH Act proposed penalties that are calculated as a percentage of Medicare payments if hospitals do not demonstrate the meaningful use of EMRs by 2016.

This paper is related to several literatures. Studies of the impact of technology on productivity have documented that the gains from IT rely on organizational and labor complementarities (Bloom *et al.*, 2012; Bresnahan *et al.*, 2002; Brynjolfsson and Hitt, 2003). Dranove *et al.* (2012) show that such complementarities are also important in the specific case of health IT. Buntin *et al.* (2011) provide a comprehensive review of many studies in the health services literature that document evidence of positive impacts of health IT; in contrast to these studies, many of which are small scale or cross-sectional, some recent papers find smaller impacts of EMRs at the hospital level. Using longitudinal data, McCullough *et al.* (2010) and Agha (2014) show that IT has little or no impact on average hospital quality. Miller and Tucker (2011) find that increased health IT penetration at the county-level is associated with a small decline in infant mortality rates. I am able to conduct a more detailed empirical analysis at the patient level to uncover evidence of heterogeneous impacts. Therefore, this paper builds upon and complements recent studies that have looked at the effects of EMRs on patient-level outcomes. McCullough *et al.* (2013) show that health IT improves quality by facilitating coordination and communication across providers, which leads to relatively high benefits among high-risk patients. On the other hand, Freedman *et al.* (2014) find that EMRs with clinical decision support are effective at reducing certain adverse events for less complicated cases.

One advantage of this study relative to the literature is that I look at the time period since 2008. Most studies on health IT consider an earlier time period when information systems were not very advanced and only the most innovative hospitals had fully implemented EMRs. Furthermore, I propose a conceptual framework for the effects of IT adoption on operational efficiency and care coordination, which leads to empirical tests to distinguish between the differing roles of IT in service delivery organizations. I also provide evidence of specific scenarios in which EMRs can help improve health care outcomes, such as the case of repeat patients, and scenarios in which EMRs can lead to more resource use, such as the case of computerized order entry.

The rest of this chapter is structured as follows. Section 1.2 lays out the conceptual framework in more detail and derives a set of testable hypotheses. Section 1.3 provides background on EMRs and their adoption in US hospitals. Section 1.4 presents some case studies demonstrating the effects of EMR adoption. Section 1.5 outlines the empirical strategy and describes the data. Section 1.6 presents the main results in the paper. Section 1.7 discusses if EMRs are worth the cost, both from the perspective of society and of a hospital. Section 1.8 concludes.

1.2 Conceptual Framework and Hypothesis Development

To direct the empirical analysis, I develop a simple model of how IT might affect service delivery in a hospital setting. The key feature of the model is the simultaneous consideration of task execution and information management. This framework yields several hypotheses about how IT affects productivity based on properties of the interaction such as its complexity and its frequency. In this section, I focus on the intuition of the model and the mapping from theory to empirical tests.

An example will help to illustrate the key ideas in this framework. Consider a patient who arrives at the emergency department with chest pain and shortness of breath. He might be diagnosed with a heart attack, necessitating the immediate initiation of well-established treatment protocols such as thrombolytic therapy and catheterization.[5] His condition could also turn out to be an exacerbation of congestive heart failure (CHF), necessitating hospital admission for medical observation and management. In the case of heart attack, which requires immediate intervention, there may not be much time to interact with the IT system. In the case of CHF, several steps have to be taken that the EMR could make more efficient. The EMR can instantaneously transmit the initial history taken by the ED doctor to the clinical team in the medical ward, who can start preparing without waiting for the paper folder to arrive. Moreover, the EMR enables parallel processing, allowing any member of the team to access the patient's information simultaneously regardless of their location in the hospital. Nurses who follow through with the doctor's instructions would not have to deal with illegible handwriting. These features could speed up the care process and reduce the probability of adverse events due to medical errors. The EMR might also address the additional needs of particularly complex patients. If the patient has multiple conditions, specialists from different medical departments can view each other's notes on the EMR before proceeding with treatment. If the patient had been to the same hospital before, clinicians can look up past notes on the EMR.

[5] Thrombolytic therapy involves the injection of clot-busting drugs, whereas catheterization entails inserting a catheter with a tiny balloon that blows up to clear the blocked blood vessel.

In light of this context, I present a more general framework, which could be applicable in any service setting. In a large firm, it is useful to divide activities between *managing* and *doing*, where managing is figuring out what to do in contrast to doing it (Radner, 1992). Given the information-intensive nature of health care, clinicians spend a substantial amount of time on such management. Therefore, I follow Radner (1992) and assume that there are two broad sets of tasks that health care providers need to be accomplish once a patient arrives at the hospital. First, there is a pre-established workflow that has to be carried out, and second, there is a body of information that has to be managed. I call the first set of activities *task execution* and the second set of activities *information management*.

Let the amount of work that has to be done for task execution be L. The time required for each unit of work is t. Therefore, the total time required for task execution is tL. Such tasks might include medication administration and the transmission of patient information such as lab results from one department of the hospital to another.

At the same time, in order to figure out what to do, clinicians need to process a certain volume of information, V, about the interaction. In addition to managing information, doctors have to communicate with each other and nurses have to communicate with doctors to figure out how exactly to take care of the patient. Let C be the cost of coordinating different employees.[6] The time required for information management, M, is a function of the volume of information and the cost of coordinating different employees and is increasing in both these variables:

$$M = f(V, C).$$

To simplify the analysis, I assume that the two activities, task execution and information management, take place simultaneously such that whichever activity requires more time acts as the bottleneck for healthcare production. The total time, T, required for production is then given by:

$$T = \max\{tL, M\}$$

Given this set-up, what is the impact of IT in a hospital? First, EMRs have the potential to

[6]For the purpose of this analysis, I assume that C is a fixed cost of communication across workers that is independent of V.

improve workflow and reduce the time required to perform each task:

$$\frac{\partial t}{\partial IT} < 0$$

There are many examples of improved operational efficiency. For instance, EMRs enable the parallel processing of information, allowing all members of the clinical team to simultaneously view the patient's record. Ancillary departments such as pathology and radiology can instantaneously transfer test results to attending physicians. Clinical decision support provides timely reminders for tasks such as medication administration and replacement of intravenous lines.

While features such as clinical decision support could also make management easier by reminding the physician of established guidelines, the effect on managerial efficiency is ambiguous since EMRs increase the amount of information about each case.

$$\frac{\partial V}{\partial IT} > 0$$

The EMR might display an excessive amount of information to the clinician, which results in information overload.[7] Part of this disruption is temporary. Over time, we should see improvements in poorly designed software that cannot synthesize clinical information smartly. However, part of this effect is permanent: more information is acquired because the cost of acquiring information has gone down. Clinicians can ask for more diagnostics at low time cost and hassle.

I also incorporate the fact that IT lowers communication costs,[8] which solves two components of coordination failure. First, IT could lower the coordination cost among workers by enabling faster communication channels between employees. Specialists who are consulted can read the patient's history on the EMR without having to get in touch with the primary team members who may not be immediately available. Second, IT could lower the coordination cost over time by facilitating storage and retrieval of information about a patient, making future encounters easier

[7] The idea that the limited bandwidth could lead to cognitive overload is well documented in the management and economics literature (Gino, 2013; Mullainathan and Shafir, 2013).

[8] Communication technologies embedded in IT systems can have large effects on firms (Garicano, 2000; Bloom *et al.*, 2009).

to manage.

$$\frac{\partial C}{\partial IT} < 0$$

Thus, improvements in IT can simultaneously affect V and C, albeit in different directions. Whether M increases or decreases as a result of investment in IT depends on which effect dominates. If the greater information management requirements outweigh the benefits from easier coordination, we will see an increase in M. On the other hand, if the benefits from coordination are bigger than the costs of managing more information, we will see a decrease in M.

The above analysis suggests that IT could have different effects on different types of patients. Some cases are relatively standard and already have protocols in place that clinicians are required to follow. A patient coming into the emergency department with a heart attack is one such example. Clear protocols exist for such cases and they are typically executed without IT. Even if such protocols are not always followed, IT might not help with management because, due to the emergent nature of these events, there is often no time to interact with the IT systems in place at the hospital. The priority is to stabilize the patient and efficient production entails bypassing the information systems.

On the other hand, when chronic medical conditions lead to hospitalization, they are often less standardized and there is scope to interact with IT systems during the course of treatment. A technology that lowers the time required to execute certain tasks can make such interactions more efficient. In particular, Autor *et al.* (2003) find that IT substituted for labor involving rules-based tasks and complemented labor involving complex communications and decision making. Task execution becomes easier for all types of interactions. However, less complex interactions that consist mainly of such rules-based tasks will benefit relatively more. Since such tasks constitute the major component of less complex interactions, delays in executing them are likely to be the bottleneck.

The benefits of improved operational efficiency might be less relevant for more complex interactions. Such cases often require input from various service providers. The delay in executing rules-based tasks, which IT can alleviate, is not the bottleneck. Rather, the time required for information management is the bottleneck. To the extent that IT makes information management more difficult, it could even slow down more complex transactions. Such complex activities might require enough customization to the specific needs of the patient that a one-size-fits-all technology designed to improve workflow might actually get in the way.[9] Moreover, to the extent that EMRs display an excessive amount of information, there could also be information overload for physicians.[10] On the other hand, since IT helps to lower coordination costs, it may make complex tasks easier by facilitating communication across multiple providers.[11] Whether IT helps with information management and hence with complex cases depends on whether the benefit of easier coordination dominates the disruptiveness of information overload for such interactions. The matrix below and the accompanying hypothesis summarizes the preceding discussion.

	Non-Standard Cases	**Standard Cases**
Less Complex Patients	Benefits	No Effects
More Complex Patients	Ambiguous Effects	Ambiguous Effects

Hypothesis 1. *IT has a larger impact for non-standard cases than for standard conditions with clear existing protocols. Among such non-standard cases, IT increases productive efficiency for less complex patients but has an ambiguous impact on more complex patients.*

There are several different mechanisms operating at the same time for more complex patients, which makes it unclear what the net effect for these patients should be. I therefore explore the impact of EMRs on these types of patients in more detail. One situation in which we would expect IT to help with more complex cases is if there is a substantial history that is involved in the interaction. Relative to complex transactions for first-time patients, IT should help with such transactions for repeat patients, because it makes coordination over time easier. For patients who are repeatedly admitted to the same hospital, EMRs can help to store data from previous visits in a readily accessible format. For instance, if the patient has an allergy to the most commonly

[9] Bartel *et al.* (2007), using unique data on IT investments in valve-making plants, find that IT leads to lower setup times, which increases the efficiency and lowers the cost of customized production. However, when an IT system is already in place and has to cater to a variety of different activities, it is hard to customize and more workarounds are involved.

[10] The medical literature has warned about too many notifications leading to alert fatigue among clinicians (Kesselheim *et al.*, 2011; Singh *et al.*, 2013).

[11] McCullough *et al.* (2013) point out that health IT may be particularly important for care coordination in complex patients who require consultation from multiple specialists.

prescribed medication for his condition, this information will show up on the EMR, leading the doctor to prescribe an alternative drug. This feature helps to avoid potential complications from an allergy that could force the patient to stay longer at the hospital or pose health risks for him. On the other hand, if the patient had been to a different hospital before, his previous information would need to be transferred by fax or in some other way.

Hypothesis 2. *EMRs have a larger positive impact on clinical outcomes for patients who have been previously admitted to the same hospital.*

In addition to having a potentially lengthy medical history, complex patients might also be candidates for multiple medical tests for any given episode of care. Certain technologies embedded in EMRs, such as computerized provider order entry (CPOE), can reduce the physician's effort cost of acquiring more information about the patient. Since CPOE makes it easy for clinicians to ask for more diagnostics to be performed, it could lead to additional services being ordered at the hospital. Typically, there is greater discretion for doctors to order more tests for the most complicated cases, and so we would expect to see this phenomenon for relatively complex patients. Such additional testing could lead to information overload, and this effect will not disappear over time, in contrast to information overload due to technological constraints, such as poorly designed software, that should improve over time.

Hypothesis 3. *Computerized provider order entry can result in more information gathering activities, leading to higher resource use at the hospital for complex patients.*

So far, I have considered heterogeneous impacts of EMRs based on patient complexity, and discussed the distinct channels for more complex patients. However, EMRs could also have different impacts based on characteristics of the adopting hospitals. For instance, one would also expect to see benefits for complex patients if certain organizational features make it easier to leverage information technology for coordination. There is a large literature showing that the gains from information technology depend upon both organizational and labor complementarities (Bresnahan *et al.*, 2002).[12] In healthcare, there are several sources of such complementarity at the

[12] For instance, Bloom *et al.* (2012) find that the US-based firms operating in the UK earned higher returns from IT investments than non-US based firms. These high returns are a consequence of US firms' internal organizational structures that complemented IT investments. Dranove *et al.* (2012) show that even though EMR adoption is associated

organizational level. I specifically explore whether the type of health insurance carried by the majority of patients modifies the impact of EMRs on complex cases. Public insurance programs, including Medicare and Medicaid, pay low rates to hospitals relative to private insurers. Hospitals with a large share of publicly insured patients, therefore, have a greater incentive to leverage EMRs for curbing resource use. Moreover, the HITECH Act proposed penalties that are calculated as a percentage of Medicare payments, if hospitals do not demonstrate the meaningful use of electronic health records by 2016.

Hypothesis 4. *Hospitals with a high share of publicly insured patients are more likely to leverage IT to help with coordination.*

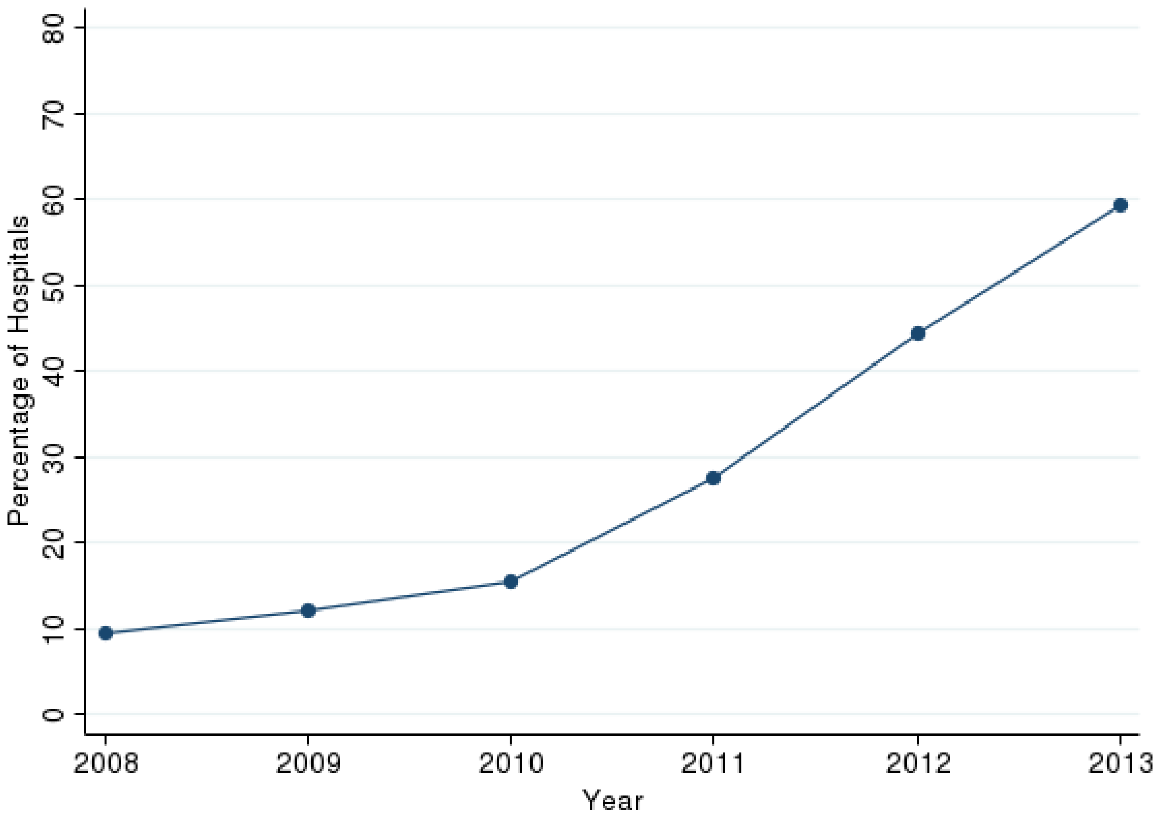
1.3 Background on the Adoption of EMRs

In order to investigate the impact of IT in the health care sector, I consider the specific example of the adoption of electronic medical records (EMRs) by hospitals. The transition to IT has been gradual in health care for several reasons. There have been few incentives, the reimbursement model does not reward process innovation, and liability is a very big consideration. However, EMRs have diffused rapidly over the time period in our study. As Figure 1.1 shows, less than 10% of U.S. hospitals had a basic EMR in 2008. This number is close to 60% by 2013.

Table 1.1 defines a basic and comprehensive EMR. An EMR has four functionalities. The first is storing information about the patient, including patient demographics, physician notes, problem lists and medication lists. All EMR systems should have this information. The second functionality is storing results such as lab reports, radiology reports and diagnostic test results. Advanced EMRs can also store images. The third functionality is computerized provider order entry (CPOE), which allows physicians to order lab tests, radiology tests, medications and consultations electronically. CPOE prevents the fulfillment of prescriptions that do not meet dosage requirements. The last category is clinical decision support (CDS), which provides clinical guidance, reminders, and various kinds of interaction alerts such as drug-drug interactions and drug-allergy interactions. For instance, CDS systems alert nurses when it is time to remove or replace a central line, reducing

with an initial increase in costs, hospitals in favorable locations with access to complementary inputs are able to lower their costs after three years

Figure 1.1: *Diffusion of Electronic Medical Records*



Calculations based on data from the AHA Health IT Supplement Survey. A basic EMR includes all the functions described in Table 1.1 present in at least one major clinical unit of the hospital.

the risk of central line-associated bloodstream infections, a common hospital-acquired condition.

Table 1.1: *Features of Basic and Comprehensive EMR*

	Basic EMR	Comprehensive EMR
Clinical Documentation	Demographic Characteristics, Physician Notes, Nursing Notes Problem Lists, Medication Lists, Discharge Summaries	Basic EMR + Advanced Directives
Test and Imaging Results	Lab Reports, Radiologic Reports, Diagnostic Test Results	Basic EMR + Radiologic Images Diagnostic Test Images, Consultant Reports
Computerized Provider Order Entry	Medications	Basic EMR + RadiologicTests, Lab Tests, Consultation Requests, Nursing Orders
Clinical Decision Support		Guidelines, Reminders, Drug-Allergy Alerts, Drug-Drug Interaction Alerts, Drug-Lab interaction Alerts, Drug Dose Support

Functionalities constituting a basic or comprehensive EMR were defined by the expert panel that developed the AHA Health IT Supplement Survey. More details can be found in the following article: Jha, Ashish K., Catherine M. DesRoches, Eric G. Campbell, Karen Donelan, Sowmya R. Rao, Timothy G. Ferris, Alexandra Shields, Sara Rosenbaum, and David Blumenthal. "Use of Electronic Health Records in US Hospitals." New England Journal of Medicine 360, no. 16 (2009): 1628-1638.

If EMRs are so helpful, why has adoption lagged behind? Providers typically cite the prohibitive cost of health IT as the key barrier to adoption. A complete EMR costs about $20 million in addition to annual operating costs of about $3 million (Laflamme *et al.*, 2010). There are several components to adopting a new EMR system: the initial fixed cost of the hardware, software, and technical assistance necessary to install the system; licensing fees; the expense of maintaining the system; and the opportunity cost of the time that health care providers could have spent seeing patients but instead must devote to learning how to use the new system and how to adjust their work practices accordingly (Orszag, 2008). Moreover, the kind of quality improvement delivered by EMRs does not lead to financial benefits because payers do not generally reimburse providers more for using EMRs and because patients or doctors rarely choose hospitals based on their EMR system (Cutler, 2014).

Over the last few years, there have been several policy changes that make this a particularly interesting time to study EMRs. The Health Information Technology for Economic and Clinical Health (HITECH) Act of 2009 authorized nearly $30 billion to increase the adoption of electronic health record systems, with much of this money in the form of incentive payments to hospitals and eligible providers for meeting specific *meaningful use*. Hospitals have until the end of 2015 to deploy certified electronic health records or face fines starting at $2,000 a bed in the first year and up to $35,000 a bed by 2019 (Laflamme *et al.*, 2010). There have been other relevant policy changes. The Affordable Care Act has promoted the formation of Accountable Care Organizations (ACOs), groups of doctors and hospitals who coordinate with each to provide care. More integrated providers such as ACOs could increase the scope for IT use. There has also been a move from volume-based payment to value-based payment. These complementary changes could also facilitate IT use in organizations that do adopt EMRs.

1.4 Case Studies of Organizations with EMRs

Many early adopters of EMRs have seen positive results. In 1996, Maimonides Medical Center (MMC), a 705-bed tertiary hospital located in Brooklyn, New York, allocated resources for the adoption of the Maimonides Access Clinical System EHR, which transformed the delivery of health care at MMC (Daurio *et al.*, 2009). MMC saw a 68% decrease in medication processing time, a 55% decrease in medication discrepancies, and a 58% reduction in problem medication orders. Duplication of ancillary orders decreased by 20% overall, including a 48% reduction in duplicate laboratory diagnostic tests. Accessibility of clinical data improved time of diagnosis and treatment, contributing to a 30.4% reduction in the average length of a patient's hospital stay.

Sentara Healthcare, a not-for-profit health care organization serving more than 2 million people in Virginia and North Carolina, implemented an EHR project over a five-year period after signing a contract with Epic in 2005. [13] The adoption of the EMR resulted in workflow improvements at the hospital. For instance, CPOE significantly reduced turn around time for order processing and patient care delivery. The average time for administration of a medication dose after order creation decreased from approximately 90 minutes to 30 minutes or less. Furthermore, the EMR resulted in improved adherence to process-of-care guidelines. From 2009 to 2010, the percentage of patients

[13] Source: Epic Systems Corporation

with angioplasty within 90 minutes of arrival increased from 78% to 90% and the percentage of outpatient surgery patients who had antibiotics started within 60 minutes of incision increased from 84% to 92%.

Patients with specific conditions such as congestive heart failure saw improvements in many settings after EMR adoption. Elderly patients are often vulnerable to the development of deep vein thrombosis (DVT) and pulmonary embolism as a result of hospitalization.[14] Despite published guidelines for the prevention of DVT, physicians often underutilize preventive treatment (prophylaxis). Brigham and Women's Hospital introduced an alert-based computerized decision support strategy and evaluated the impact on prophylaxis use and the subsequent 90-day incidence of symptomatic DVT in high-risk hospitalized patients (Piazza and Goldhaber, 2009). Electronic alerts more than doubled the rate of DVT prophylaxis orders from 14.5% to 33.5% compared with the control group and decreased the risk of symptomatic DVT by 41%. When physicians and pharmacists in Kaiser Permanente Colorado developed an electronic critical drug interaction alert program (CDIX), electronic screening was coupled with active intervention to prevent dispensing of critically interacting drug combinations. Following CDIX implementation, the overall rate of co-dispensing dropped by 31% from 21.3 to 14.7 per $10,000$ prescriptions, based on monthly electronic pharmacy data (Humphries *et al.*, 2007).

Despite the success stories, the response to EMRs has not been unanimously positive among early adopters. Many physicians complain that EMRs actually increase the amount of time they have to spend documenting actions and detract from taking care of patients (CJ *et al.*, 2014). This problem can be particular severe for more complex cases where there is a large amount of medical history. For instance, one doctor described trying to look for information in an electronic record as follows, "...it's like getting a big box full of packaging material, and there's a thumb drive in it."[15] Functionalities such as CPOE have also been known to facilitate medical errors (Koppel *et al.*, 2005; Han *et al.*, 2005). Some of these drawbacks are due to poorly designed software and should disappear with time, but some of the problems could also persist over time. In order to

[14]DVT is a blood clot that forms in a vein deep in the body, usually in the lower leg or thigh. This blood clot can break off and travel through the bloodstream to an artery in the lungs where it blocks blood flow, resulting in a very serious condition called pulmonary embolism, which can damage the lungs and other organs and lead to death

[15]<http://www.npr.org/blogs/health/2014/11/07/361148976/electronic-medical-records-built-for-efficiency-often-backfire?sc=tw>

systemically understand when EMRs are most useful and when they can be potential harmful, I next move to an empirical analysis of the effects of EMR adoption around the time of the passage of the HITECH Act.

1.5 Empirical Strategy

1.5.1 Data

In order to investigate the effect of EMR adoption on health care outcomes, I combine detailed hospital-level data on the adoption of electronic medical records with detailed hospital and patient level information from 2008 to 2011. I use data on the adoption of electronic medical records from the AHA Health IT Supplement. This survey has been conducted as a supplement to the AHA annual survey since 2008 and asks detailed questions about EMR adoption so that we know whether a hospital has each of the twenty-four functionalities listed in Table 1.1. A major advantage of this dataset is that there is a strong correlation between the measured EMR functions and the meaningful use criteria outlined in regulations that followed the HITECH Act. From the AHA Annual Survey, I obtain data on hospital characteristics including number of admissions, number of beds, ownership status, system membership, trauma center status, residency programs, medical school affiliation, hospitalist programs, and teaching intensity. I obtain outcome data at the hospital-level from Medicare's Hospital Compare website, which includes quality measures that focus on heart attack, pneumonia, and heart failure for all US acute care hospitals. Table 1.2 summarizes the characteristics of hospitals by adoption status. Relative to the early adopters, hospitals which had not yet adopted an EMR by 2011 were smaller, as measured by number of admissions and number of beds. They were also less likely to be a trauma center, have a residency program, or have a hospitalist program.

I obtain patient level data from the MEDPAR 100% inpatient Medicare claims data. I only include Medicare fee-for-service patients aged 65 and older, who have been enrolled for all twelve months of the year. The MEDPAR data allow me to investigate several dimensions of patient heterogeneity. I consider patients suffering from pneumonia, congestive heart failure (CHF), heart

Table 1.2: *Average Baseline Characteristics for Different Categories of Hospitals*

Variable	AlwaysEMR	Compliers	Non-Adopters
Hospitalist Program	0.728	0.649	0.525
Teaching Intensity (residents per bed)	0.133	0.092	0.041
Trauma Center	0.462	0.408	0.339
For-profit Hospital	0.094	0.111	0.188
Not-for-profit hospital	0.751	0.722	0.636
No. of Admissions	15455	13647	9465
No. of Beds	302	272	204
Medical School Affiliation	0.454	0.452	0.267
Residency Program	0.374	0.403	0.198
System Member	0.622	0.643	0.595
Medicaid Discharges	2975	2759	1730
Medicare Discharges	6035	5522	4049
Number of hospitals	350	367	1567

Source: AHA Annual Survey. The values of these variables are baseline characteristics from the year 2008. AlwaysEMR already had EMR in 2008. Compliers adopted EMRs in 2009, 2010 or 2011. Non-Adopters did not have EMR by 2011.

attack or acute myocardial infarction(AMI) and hip fracture.[16] Pneumonia, AMI, and CHF are common conditions with substantial mortality and morbidity, and are part of the core measure set currently reported by Medicare. These conditions impose a substantial burden on patients and the healthcare system, and there is marked variation in outcomes by institution. I also use hip fracture because it is a common reason why Medicare patients end up in the hospital.

I consider patients with AMI or hip fracture to fall in the category of diseases with clear protocols, which limits the scope for EMRs to help. For instance, in the case of AMI, time is of the essence, and clinicians have to take several steps immediately to confirm an AMI, to administer medications, and to restore blood flow to the heart. After this initial period of treatment, the remainder of the hospital stay is primarily rest and recovery. In the case of hip fracture, early surgery within 48 hours should occur for most patients, followed by rest and recovery. On the other hand, pneumonia and CHF require continuous monitoring throughout the hospital stay and there is more potential for EMRs to help. For instance, evidence-based recommendations from CDS software can help to standardize care by mitigating the consequences of variation in

[16]CHF is a condition in which the heart can no longer pump enough blood to the rest of the body. It is the most common diagnosis for the Medicare population. Pneumonia is a lung infection where treatment requires blood culture testing to determine the type of bacteria and the administration of the appropriate antibiotics. AMI results from the interruption of blood flow to a part of the heart, causing heart cells to die. It is the leading cause of death in the US.

Table 1.3: *Summary Statistics of Patient Characteristics by Primary Diagnosis*

	Pneumonia	CHF	AMI	Hip Fracture	All Patients
Age	80.14	80.71	78.73	83.42	80.58
Female	0.550	0.553	0.493	0.738	0.569
Repeat Admission	0.553	0.697	0.445	0.372	0.560
Repeat Admit at Same Hospital	0.454	0.586	0.275	0.273	0.444
High No. of Secondary DX	0.772	0.870	0.765	0.713	0.798
Admitted to Hospital with EMR	0.291	0.309	0.311	0.299	0.303
Length of Stay (Days)	5.693	5.200	5.358	5.762	5.461
Thirty Day Mortality Rate	0.095	0.088	0.112	0.062	0.090
Thirty Day Readmission Rate	0.205	0.281	0.291	0.281	0.260

Notes: Patient level data is obtained from the MedPar Inpatient Database. The column combines all patients with pneumonia, congestive heart failure, AMI, and hip fracture. The thirty-day readmission rate indicates whether the patient went back to any hospital for any reason within thirty days of discharge for a given admission. Data is from years 2008 to 2011.

physician beliefs unsupported by clinical evidence (Cutler *et al.*, 2013). Appendix A.3 shows clinical pathways for these four conditions.

The primary dependent variable I focus on to measure resource use is the length of stay for a given admission. To the extent that patients would like to stay at the hospital for as few days as possible, it can also be interpreted as a measure of quality. Adverse events and medical errors, for instance, can increase the length of stay. I also consider two explicit measures of the quality of care, the thirty-day mortality rate and the thirty-day readmission rate. Patients returning to the hospital shortly after they are discharged impose an enormous cost on Medicare, which has started to reduce payments for readmissions, exposing hospitals to considerable financial risks.[17] Table 1.3 summarizes patient-level characteristics by disease.

1.5.2 Research Design

To identify the effect of IT on outcomes, I employ a difference-in-difference identification strategy, relying on variation in the timing of adoption of electronic medical records. For my baseline

[17]In its patient safety and quality initiative, the Centers for Medicare and Medicaid Services has estimated the cost of avoidable readmissions at more than $17 billion a year. In fiscal year 2013, hospitals faced a penalty equal to 1% of their total Medicare billings if an excessive number of patients are readmitted. The penalty rises to 2% in 2014 and 3% in 2015

specifications, I estimate the following regressions at the patient level:

$$Y_{iht} = \beta_1 EMR_{ht} + \beta_2 EMR_{ht} * Complex_{iht} + \alpha_j + \gamma_t + \delta_1 X1_{ht} + \delta_2 X2_{iht} + \epsilon_{ijt}$$

Y_{iht} is the outcome variable for patient i, admitted to hospital h at time t. I study three patient-level outcomes: length of stay, thirty-day mortality and thirty-day readmission. EMR_{ht} is an indicator variable for whether hospital h has adopted a basic EMR system in year t or in an earlier year. $Complex_{iht}$ is an indicator variable for whether a given admission is a complex patient. I measure the complexity of the patient in two distinct ways: the number of secondary diagnoses that is associated with each inpatient admission and whether patients have been hospitalized in the last twelve months. A large number of secondary diagnoses or frequent hospitalization indicates a higher level of complexity.[18] The coefficients β_1 and β_2 are of particular interest. β_1 represents the effect of EMRs for simple patients, and β_2 indicates the marginal impact on complex patients in addition to the baseline effect. The mean effect on complex patients is given by the sum of these two coefficients. $X1_{ht}$ is a vector of hospital characteristics including number of admissions, number of beds, ownership status, teaching status, hospitalist use, system membership, trauma center status, and the number of Medicare and Medicaid discharges. Hospital fixed effects, α_j, control for unobserved hospital characteristics that do not change over time, and year fixed effects, γ_t, control for time trends that affect all hospitals. Patient-level characteristics, $X2_{iht}$, include age, sex, race, and the interactions of these demographic variables, past admission, and a set of diagnosis-related group (DRG) dummies. When estimating these regressions, I ensure that the standard errors, ϵ_{ijt}, are clustered at the hospital level to account for correlation across patients within the same hospital and for the same hospital over time.

Under the HITECH Act, different hospitals received different incentive payments based on the number of admissions as well as the Medicare and Medicaid share of patients. In line with some recent literature (Dranove *et al.*, 2014), I find empirical evidence that the subsidies stimulated the adoption of EMRs.[19] However, this association is not strong enough to use the HITECH subsidies

[18] I assign patients with more than 8 secondary diagnoses as complex patients, which leads to about 2/3rds of the patient being categorized as complex. The Medpar data are top coded at 9 secondary diagnoses prior to 2011, so it is not possible to use a higher threshold for complexity.

[19] An additional \$1 million of incentive payments is associated with an increase in the probability of EMR adoption of more than 2 percentage points.

as an instrument for EMR adoption as part of a viable instrumental variable strategy. Therefore, I rely on variation in the timing of adoption to identify the effect of EMRs on patient-level outcomes.

The variation in EMR use is at the hospital-by-year level, so the key identifying assumption is that the adoption decision is independent of other hospital-by-year shocks. Several robustness tests validate this assumption. For a given patient, being part of the treatment group is getting admitted to a hospital which adopted a basic EMR system between 2009 and 2011. I look at the difference between members of this group before and after IT adoption at the hospital, relative to the trend in the control group, which comprises patients admitted to hospitals that already had a basic EMR system by 2008 or did not yet adopt EMRs by 2011. The parallel trends assumption is that patients admitted to hospitals which adopted EMRs during this period experience the same trends in the outcome measures as patients admitted to other hospitals.

The most plausible threat to identification is the adoption of concurrent hospital-wide quality improvement initiatives. If hospitals were engaging in other quality improvement initiatives at the same time as they were adopting electronic medical records, my estimates would be biased. The crux of my argument relies on the heterogeneous impact of EMRs on different types of patients. Therefore, such unobserved quality improvements would need to have a similar differential impact on patients. While it is possible that there were unobserved hospital-level changes over this time period, it is less likely that were unobserved management changes that had the same pattern of effects on different types of patients. Moreover, it is reasonable to interpret any management initiatives that were rolled out along with IT systems as part of the treatment effect. Such initiatives are clearly sufficiently complementary with the digitization of medical records to go hand in hand with EMR adoption.

One potential issue with EMRs is that hospitals may be using them to game the system by engaging in *upcoding* behavior such as inflating the number of diagnoses. This issue is of particular concern in my case since I use the number of diagnoses as one measure of patient complexity. There have been widespread stories about hospitals strategically using the better documentation made possible by EMRs to select billing codes that reflect more intensive care or a sicker patient population, thus leading to higher reimbursement (Abelson *et al.*, 2012).[20] I directly test for such

[20]EMRs may degrade the quality of documentation by enabling record cloning - copying and pasting the same examination findings into the records for multiple patients -which could similarly drive up reimbursement by

gaming behavior in my sample by investigating the effect of EMR adoption on the reported number of secondary diagnoses. Table A.4 in Appendix A shows the results of this empirical exercise. I find no statistically significant relationship between EMR adoption and the number of secondary diagnoses reported.

Another concern with this research design is that patients could be selectively sorting into hospitals with EMRs. If healthier patients are more likely to do this, I would find a positive impact of EMRs where none exists. But there is some evidence that this scenario is unlikely. Consumers still have a very limited idea about the quality of their health care providers. Evidence from the introduction of hospital report cards suggests that patient preferences are weakly related to measurable quality and therefore IT utilization is unlikely to affect hospital volumes(Cutler *et al.*, 2004). Thus, it is reasonably unlikely that there is significant patient sorting due to consumers choosing hospitals on the basis of whether they have EMRs. In particular, I find that there is no significant change in the number of admissions to a hospital following EMR adoption as shown in Table A.1 in Appendix A.

1.6 How Do EMRs Affect Patient Outcomes?

In order to provide context for the patient-level analysis, I start by investigating outcomes at the hospital level to estimate the average effect of EMR adoption on hospital level outcomes. Using a difference-in-difference framework, I find that there are very small effects on length of stay and clinical outcomes over the first few years. Table 1.4 summarizes these findings, which are robust to the use of different empirical strategies.[21]

For all four conditions that I study, EMR adoption has no statistically significant effect on length of stay, thirty-day mortality or thirty-day readmission. The effect on length of stay is less than 1% in all cases, and the effect on mortality and readmission is less than half a percentage

documenting and then billing for care that did not occur. Adler-Milstein and Jha (2014) find no evidence of upcoding whereas Li (2013) finds some evidence for upcoding.

[21] I conduct an event study analysis, looking at hospitals which adopted EMR at different times, and check for changes in the outcome variables following adoption of EMRs. I also use a propensity score matching method to compare similar hospitals, to check if the the adoption of EMRs is associated with any change in hospital level outcomes. I create three groups of hospitals: those which already had basic EMR by 2008; those which adopted EMR between 2009 and 2011; and those which had not adopted EMR by 2011. I then compare the change in outcome variables in each group relative to matched controls from each of the other groups.

Table 1.4: *Effect of EMR on Hospital Level Outcomes*

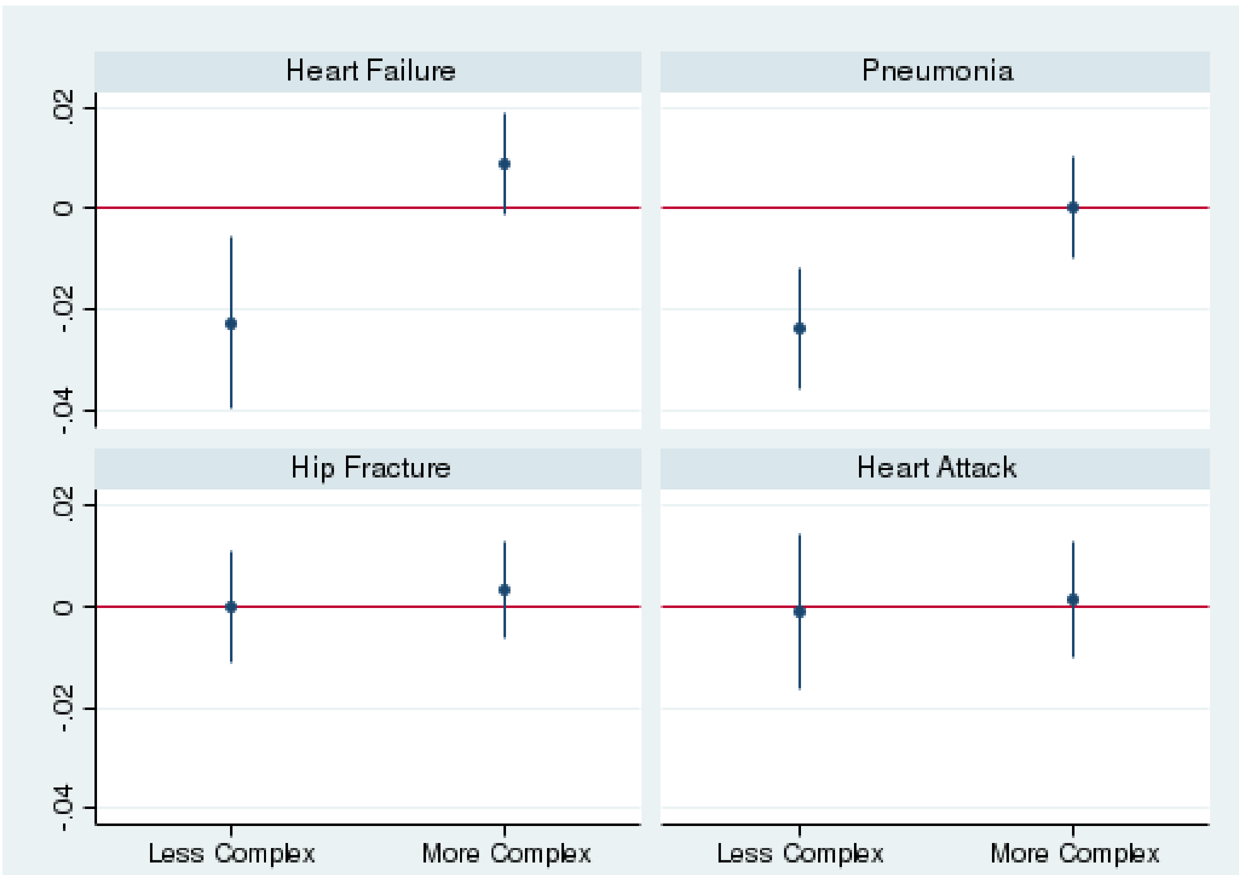
Effect of EMR on Hospital-Level Outcomes by Disease			
	Log Length of Stay	**Thirty-Day Mortality Rate**	**Thirty-Day Readmission Rate**
Disease			
Pneumonia	-0.00854	-0.000267	-0.00189
	(0.00729)	(0.00208)	(0.00324)
CHF	0.00833	0.000490	0.000747
	(0.00751)	(0.00196)	(0.00301)
AMI	-0.0000613	-0.00297	0.000210
	(0.00951)	(0.00277)	(0.00447)
Hip Fracture	0.00306	-0.000763	0.00400
	(0.00723)	(0.00237)	(0.00544)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Standard errors are in parentheses and are clustered at the hospital level. Each coefficient represents the effect of EMR adoption on the outcome variable for the given disease, based on hospital-level regressions of the outcome on EMR adoption. All regressions include hospital and year fixed effects, as well as a set of hospital-level control variables including size, ownership status, teaching status, hospitalist use, system membership, trauma center status, and Medicare/Medicaid discharges.

point. These results are in line with some recent studies, which also find small impacts of EMRs at the hospital level (Agha, 2014; McCullough *et al.*, 2010).

However, theory suggests that patient level heterogeneity in outcomes is important. Therefore, in order to understand how EMRs affect productive efficiency and coordination at the patient level, I move to patient level data. Hypothesis 1 predicts that EMRs will have different impacts on different kinds of patients. To test these predictions, I estimate equation (1) separately for all four conditions that I study. Tables 1.5, 1.6 and 1.7 show the results of these regressions. In these tables, $Complex$ is a binary variable indicating that the patient has a high number of secondary diagnoses.

Figure 1.2: *Effect of EMR on Length of Stay by Disease and Patient Complexity*



The y-axis shows the percentage change in length of stay after EMR adoption, divided by 100. These values are based on the regression results shown in Table 5 for less complex patients and more complex patients. Standard error bars show 95% confidence intervals.

Table 1.5: *Effect of EMR on Length of Stay*

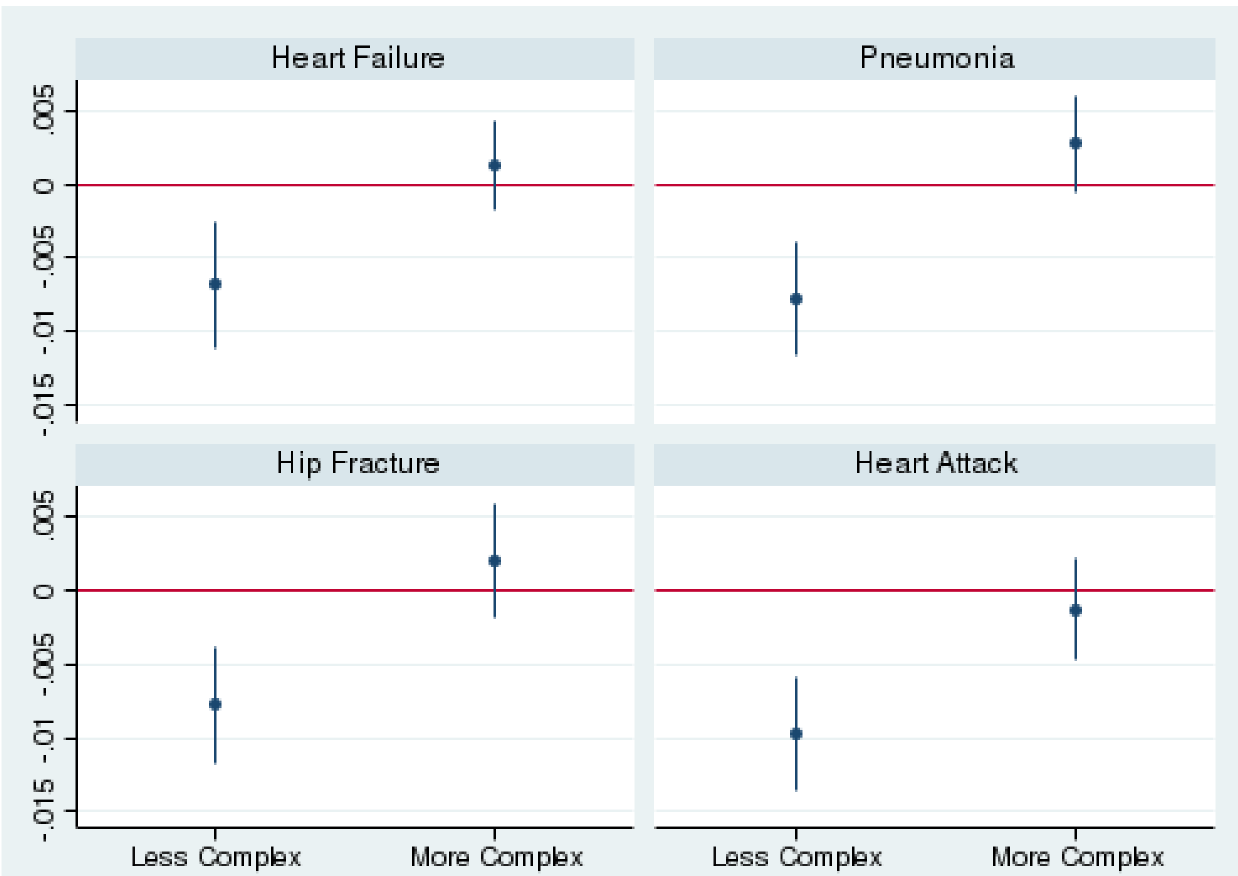
	Dependent Variable: Log Length of Stay							
	Pneumonia		CHF		AMI		Hip Fracture	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EMR	-0.00460	-0.0239***	0.00568	-0.0226**	0.000813	-0.00105	0.00230	-0.0000940
	(0.00480)	(0.00607)	(0.00493)	(0.00859)	(0.00547)	(0.00782)	(0.00467)	(0.00551)
EMR*Complex		0.0241***		0.0314***		0.00233		0.00326
		(0.00536)		(0.00831)		(0.00778)		(0.00439)
N	864927	864927	1061605	1061605	512958	512958	427160	427160
adj. R^2	0.273	0.273	0.242	0.242	0.415	0.415	0.308	0.308
F-Test (EMR + EMR*Complex=0)		0.967		0.0818		0.827		0.516

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Standard errors are in parentheses and are clustered at the hospital level. All regressions include hospital and year fixed effects, as well as a set of hospital-level control variables including size, ownership status, teaching status, hospitalist use, system membership, trauma center status, and Medicare/Medicaid discharges. Patient-level characteristics include age, sex, race, and the interactions of these demographic variables, past admission, and a set of diagnosis-related group (DRG) dummies.

The odd-numbered columns in Table 1.5 show results from patient level regressions and indicate that, on average, EMR adoption is not significantly associated with a change in length of stay for patients with any of the four diseases. I also show results from regressions in which I interact EMR adoption with an indicator variable for patient complexity. The first row in the even-numbered columns of Table 1.5 shows results for less complex patients. I find that for CHF and pneumonia patients with a low number of secondary diagnoses, EMR adoption is associated with a decrease of more than 2% in the length of stay. The second row shows the impact of EMRs on more complex patients relative to less complex patients, and there is a statistically significant difference between patients in these two categories. To get the overall effect on more complex patients we sum up the first and second row. It appears that while EMR adoption is associated with a slight increase in length of stay for more complex patients, this result is not statistically significant. I contrast my results for CHF and pneumonia patients with those for patients who suffer from an AMI or a hip fracture. As indicated by column 6 and column 8, results for patients with AMI and hip fracture are in the same direction, but they are much smaller in magnitude and not statistically significant. These findings are robust to dropping outliers with particularly high lengths of stay from the analysis. I estimate these specifications after dropping patients above the 95th percentile with lengths of stay greater than 13 days, and find quantitatively similar results.

One concern with using the length of stay as a dependent variable is that it is not an ideal measure of the quality of care. The quality of care might actually be worse if patients are being rushed out too quickly. Therefore, I test how the quality of care is affected by looking at the thirty-day mortality rate and the thirty-day readmission rate for patients in my sample. Tables 1.6 and 1.7 show results with these quality measures as the dependent variables. I find no evidence that there is lower quality of care associated with shorter lengths of stay. In fact, the results are in the same direction as the length of stay results. As Table 6 indicates, thirty-day mortality is reduced by roughly 0.8 percentage points for less complex patients, with no significant impact for more complex patients. According to Table 1.7, thirty-day readmission is also reduced by 0.8 percentage points for less complex patients, with no significant impact for more complex patients. The mortality results hold even for AMI and hip fracture patients, while the readmission results hold for AMI patients. It appears that EMR adoption is associated with changes in quality outcomes for less complex patients in such cases, even though it does not significantly affect

Figure 1.3: *Effect of EMR on Thirty-Day Mortality by Disease and Patient Complexity*



The y-axis shows the percentage point change in mortality rate after EMR adoption, divided by 100. These values are based on the regression results shown in Table 6 for less complex patients and more complex patients. Standard error bars show 95% confidence intervals.

the length of stay. Additionally, I use a combined measure and estimate regressions in which the dependent variable is either mortality or readmission within thirty days of discharge. I find quantitatively similar results.

Table 1.6: *Effect of EMR on Thirty Day Mortality Rate*

	Dependent Variable:Thirty Day Mortality							
	Pneumonia		**CHF**		**AMI**		**Hip Fracture**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EMR	0.000622	-0.00775***	0.000458	-0.00686**	-0.00304	-0.00979***	-0.000611	-0.00777***
	(0.00160)	(0.00196)	(0.00154)	(0.00218)	(0.00163)	(0.00196)	(0.00184)	(0.00199)
EMR*Complex		0.0105***		0.00814***		0.00850***		0.00976***
		(0.00168)		(0.00180)		(0.00171)		(0.00173)
N	870084	870084	1070108	1070108	526359	526359	428546	428546
adj. R^2	0.096	0.096	0.081	0.081	0.411	0.411	0.106	0.106
F-Test (EMR + EMR*Complex=0)		0.104		0.410		0.455		0.318

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Standard errors are in parentheses and are clustered at the hospital level. All regressions include hospital and year fixed effects, as well as a set of hospital-level control variables including size, ownership status, teaching status, hospitalist use, system membership, trauma center status, and Medicare/Medicaid discharges. Patient-level characteristics include age, sex, race, and the interactions of these demographic variables, past admission, and a set of diagnosis-related group (DRG) dummies.

Table 1.7: *Effect of EMR on Thirty Day Readmission Rate*

	Dependent Variable:Thirty Day Readmission							
	Pneumonia		**CHF**		**AMI**		**Hip Fracture**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EMR	-0.00129	-0.00870**	-0.0000547	-0.00845*	-0.000528	-0.0117*	0.00380	-0.000916
	(0.00255)	(0.00313)	(0.00235)	(0.00377)	(0.00342)	(0.00498)	(0.00426)	(0.00514)
EMR*Complex		0.00941***		0.00939**		0.0144**		0.00654
		(0.00251)		(0.00325)		(0.00471)		(0.00420)
N	794559	794559	988246	988246	469337	469337	404099	404099
adj. R^2	0.032	0.032	0.022	0.022	0.094	0.094	0.139	0.139
F-Test (EMR + EMR*Complex=0)		0.786		0.692		0.463		0.208

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Standard errors are in parentheses and are clustered at the hospital level. All regressions include hospital and year fixed effects, as well as a set of hospital-level control variables including size, ownership status, teaching status, hospitalist use, system membership, trauma center status, and Medicare/Medicaid discharges. Patient-level characteristics include age, sex, race, and the interactions of these demographic variables, past admission, and a set of diagnosis-related group (DRG) dummies.

It is evident there are several simultaneous channels operating for more complex patients. EMRs might be disruptive for such cases to the extent that they result in information overload and impose standardization. On the other hand, EMRs may facilitate improved care coordination. In order to understand the specific circumstances under which EMRs are most helpful for such cases, I next present results on what factors could modify the effect of EMRs on the outcomes for more complex patients who repeatedly come back to the hospital.

1.6.1 Storage of Information over Time

Hypothesis 2 predicts that repeated interaction at the same facility is one situation in which EMRs help to solve the coordination problem for complex patients. To test this prediction, I estimate a version equation (1) in which I measure complexity by previous hospitalization. In particular, I interact the EMR adoption variable with an indicator variable for whether the patient had been hospitalized in the last 12 months. I also include a triple interaction term which additionally indicates if the previous admission was at the same hospital.

Tables 1.8 through 1.10 show results from this specification. Patients who have been hospitalized in the previous twelve months have higher lengths of stay in the presence of EMRs but this effect disappears for those patients coming back to the same hospital. Column 2 in Table 1.8 indicates that for pneumonia patients coming to a hospital with an EMR, being a repeat admit is associated with a 2.59 percentage point increase in the length of stay relative to those who had not been admitted to a hospital in the preceding twelve months. However, if the previous admission was at the same hospital, this effect is reduced by 1.39 percentage points. Thus, more than half the relative effect of being a complex patient disappears. Column 4 shows that this phenomenon is even starker for patients with congestive heart failure. Being a repeat admit is associated with a 2.73 percentage point increase in the length of stay relative to those who had not been admitted to a hospital in the preceding twelve months. This effect is reduced by 2.37 percentage points if the previous admission was at the same hospital.

Table 1.8: *Effect of EMR on Length of Stay*

	Dependent Variable: Log Length of Stay							
	Pneumonia		**CHF**		**AMI**		**Hip Fracture**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EMR	-0.00460	-0.0117*	0.00568	0.000377	0.000813	0.000858	0.00230	0.00418
	(0.00480)	(0.00492)	(0.00493)	(0.00520)	(0.00547)	(0.00568)	(0.00467)	(0.00498)
EMR*Readmission		0.0259***		0.0273***		0.0154		0.00718
		(0.00548)		(0.00656)		(0.0109)		(0.00592)
EMR*Readmission*SameHospital		-0.0139*		-0.0237***		-0.0254*		-0.0139*
		(0.00548)		(0.00653)		(0.0112)		(0.00636)
N	864927	864927	1061605	1061605	512958	512958	427160	427160
adj. R^2	0.273	0.258	0.242	0.228	0.415	0.398	0.308	0.289
F-Test (EMR + EMR*Readmission = 0)		0.0367		0.000353		0.117		0.0912
F-Test ($\sum$ All 3 Coefficients = 0)		0.955		0.437		0.201		0.648

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Standard errors are in parentheses and are clustered at the hospital level. All regressions include hospital and year fixed effects, as well as a set of hospital-level control variables including size, ownership status, teaching status, hospitalist use, system membership, trauma center status, and Medicare/Medicaid discharges. Patient-level characteristics include age, sex, race, and the interactions of these demographic variables, past admission, and a set of diagnosis-related group (DRG) dummies.

Interestingly, in columns 6 and 8, we see a statistically significant effect even for heart attack and hip fracture patients who have been to the same hospital before. In the baseline, going to a hospital with an EMR does not affect the length of stay for these patients, whether they have been to admitted to a hospital within the last twelve months or not. However, having been admitted to the same hospital in the last twelve months changes the effect on length of stay by 2.54 percentage points for AMI patients, and 1.39 percentage points for hip fracture patients. It is possible that when such patients are registered at the ED, their patient records provide information, for instance on drug allergies, that enable doctors to treat them better. There is no time to further interact with the EMR before providing the most crucial elements of the treatment other than a quick automatic check to see any relevant information in case of previous admission. I repeat these regressions using thirty-day mortality and thirty-day readmission as dependent variables but, as shown in Tables 1.9 and 1.10, there are no statistically significant results for these outcome measures.

Table 1.9: *Effect of EMR on Thirty Day Mortality Rate*

	Dependent Variable:Thirty Day Mortality							
	Pneumonia		**CHF**		**AMI**		**Hip Fracture**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EMR	0.000622 (0.00160)	-0.00272 (0.00171)	0.000458 (0.00154)	-0.00452** (0.00165)	-0.00304 (0.00163)	-0.00398* (0.00167)	-0.000611 (0.00184)	-0.00220 (0.00191)
EMR*Readmission		0.00945*** (0.00268)		0.00628** (0.00206)		-0.00115 (0.00222)		0.00414 (0.00285)
EMR*Readmission*SameHospital		-0.00417 (0.00270)		0.000911 (0.00211)		0.00581* (0.00274)		0.000595 (0.00320)
N	870084	870084	1070108	1070108	526359	526359	428546	428546
adj. R^2	0.096	0.099	0.081	0.082	0.411	0.411	0.106	0.106
F-Test EMR + EMR*Readmission = 0		0.0166		0.444		0.0457		0.528
F-Test ($\sum$ All 3 Coefficients = 0)		0.172		0.118		0.765		0.295

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Standard errors are in parentheses and are clustered at the hospital level. All regressions include hospital and year fixed effects, as well as a set of hospital-level control variables including size, ownership status, teaching status, hospitalist use, system membership, trauma center status, and Medicare/Medicaid discharges. Patient-level characteristics include age, sex, race, and the interactions of these demographic variables, past admission, and a set of diagnosis-related group (DRG) dummies.

Table 1.10: *Effect of EMR on Thirty Day Readmission Rate*

	Dependent Variable:Thirty Day Readmission							
	Pneumonia		**CHF**		**AMI**		**Hip Fracture**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EMR	-0.00129	-0.00670**	-0.0000547	-0.00627*	-0.000528	-0.00301	0.00380	-0.000443
	(0.00255)	(0.00259)	(0.00235)	(0.00271)	(0.00342)	(0.00370)	(0.00426)	(0.00445)
EMR*Readmissiont		0.0125***		0.00726*		0.00222		0.0158**
		(0.00375)		(0.00364)		(0.00430)		(0.00571)
EMR*Readmission*SameHospital		-0.00292		0.00190		0.00788		-0.00523
		(0.00388)		(0.00350)		(0.00501)		(0.00596)
N	794559	794559	988246	988246	469337	469337	404099	404099
adj. R^2	0.032	0.042	0.022	0.030	0.094	0.096	0.139	0.139
F-Test (EMR + EMR*Readmission $= 0$)		0.164		0.785		0.868		0.0194
F-Test ($\sum$ All 3 Coefficients $= 0$)		0.316		0.258		0.126		0.0565

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Standard errors are in parentheses and are clustered at the hospital level. All regressions include hospital and year fixed effects, as well as a set of hospital-level control variables including size, ownership status, teaching status, hospitalist use, system membership, trauma center status, and Medicare/Medicaid discharges. Patient-level characteristics include age, sex, race, and the interactions of these demographic variables, past admission, and a set of diagnosis-related group (DRG) dummies.

Table 1.11: *Effect of CPOE on Hospital Charges for Pneumonia and Heart Failure*

	Dependent Variable: Log Billed Charges			
	Pneumonia		CHF	
	Laboratory	**Radiology**	**Laboratory**	**Radiology**
CPOE	-0.00736	-0.00492	-0.00958	-0.0124
	(0.00627)	(0.00706)	(0.00736)	(0.00787)
CPOE*Readmission	0.0236***	0.0274**	0.0479***	0.0465***
	(0.00625)	(0.00980)	(0.00893)	(0.0115)
CPOE*Readmission (Same Hospital)	-0.0232***	-0.0216*	-0.0418***	-0.0481***
	(0.00602)	(0.00965)	(0.00823)	(0.0110)
N	840736	834995	1028903	1015707
adj. R^2	0.489	0.242	0.461	0.208
F-Test (p value) (CPOE+CPOE*Readmission=0)	0.0332	0.0308	0.000107	0.00289
F-Test (p value) ($\sum$ All 3 Coefficients = 0)	0.261	0.896	0.604	0.0363

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors are in parentheses and are clustered at the hospital level. All regressions include hospital and year fixed effects, as well as a set of hospital-level control variables including size, ownership status, teaching status, hospitalist use, system membership, trauma center status, and Medicare/Medicaid discharges. Patient-level characteristics include age, sex, race, and the interactions of these demographic variables, past admission, and a set of diagnosis-related group (DRG) dummies.

1.6.2 Effect of CPOE on Hospital Charges

It is possible that doctors spend more resources when certain features of an EMR such as computerized physician order entry are available. Such features potentially make it easier for doctors to order tests and get more information.

Table 1.11 shows that, in the case of pneumonia and heart failure, CPOE increases both laboratory and radiology charges for more complex patients who repeatedly end up in the hospital. Note that in these specifications, hospital fixed effects control for different average prices across hospitals. For complex cases, there is more scope to learn about the patient, which is why there is an opportunity for physicians to order a large number of tests. For pneumonia patients, being a frequent patient is associated with a 2.35 percentage point increase in lab charges and a 2.74 percentage point increase in radiology charges relative to being a patient who has not been admitted to a hospital in the past twelve months. The effect is greater for heart failure patients for whom the corresponding increases are 4.79 and 4.65 percentage points.

Such additional tests and imaging could be one explanation for the relatively longer lengths of stay that these patients experience. Not only do the tests take time, but they could also result in information overload for any other clinician who is subsequently involved in the patient's care during the hospital stay. This effect is greatly reduced if patients have been to the same hospital before, possibly because some necessary information is already stored in the electronic medical record. For both pneumonia and heart failure patients, the relative increase in billed charges due to being a repeat admit disappears if the previous admission was at the same hospital.

Some of the additional services could be beneficial for more complex patients, but the findings also support the view that computerized order entry could have unintended consequences that act as a countervailing force to the faster ordering and administration of medications.

1.6.3 Interaction of Payer Type with EMR Use

The types of insurance plans that a hospital deals with could influence how it uses EMRs. Hospitals that have a higher share of Medicare and Medicaid patients are under relatively more financial pressure, because Medicare, and especially Medicaid, reimburses hospitals less generously relative to private insurers. Such hospitals are more likely to focus on leveraging EMRs to curb resource use. Therefore, one would hypothesize that the financial benefits of EMRs would be most obvious in hospitals with a high share of publicly insured patients since physicians have an incentive to learn how to use them properly. I test this hypothesis in Table 1.12 and find that complex CHF and pneumonia patients in such hospitals have relatively lower lengths of stay.

For pneumonia patients, being a repeat admit is associated with a 2.21 percentage point increase in the length of stay. However, if the hospital has an above median share of publicly insured patients, this effect is reduced by 1.71 percentage points. There is a similar effect for CHF patients, where the corresponding numbers are 1.39 percentage points and 1.48 percentage points. I do not observe any statistically significant effect for AMI and hip fracture patients.

Taken together, the results in this section provide evidence for the heterogeneous impacts of EMRs for different types of patients. The effects are more prominent for chronic medical conditions such as heart failure and pneumonia than for protocol-driven conditions such as hip fracture or heart attack. For the chronic diseases, there is also a larger impact for less complex patients with a lower number of secondary diagnoses. By improving workflow at the hospital,

Table 1.12: *Effect of EMR on Length of Stay by Publicly Insured Share of Patients*

	Dependent Variable: Log Length of Stay			
	Pneumonia	CHF	AMI	Hip Fracture
EMR	-0.00685	0.00546	0.00869	0.00751
	(0.00594)	(0.00670)	(0.00803)	(0.00644)
EMR*HighPublicInsurance	-0.00967	-0.00947	-0.0139	-0.00615
	(0.00912)	(0.00956)	(0.0111)	(0.00919)
EMR*Readmission	0.0221***	0.0139***	-0.00860	-0.00273
	(0.00413)	(0.00405)	(0.00859)	(0.00498)
EMR*HighPublicInsurance*Readmission	-0.0171**	-0.0148*	0.0145	-0.000478
	(0.00606)	(0.00617)	(0.0107)	(0.00560)
N	841858	1031316	496472	414890
adj. R^2	0.257	0.227	0.397	0.289

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Standard errors are in parentheses and are clustered at the hospital level. All regressions include hospital and year fixed effects, as well as a set of hospital-level control variables including size, ownership status, teaching status, hospitalist use, system membership, trauma center status, and Medicare/Medicaid discharges. Patient-level characteristics include age, sex, race, and the interactions of these demographic variables, past admission, and a set of diagnosis-related group (DRG) dummies.

EMRs can help to relieve the bottleneck for such cases. Delving deeper into more complex cases, I find evidence that EMRs help with coordination over time: there is a more beneficial impact for patients who come back to the same hospital. However, EMRs could also disrupt care for complex cases by creating information overload for clinicians. One reason is that the software is still in its infancy and cannot smartly synthesize all the relevant clinical information. This disruptive effect should disappear over time but there is a more permanent effect because technologies such as computerized order entry (CPOE) lower the cost of acquiring information. In line with this theory, I find that CPOE is associated with additional laboratory and radiology charges. Finally, I find that EMRs are more effective in hospitals with a higher share of publicly insured patients and a correspondingly greater incentive to curb resource use.

1.7 Are EMRs Worth It?

Technological innovation, primarily in the form of new products and services, accounts for a large proportion of the increase in health care costs over the last few decades (Newhouse, 1992). In contrast, process innovations such as EMRs can actually help to reduce costs in addition to improving the quality of health care. But EMRs require substantial upfront investment and, like other business process innovations, need complementary organizational change to be successful. For a 200 bed hospital, the initial cost of an EMR is \$20 million and the annual operating cost is \$3 million (Laflamme *et al.*, 2010). Assuming that a system lasts ten years before it has to be replaced, the fixed cost can be amortized to \$2 million per year. Thus, the total cost per year is \$5 million. Is this sum a worthwhile investment? In light of the results in the previous section, it is possible to formulate a rough answer to this question.

First, consider the impact of EMRs on length of stay. The marginal cost of an additional day at the hospital is approximately \$600 (Bartel *et al.*, 2014). I find that EMR adoption is associated with a 2% reduction in length of stay for less complex patients, which is equivalent to a reduction of 0.1 days given that the average length of stay is roughly 5 days. If hospitals could achieve this reduction for all patients, the cost per patient would decrease by \$60. For an average hospital that treats $10,000$ patients per year, which is reasonable based on Table 1.2, this amount translates to annual savings of \$0.6 million. Next, consider the impact of EMRs on mortality. Murphy and Topel (2006) estimate the value of a life-year for an 80-year old, the approximate mean age of patients in my sample, to be $\$150,000$, or slightly more than $\$200,000$ in 2014 dollars. I find EMR adoption to be associated with a reduction in mortality of 0.8 percentage points for less complex patients. Suppose that this reduction can be extrapolated to all patients with one caveat. Since not all hospitalized patients are at a serious risk of dying, as a rough estimate let me assume that 30-day mortality is a relevant outcome only for Medicare patients, who make up about 40% of hospital admissions. In that case, an average hospital that sees $4,000$ Medicare patients per year will save 32 lives or \$6.4 million based on the Murphy and Topel (2006) estimate.

While this calculation relies on many assumptions, at first glance, the estimated benefit exceeds the cost of adopting an EMR system. One important assumption is the extrapolation of the results I find for less complex patients to all patients. I believe that this paper underestimates the potential benefits of EMRs for more complex patients because of the absence of interoperability during the time period of this study. Without interoperable EMRs, it is hard to retrieve previous information about the patient if they had been to a different hospital before or to transfer records from physician practices.

In fact, handoffs across care settings are the most critical points at which information about the patient is likely to get lost (Wachter *et al.*, 1999). The fact that EMRs are not interoperable across hospitals or between hospitals and outpatient clinics makes such loss of information more likely. In recent years, it has become more important to prevent such loss of information because of the emergence of hospitalists who take over the responsibility for patients who are admitted to hospitals by their PCPs. Unlike PCPs, hospitalists have had no prior interaction with the patient and therefore would find the patient history contained in the EMR particularly useful. In some health systems, it is possible for clinicians at the hospital to access records from affiliated physician practices, but this arrangement is the exception rather than the rule. The government has required that installed EMRs have the ability to exchange clinical information, but the first stage meaningful use criteria do not stipulate that hospitals actually exchange information. As the second stage goes into effect, we are likely to see greater interoperability of EMRs and potentially larger benefits for more complex patients who interact with the health care system through multiple organizations.

Even if the social benefits of EMRs exceed the costs, it might not be worth it for hospitals to invest in EMRs because they cannot fully internalize the benefits. To the extent that hospitals care about patient health, they internalize some of the benefits. Hospitals also benefit from efficiency improvements such as reduction in nurses' unproductive time and savings in medical records departments. However, insurance companies do not reimburse more for hospitals with an EMR. Moreover, if patients are not aware that hospitals are using EMRs and that they are achieving better outcomes, it might not be possible for hospitals to gain market share. Hospitals have traditionally not realized most of the clinical savings that accrue from greater operational efficiency. This situation is a stark contrast to other industries and is largely a product of fee-for-service reimbursement models, which reward providers for performing more services. Indeed, hospitals paid on a fee-for-service basis might actually lose money if patients stay fewer days but those paid via a prospective payment system might benefit because they get to keep any cost savings

The recent surge in hospital adoption of EMRs indicates that the HITECH Act and concurrent policy changes have been successful in tilting the balance in favor of EMR adoption. While the HITECH Act did not provide enough subsidies to fully cover the cost of installing an EMR system, it did promise a substantial amount. Based on the formulas, a hospital with 10,000 admissions per year, of which 60% are either Medicare or Medicaid patients, could receive around $6 million over the course of several years, which is about a third of the initial cost of an EMR. While this amount does not seem to be a substantial portion of the cost, it could well push many hospitals over the margin once they account for the benefits of EMR adoption.

1.8 Conclusion

As the price of computing power has fallen, computers have increasingly displaced workers in accomplishing explicit, codifiable tasks that follow precise procedures (Autor, 2014). On the other hand, computers cannot improvise solutions for unexpected cases and automation is difficult for tasks requiring flexibility and judgment (Levy and Murnane, 2012). It is possible that IT has a more nuanced impact on healthcare organizations than it did in other service industries because such complex tasks form a larger proportion of what doctors have to do. There is more variability and uncertainty at the point of service in health care than in any other economic activity. In the absence of an inventory of standardized health services, clinicians must customize their work at the point of care on a "just-in-time" basis (Burns, 2012). Moreover, the consequences of production mistakes can be large in health care, both in terms of quality and in terms of cost.[22] Since two of the biggest culprits behind the high level of health care spending in the US are operational inefficiency and lack of coordination (Cutler, 2011), I frame the adoption of health IT in terms of its effects on operational efficiency and care coordination.

I investigate these mechanisms in a hospital setting by looking at the impact of EMR adoption on the length of stay and quality of care. I find reductions in length of stay and improvements in quality outcomes for less complex patients with congestive heart failure and pneumonia. For such cases, coordination is less likely to be an important part of the production process, and I attribute the results to an improvement in operational efficiency. In contrast, I find that there are no improvements on average for more complex patients for whom coordination is more likely to be important. Thus the beneficial effects of easier coordination do not appear to outweigh the disruption that EMRs entail for such complex cases.

The theory highlights several reasons why this technology might make production inefficient

[22] According to studies reviewed by the Institute of Medicine, approximately 98,000 people die each year in US hospitals from medical error (Kohn *et al.*, 2000). Failures in care delivery and care coordination account for over $160 billion of excessive Medicare spending (Berwick and Hackbarth, 2012).

for complex cases, and anecdotal evidence from physicians corroborate this view (Park *et al.*, 2012). Unlike for simple patients, the fact that some tasks get done faster has less marginal impact since such tasks are unlikely to be the bottleneck for complex cases. On the contrary, a large amount of information is presented to clinicians which could lead to information overload. I only look at a few years of data that cover the initial surge in EMR adoption at hospitals. In the long run, as IT systems become more sophisticated, they may improve outcomes for more complex transactions as well. While that outcome is not yet evident in my setting, I do find specific circumstances in which the disruption is smaller for more complex cases: when patients have been to the same hospital before and when the hospital faces financial incentives to lower resource use.

If the digitization of records actually helps with the simplest cases, we should see the largest effects for certain patients who are not even hospitalized but seen in outpatient clinics. Since the dataset for this study is limited to the inpatient setting, I cannot form an estimate of the benefits of EMRs based on their value in physician practices. As EMRs become more interoperable, it would be particularly interesting to estimate the additional benefits of sharing information across care settings. The widespread diffusion of EMRs makes it imperative to understand how they will affect health care delivery organizations. If the benefits of EMRs that I find in specific cases can be replicated for all patients, the additional value from this technology will far surpass its costs.

Chapter 2

Process Specialization and the Coordination of Complex Tasks: Evidence from the Management of Hospital Inpatients[1]

2.1 Introduction

An important question in any service setting is the extent to which employees should specialize and the relevant dimensions of that specialization. If transactions are relatively straightforward and do not require customization, a reasonable approach would be to specialize on the basis of tasks. Workers can then leverage the benefits of task repetition just as in Adam Smith's pin factory (Smith, 1776). Such specialization leads to improved productivity, as has been established in many different work environments, ranging from surgical care to software development (Hatch and Mowery, 1998; Reagans *et al.*, 2005; Staats and Gino, 2012; Fong Boh *et al.*, 2007; Kang and Hahn, 2009).

When transactions are particularly complex, however, it may be necessary for someone to coordinate the process as a whole. An employee who specializes in a particular task may not

[1]Co-authored with Robert Huckman

be well suited to play this coordination role because the transaction is not an atomistic task and requires the input of several task specialists. One solution could be the deployment of customer specialists who eschew focusing on particular domains and instead perform multiple tasks for a small group of customers. Repeated interaction with the same customer allows these workers to develop a better understanding of the customer's preferences and standard operating procedures (March and Simon, 1993; Boone *et al.*, 2008), to improve communication with the customer (Arrow, 1974; Weber and Camerer, 2003), and to elicit information from the customer (Simonin, 1997; Inkpen, 2007). Such customer-specific experience is particularly useful in situations in which the customer and service provider must interact to "co-produce" a service (Larsson and Bowen, 1989).

Co-production, however, might not be of the utmost importance for some of these complex transactions. Rather, the most crucial ingredient in production might be the coordination of the various activities that constitute the provision of the service. It is, therefore, possible that the most critical form of expertise would then be process-specific experience rather than task-specific or customer-specific experience.

To address this third dimension, we propose a category of specialists called *process specialists*. These workers have neither task-specific experience nor customer-specific experience but they have an ability to help customers navigate complex transactions by virtue of being immersed in an environment where such transactions are taking place. Note that these process specialists are not just workers who have been exposed to different domains. One recent phenomenon in the reorganization of work in firms is the shift from "Tayloristic" organization – characterized by task specialization – to holistic organization featuring job rotation, integration of tasks, and learning across tasks (Lindbeck and Snower, 2000). We think of the process specialists as workers who, rather than having multiple skills from different domains, specialize in the ability to guide the customer through a transaction. It is possible to think of process specialists as managers. We focus, however, on the importance of the coordination role rather than the supervisory or leadership roles because a key element of the job is the coordination of task specialists.

When shepherding a customer through a complex process, it helps to have process-specific expertise as well as customer-specific expertise. The relative importance of customer-specific experience versus process-specific experience depends on some parameters. We focus on one specific element – the need for coordination among different parts of the organization. When interacting with different departments in the organization is necessary, knowledge of the organization is particularly important. In this paper, we show that as the complexity of the transaction increases and coordination becomes more crucial, process-specific experience trumps customer-specific experience. Thus firms might need process specialists for complicated non-atomistic tasks, which often span multiple domains and for which coordination is relatively more important than co-production with customers.

We shed light on this issue by considering the management of patients admitted to a hospital. We focus on the idea that such patients might require consultation from various domain specialists. For instance, imagine a patient with end-stage renal disease who suffers from a heart attack, shows up in the emergency room, and gets admitted to the hospital. This patient will be seen by a cardiologist but will also need consultations from a nephrologist to manage her renal disease while she is recovering from the heart attack. Patients who suffer from chronic conditions such as diabetes, for whom complications might flare up while in the hospital, are also likely to require the attention of different medical specialists. It is imperative that someone coordinates the various specialists providing care because lack of coordination can lead to higher costs, lower quality, or both. Advocates for hospital patients and their families suggest that confusion about who is managing a patient's care – and lack of coordination among those caregivers – is endemic, contributing to the estimated 98,000 deaths from medical errors each year (Kohn *et al.*, 2000). A landmark report by the Institute of Medicine cited the fragmented health-care system and patients' reliance on multiple providers as a leading cause of medical mistakes (Kohn *et al.*, 2000).

Traditionally, when a patient is admitted to the hospital in the United States, his primary care physician (PCP) coordinates his care and travels to the hospital to check up on him. While the PCP may be quite familiar with the patient, she may be less familiar with the inner workings of the hospital. The PCP thus has customer-specific expertise. This type of knowledge is especially important in health care: the physician-patient relationship is considered sacred and the continuity of care is considered to be crucial (Saultz and Lochner, 2005). Over the past two decades, the hospitalist model has supplanted the traditional model of care. A hospitalist is a full-time physician who spends all of his or her professional time at the hospital and does not see patients outside. Hospitalists have greater supply-side knowledge than traditional PCPs. They are more familiar with nurses, hospital support staff, and have better knowledge of how to work with the various departments in a hospital such as radiology, pathology, and other support services. They are process specialists.

In the traditional model, the PCP is the coordinator for patients both inside and outside the hospital, whereas in the hospitalist model the coordination role gets split up: the hospitalist coordinates inside the hospital and the PCP coordinates outside the hospital.[2] Who is the best coordinator for inpatients depends on whether knowing the customer is more important relative to knowing the process. In this paper, we investigate the tradeoff between customer-specific and process-specific experience. Moreover, we provide evidence that as the complexity of the transaction increases such that the treatment process entails greater coordination of different activities within the hospital, process-specific experience becomes relatively more important.

Using hospital data from the American Hospital Association (AHA) and discharge-level data from the Nationwide Inpatient Sample (NIS) database maintained by the Agency for Healthcare Research and Quality (AHRQ), we investigate whether hospitals that employ hospitalists achieve reductions in risk-adjusted length of stay between 2003 and 2010, a period of rapid growth in the adoption of hospitalist programs in the United States. We further explore whether the effect of hospitalists on length of stay varies by patient complexity and show that hospitalist use is associated with greater reductions in length of stay as the complexity of patient illness increases. For simple patients with no comorbidities, we find that adoption of a hospitalist program is associated with a slight increase in the risk-adjusted length of stay. On the other hand, for patients with three or more comorbidities, our most complex category, adoption of a hospitalist program is associated with a 4% reduction in risk-adjusted length of stay. We find that this result is driven by hospitals where other physicians affiliated with the hospital are not typically employed.[3] We also find similar results for mortality, but the magnitude of the impact is quite small. Notably, we find no effect of hospitalist programs on length of stay for a placebo condition - pregnancy with normal delivery.

[2]Many question how well PCPs currently play this role (Bodenheimer, 2008; O'Malley and Reschovsky, 2011).

[3]This result provides additional support for the theory that hospitalists help by improving care coordination. Salaried physicians typically have similar incentives for care coordination, whereas non-salaried physicians often face fee-for-service reimbursement schedules and do not have an incentive to engage in care coordination. Since hospitalists have a significant marginal impact only in those hospitals where physicians are not typically employed, we believe that care coordination might be the mechanism through hospitalists reduce length of stay.

The remainder of this paper is organized as follows. Section 2 provides background on the emergence of hospitalists. Section 3 lays out a conceptual framework and develops hypotheses. Section 4 outlines the data and empirical strategy. Section 5 presents results and robustness checks. Section 6 includes a discussion of the results. Section 7 concludes.

2.2 The Emergence of Hospitalists

The use of hospitalists to manage inpatient care is a relatively new phenomenon in the United States. The term *hospitalist* was first introduced in 1996 in an article in the New England Journal of Medicine (Wachter and Goldman, 1996). Since then, hospitalists have became the fastest growing specialty in the United States, challenging the traditional model of care in which primary care physicians take care of their hospitalized patients by doing rounds at the hospital (Wachter and Goldman, 2002). Fuchs (2012) points out that the number of hospitalists has grown from under a thousand 15 years ago to approximately $30,000$ in 2011.

Hospitalists are typically hired on the presumption that they are better positioned than PCPs to manage hospital resources and reduce hospital expenditures without adversely affecting quality. Potential roles include triage in the emergency department, management of patients in the intensive care unit, pre-operative and post-operative management of surgical patients, and leadership in hospital quality improvement and regulatory work. Though primary care physicians initially resisted this change in professional responsibilities, many now prefer the new system because they perceived rounding on their hospitalized patients not to be an efficient use of their time (Fuchs, 2012). On the other hand, hospitalists may actually thrive in the inpatient setting. Cebul *et al.* (2008) argue that hospitalists could be well-positioned to make investments in hospital-specific human capital and also to participate in initiatives to improve the efficiency of inpatient care.

The cost-cutting measures may even improve the quality of care received by patients since hospitalists often focus on process innovations such as the implementation of checklists (Pronovost *et al.*, 2006; Gawande, 2010). The health policy literature provides substantial support for this view. According to Wachter and Goldman (2002), most studies find that implementation of hospitalist programs is associated with significant reductions in resource use, usually measured as hospital costs (average decrease, 13.4%) or average length of stay (average decrease, 16.6%). Meltzer *et al.* (2002) show that improvements increase over time in association with disease-specific experience.

While proponents of the hospitalist model claim that the advantages include enhanced knowledge of hospital operating procedures, greater familiarity with hospital staff, and increased accessibility to patients, critics are quick to highlight the drawbacks. The transfer of patients from their primary care physicians to hospitalists may create the so-called "information voltage drop", which could lead to discontinuity of care and potential loss of information. Such mistakes are likely when records are not properly organized, for instance, in the absence of electronic medical records. Moreover, patients could be dissatisfied when they see an unfamiliar provider at the hospital instead of their usual doctor. Recent work by Kuo and Goodwin (2011) finds that decreased length of stay and hospital costs associated with hospitalist care are offset by higher medical utilization and costs after discharge. Further, it is theoretically plausible that any efficiency improvements due to the use of hospitalists may be offset to some degree by increased costs during a patient's hospital stay.[4] This latter result could occur if hospitalists are not as well positioned as PCPs to take advantage of patient-specific relationships or information that might lead to more efficient treatment within the hospital (Coffman and Rundall, 2005).

Meltzer and Chung (2010) highlight the decision to use hospitalists from a physician's perspective, relying on the insights of Becker and Murphy (1992) to build a model with switching costs and coordination costs. Meltzer and Chung (2010) show that the hospitalist model is most likely to be prevalent when the costs for providers to switch between the outpatient and inpatient settings are high, or when the cost of coordinating between hospitalists and primary care physicians is low.

2.3 Conceptual Framework

In any service organization, workers may develop specific sets of skills based on how they spend most of their time. Employees who interact with clients cultivate important relationships with them and may be more familiar with the needs of specific customers. On the other hand,

[4] For instance, it might be harder for hospitalists to retrieve the patient's past medical history, since this involves communicating with the patient's primary care doctor and getting past notes.

employees whose jobs focus on the internal operations of a firm may have greater knowledge of important processes within the company and develop more firm-specific human capital. Such workers may be particularly well suited to optimally using the resources available to them in order to maximize the efficiency of production. This notion leads us to our first hypothesis.

Hypothesis 1: The use of process specialists is associated with efficiency improvements due to reductions in resource use.

There is a distinction between customer specialists and process specialists, and it is possible to conceive of primary care physicians and hospitalists as occupying these different roles, respectively, in the delivery of health care. In an inpatient setting, hospitalists have greater supply-side knowledge than traditional primary care physicians. As such hospitalists may be better able to coordinate care and respond to clinical data in real time (Wachter *et al.*, 1999). They know the hospital environment better and have more process familiarity. We can think of two components to this familiarity. Some of the familiarity is the result of working in an inpatient setting all the time regardless of the specific hospital. By virtue of the sheer number of inpatient cases they see, hospitalists develop expertise through volume-based learning. This argument is based on the idea of the learning curve, a well documented phenomenon in the study of organizations (Yelle, 1979; Argote, 2013) in general as well as for healthcare settings in particular (Hannan *et al.*, 1997; Luft *et al.*, 1987). In addition the process familiarity may stem from working in a specific hospital. The rationale for firm-specific performance is based on the potential complementarity between a worker and the human, physical, or organizational assets held by a given firm (Huckman and Pisano, 2006). In our setting, hospitalists could be more familiar than PCPs with nurses and hospital support staff. As such, they may have better knowledge of how to work with the various departments in a hospital such as radiology, pathology, and other support services.

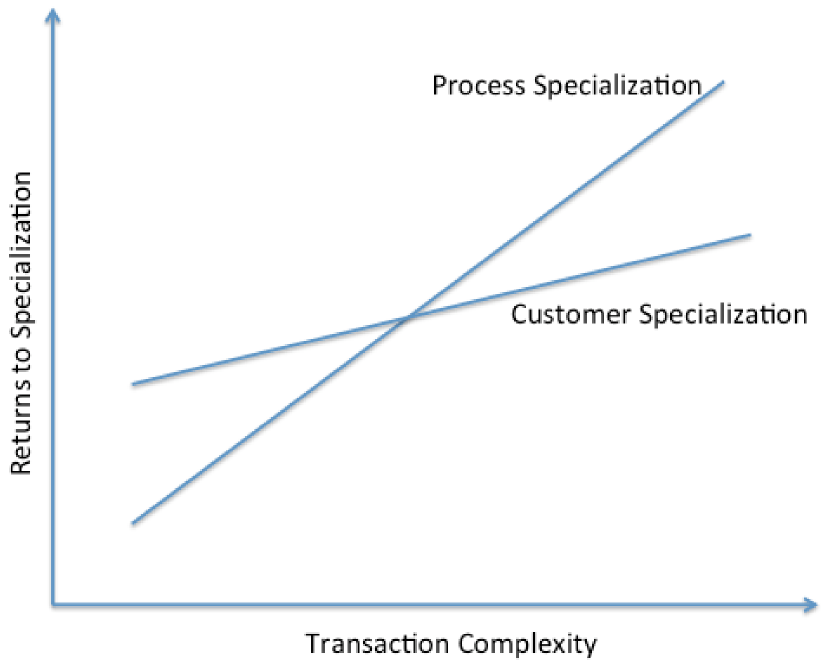
The hospitalist model is thus an example of specialization that leverages process familiarity. Becker and Murphy (1992) propose that one of the crucial limits to specialization of labor is the challenge of coordinating specialized workers. Hospitalists do create some additional coordination costs of their own because office-based physicians hand their patients off to hospitalists when patients enter the hospital (Meltzer, 2001; Wachter *et al.*, 2004). The medical literature raises the issue of the “information voltage drop” that results when patients are transferred from one physician to another (Wachter *et al.*, 1999). If the doctor is able to tend to the patient’s needs better in the traditional PCP model, a switch to the hospitalist model will potentially result in worse outcomes for the patient. To the extent that the disruption impedes recovery and results in the patient staying longer at the hospital, costs will also increase. Ultimately, the effect of the hospitalist model on inpatient care quality will depend on whether the benefits from process specialization exceed the heightened costs of coordination with primary care providers (Cebul *et al.*, 2008).

The traditional PCP model leverages customer familiarity. The typical primary care physician sees patients in his or her clinic and travels to the hospital to check in on hospitalized patients. It is consistent with the notion that customer-specific human capital maybe important in service transactions and that such capital is developed through repeated interactions with the same customers (Clark *et al.*, 2013). Note that this relationship is also an example volume-based learning but is a function of frequent encounters with the same patient leading to the development of *demand-side* knowledge. In comparison, the hospitalist model relies on volume-based learning relying on repeated encounters with the same hospital protocols leading to the development of *supply-side* knowledge.

The impact of hospitalists depends on which domain of knowledge is more important in a given setting. It is theoretically ambiguous whether hospitalists improve quality and efficiency. Given that the hospitalist model has proliferated rapidly, it is important to investigate empirically whether the benefits of the hospitalist model outweigh the costs. To measure the impact of hospitalists on efficiency, we follow the literature and consider length of stay as a measure of resource use. To the extent that patients are better off, *ceteris paribus*, when they do not have to stay in the hospital longer than necessary, it is also possible to interpret risk-adjusted length of stay as a measure of quality. We hypothesize that hospitalists will reduce the length of stay for patients admitted to the hospital. We would expect this result if the benefits of process familiarity outweigh those of customer familiarity in the setting of inpatient care. We believe that this might be true if, as suggested by proponents of the hospitalist movement, process familiarity enables hospitalists to be more efficient caregivers who can respond quickly to an inpatient's needs and coordinate care.

Process specialists could have a more nuanced impact on the efficiency of transactions. In particular, the returns to process specialization may be contingent on the complexity of the

Figure 2.1: *Transaction Complexity and Returns to Specialization*



transaction. When transactions are particularly complex, process specialization might be especially important to coordinate the various components of production. This expectation leads to our second hypothesis:

Hypothesis 2: The efficiency benefits of process specialists are greater for more complex transactions and are smaller for routine transactions that do not involve multiple task specialists

The above figure illustrates one situation which is consistent with Hypothesis 2. Even when the returns to both process and customer specialization are increasing in the complexity of the transaction, as long as the former is increasing faster than the latter, the net benefit of using a process specialist instead of a customer specialist will be higher for more complex transactions. In the particular scenario sketched out, process specialists are worse than customer specialists unless transactions are sufficiently complex.

In our setting, it is possible that the effect of hospitalists may vary based on the complexity of the patient population. If hospitalists are relatively good at certain tasks that become more important when patient complexity increases, it is possible that they will have a particularly strong impact for such patients. For example, patients who have multiple comorbidities require careful coordination because of the need to follow directions from several specialists or manage different medications. In such situations, having a hospitalist program would be very helpful. On the other hand, relatively simple cases might not require as much coordination meaning that the marginal impact of hospitalists is not big. It is also possible that the drawbacks of the hospitalist model are increasing in patient complexity. The main disadvantage that we pointed out earlier is that unlike a patient's primary care physician, a hospitalist would know relatively little about the patient's background. This lack of knowledge could be particularly harmful for patients who have more comorbidities. However, we would still expect hospitalists to have a larger impact on more complex cases if, as patient complexity increases, the benefits of hospitalist programs rise faster than the costs of these programs.

To the extent that hospitalists improve workflow in hospital wards, the existence of hospitalists might improve efficiency for all patients who go through the ward. However, there are certain cases where we expect hospitalists to have a smaller impact including cases such as pregnancies leading to normal delivery or simple surgical cases. In the instance of routine cases, we believe that there is an underlying reason why hospitalists are less likely to play a role in the patient's care. The routine cases may be more likely to have accepted (or protocol-driven) approaches to treatment that may obviate the need for a hospitalist to play a coordinative role. The more routine approach to care may substitute for the hospitalist in these cases.

While the primary impact of a process specialist may be seen on measures of efficiency, it is theoretically possible that such impacts may filter through to quality outcomes as well. Just as in the case of efficiency outcomes, the impact of process specialists may be contingent on the complexity of the transaction.

Hypothesis 3: Process specialists are associated with an improvement in service quality and this effect is greater for more complex transactions.

One unambiguous measure for measuring quality in our setting is mortality, though we only observe this outcome if patients die during the course of their hospital stay. Hospitalists could have an effect on in-hospital mortality for some patients. In certain situations, the sudden deterioration of patients requires a quick response. When attending hospitalists who are somewhat familiar with the patient are around, they can tend to the patient promptly. Another channel through which hospitalists may affect the mortality rate is the reduction of hospital acquired infections, through better monitoring and the implementation of protocols such as checklists.

2.4 Data and Empirical Strategy

We use data from the Annual Survey of Hospitals by the AHA, which is sent to all registered and non-registered hospitals in the United States. Our study covers the period 2003 to 2010. The 2003 survey was the first in which hospitals were asked about the use of hospitalists. We document hospitalist use by recording responses to the question: 'Do hospitalists provide care in your hospital?'.[5]. The AHA survey data also allow us to measure key hospital characteristics such as number of admissions, number of beds, ownership status, teaching status, medical school affiliation and membership of hospital systems.

We construct our outcome measures using hospital discharge data from the Nationwide Inpatient Sample, a database maintained by the Agency for Healthcare Research and Quality (AHRQ). The NIS contains patient-level data on all inpatient hospital stays for approximately 1,000 hospitals in the United States each year. These hospitals are sampled from state-level hospital discharge databases and approximate a 20 percent stratified random sample of acute-care hospitals in the United States. Data in the NIS are reported at the level of the patient, and all discharges at a sampled hospital are included for the year in question. Our sample includes more than 3 million discharges per year for a total of about 27 million inpatient stays for the entire period 2003 to 2010.[6] The key dependent variables from the NIS include the length of stay and whether the patient died during a stay. We also obtain other patient level variables of interest including age, sex, income quartile of the patient's neighborhood, and the primary diagnosis.

2.4.1 Trends in Risk Adjusted Length of Stay

Due to heterogeneity in patient characteristics, observed length of stay may be biased against patients who are more seriously ill. We thus estimate the risk-adjusted length of stay $RAlos_{ijt}$ for

[5]The survey also asks about the number of hospitalists in a hospital, but the data is missing for a large number of hospitals

[6]We drop patients with DRGs that appear less than 100,000 times in the panel sample to make the analysis computationally tractable, but the results are robust to using other thresholds.

each patient i in hospital j in year t as follows. We pool all the patient-level observations and estimate the following regression:

$$los_{ijt} = \alpha + \beta X_i \tag{2.1}$$

where los_{ijt} is the observed length of stay for patient i in hospital j in year t, and X_i represents a vector of patient-level risk factors including age, sex, neighborhood income level, and a set of DRG (diagnosis-related group) indicators.

To calculate patient i's risk-adjusted length of stay in year t, $RAlos_{ijt}$, we use the predicted values for each patient from (1) to create the predicted length of stay $Plos_{jt}$. We use this value, along with the observed length of stay, $Olos_{jt}$, to calculate $RAlos_{ijt}$:

$$RAlos_{jt} \quad = \quad \frac{Olos_{ijt}}{Plos_{ijt}} * avglos_t \tag{2.2}$$

The observed length of stay across all hospitals in year t, $avglos_t$, is included to normalize the risk-adjusted length of stay.

Figure 2.2 shows trends in our measure of risk-adjusted length of stay, which decreased steadily from about 4.3 to 3.8 during our study period.

2.4.2 Trends in Hospitalist Use and Patient Complexity

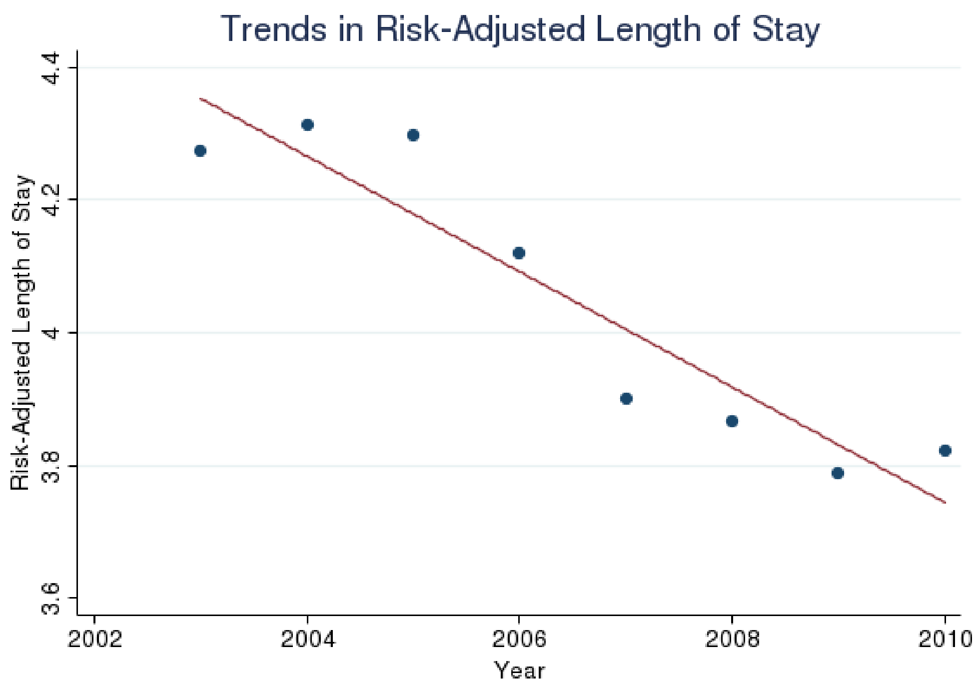
As Figures 2.3 and 2.4 show, hospitalist use increased dramatically over the period of our study. In 2003, which was the first year that the American Hospital Association asked about hospitalist programs in its Annual Survey, less than 20% of hospitals had a hospitalist program. This number rose to almost 50% in 2010.

These figures include all hospitals that are present in the AHA data. However, we get similar trends for the sub-sample of hospitals in the NIS. Figure 2.5 shows that, in our sample of discharges, the fraction of patients treated in a hospital with a hospitalist program rose from about 40% in 2003 to more than 80% in 2010.[7]

We also investigate trends in average patient complexity in a hospital from the NIS data.

[7] The fact that 80% of patients in the NIS sample were treated in a hospital with a hospitalist program in 2010 when only 50% of hospitals in the AHA sample had hospitalists implies that larger hospitals which admit more patients were the first to adopt hospitalist programs.

Figure 2.2: *Trends in Risk-Adjusted Length of Stay*



We capture complexity using comorbidity measures develop by Elixhauser et al. (1998). These measures capture the presence of approximately 30 comorbidities using indicator variables for each. We sum the number of comorbidities associated with each patient discharge to create a measure of patient complexity. As displayed in Figure 2.6, average patient complexity in our sample of hospitals – as measured by the mean number of Elixhauser comorbidities – increased from around 1.2 in 2003 to over 1.6 in 2010.

We note that while average patient complexity is increasing over this time period, risk-adjusted length of stay is going down. Hospitalist use is also going up rapidly. All of these trends are consistent with our hypothesis that hospitalists contribute to lower lengths of stay, particularly through better management of complicated cases. Figure 6 provides additional suggestive evidence of this relationship. It plots the average risk-adjusted length of stay for every hospital-year in our sample against the year relative to adoption of a hospitalist program. We see that the length of stay is relatively flat in the years leading up to the adoption of a hospitalist program. Once a

Figure 2.3: *Trends in Hospitalist Use*

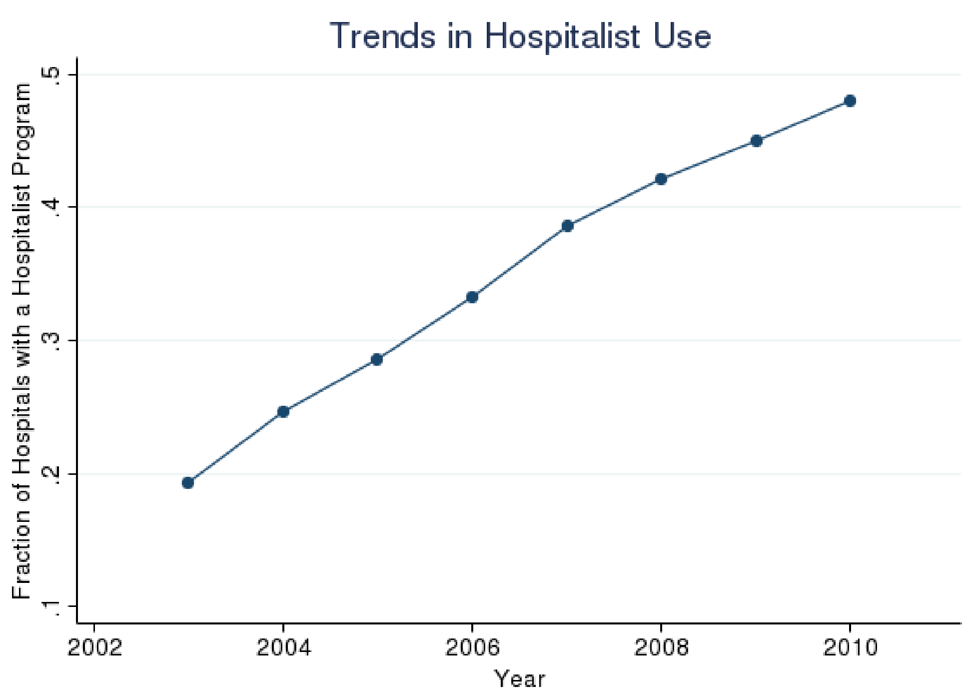


Figure 2.4: *Trends in Hospitalist Use*

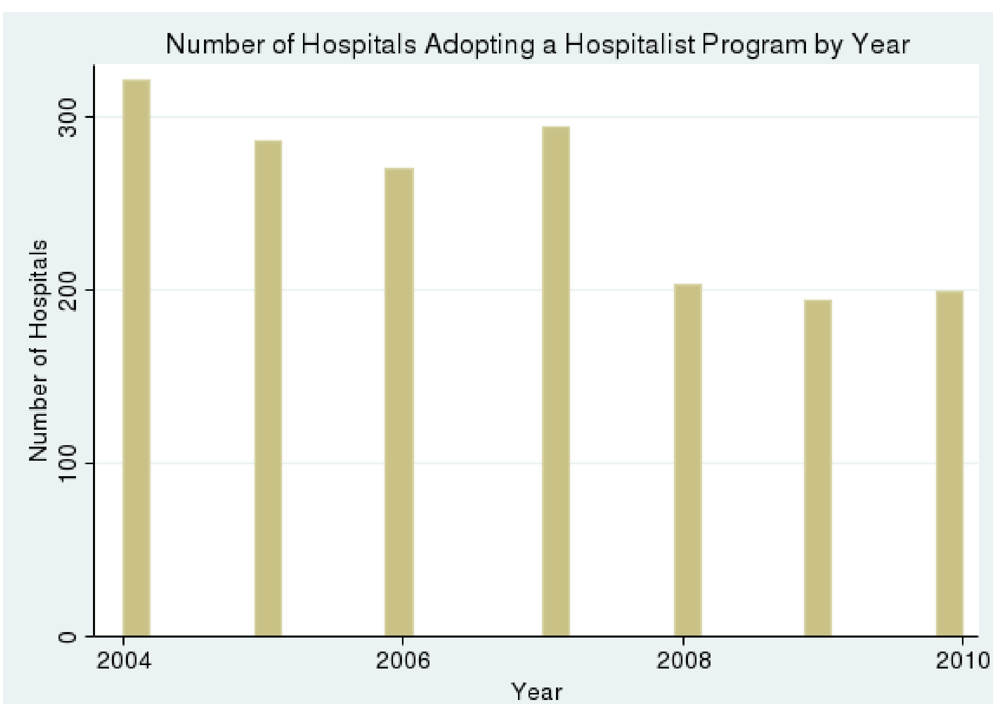
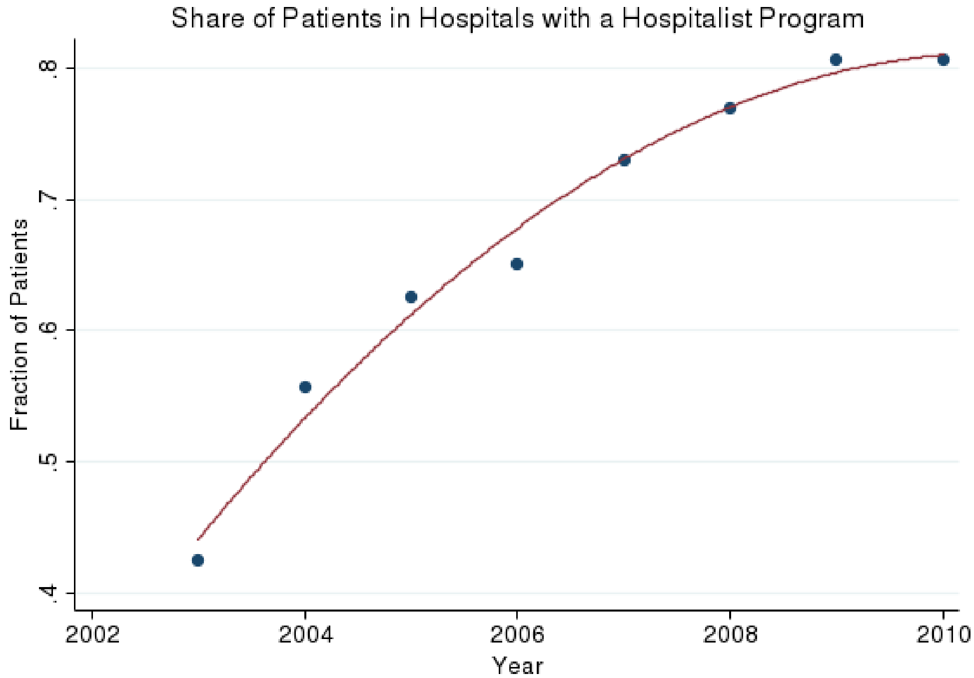


Figure 2.5: *Trends in Hospitalist Use*



hospitalist program is in place, however, length of stay declines.[8]

2.4.3 Empirical Strategy

We merge variables constructed from the NIS data into our hospital dataset from the AHA. As such, our regressions only include hospitals that are present in the NIS in a given year. We estimate regressions to investigate the association between hospitalist use and risk-adjusted length of stay for patients of varying complexity.[9] Additionally, using the diagnosis-related group (DRG), we categorize each discharge as either medical or surgical.[10] We then estimate regressions by

[8]The panel of data for Figure 6 is not "balanced" with respect to year relative to hospitalist adoption. Since, the NIS samples a slightly different set of hospitals every year, we do not observe the average length of stay for every year for any given hospital. There is no reason to believe that this feature of the data should change our conclusion regarding the general trend in the graph.

[9]We also include some specifications with mortality as the outcome variable

[10]Diagnosis-related group (DRG) is a system used to classify hospital cases into one of several hundred groups. DRGs have been used in the US since 1982 to determine how much Medicare pays hospitals for services. There were originally 467 illness categories identified in the International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM).

Figure 2.6: *Trends in Patient Complexity*

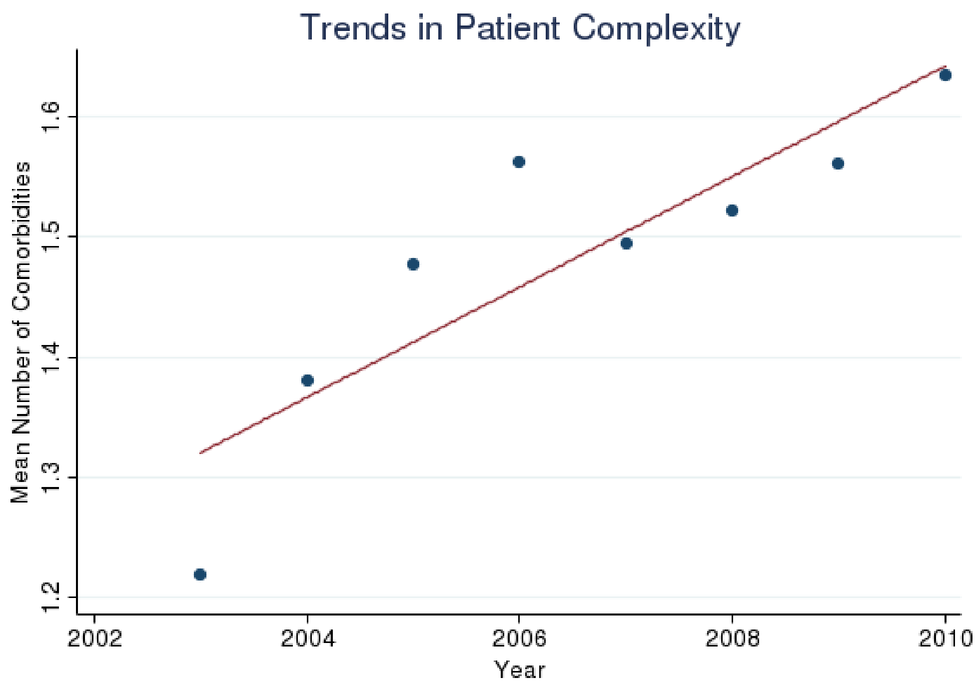
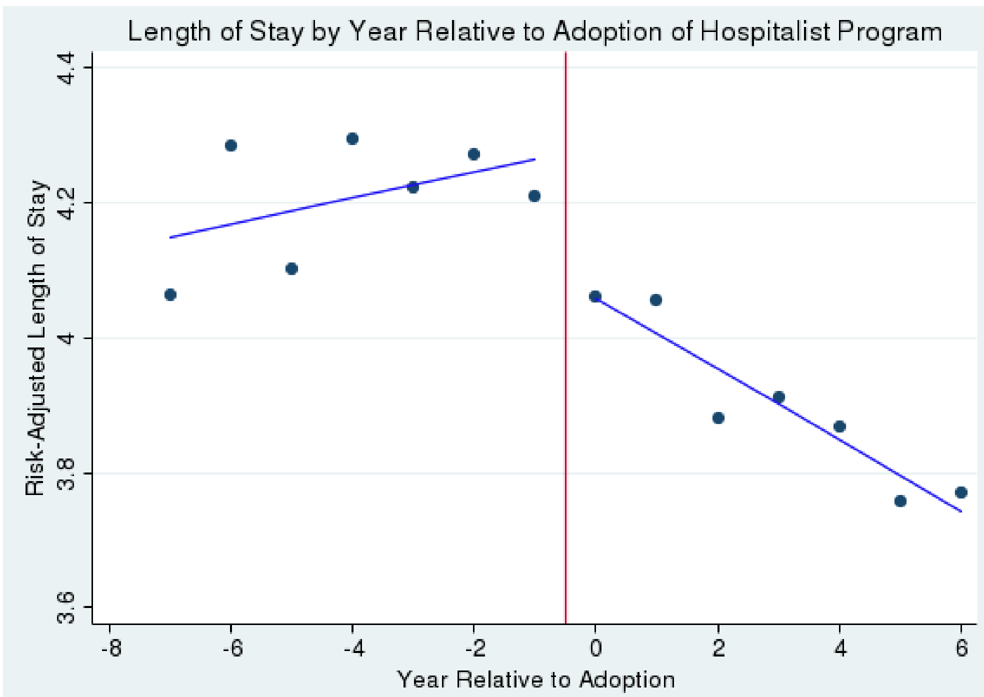


Figure 2.7: *Length of Stay by Year Relative to Adoption of Hospitalist Program*



restricting our sample of discharges to only medical patients and to only surgical patients in turn. In the table of results, we include specifications where the patient samples have been restricted to only medical or to only surgical patients because it is interesting to note any differences between these two groups of patients. On one hand, hospitalists tend to be used most frequently for medical patients, and we might expect to see stronger results for such patients. On the other hand, post-surgical patients who are transferred to general medical-surgical wards could be unobservably more complex and stand to benefit more from the care coordination that hospitalists facilitate.

We estimate the following baseline regression model to investigate the effect of hospitalist use on length of stay.

$$los_{ijt} = \sum_{c=1}^{3} \beta_{1c} complex_{cijt} + \beta_2 hsptl_{jt} + +\beta_3 X_{jt} + \beta_4 Y_{ijt} + \gamma_j + \delta_t + \epsilon_{ijt} \tag{2.3}$$

The key explanatory variable is $hsptl_{jt}$, an indicator for whether hospital j had a hospitalist program in year t. To measure patient complexity, we use indicator variables for the number of comorbidities each patient has. We divide patients into four groups: those with zero, one, two, or more than two comorbidities. We include a set of indicator variables, $complex_i$, for being in one of these groups ($c0, c1, c2$ and $c3$). The vector of hospital-level covariates $\mathbf{X_j}$ includes the log of total admissions and the log of total number of beds. The vector of patient-level covariates $\mathbf{Y_i}$ includes age, sex, neighborhood income quartile, and a set of DRG dummies. We include hospital fixed effects, γ_j, as well as a set of year dummies, δ_t. Standard errors are clustered at the hospital-year level.

Given that we are interested in the heterogeneous effects of hospitalist use and hypothesize that hospitalist impact might vary by patient complexity, we extend the above model to estimate regressions of the following form with hospital and year fixed effects:

$$\begin{aligned} los_{ijt} = &\sum_{c=1}^{3} \beta_{1c} complex_{cijt} + \beta_2 hsptl_{jt} + \sum_{c=1}^{3} \beta_{3c} complex_{cijt} * hsptl_{jt} \\ &+ \beta_4 X_{jt} + \beta_5 Y_{ijt} + \gamma_j + \delta_t + \epsilon_{ijt} \end{aligned} \tag{2.4}$$

We include interactions of the patient complexity indicator variables with the dummy variable for hospitalist use, $complex_i * hsptl_j$. Empirical identification in (4) depends on the assumption that hospitals that were adopting hospitalist programs do not take other simultaneous actions that disproportionately affected the length of stay for complex patients. That is, even if the adoption of hospitalist programs coincides with other changes unrelated to hospitalists but correlated with our outcomes of interest, we believe that such confounding is not likely to affect more complex cases differently than those that are less complex.

2.5 Results

2.5.1 Base Results

Table 2.1 presents results from our baseline regression models, in which we look at the average impact of hospitalist use on the length of stay for all patients. We also split the sample into medical and surgical patients. There is no statistically significant relationship between hospitalist use and risk-adjusted length of stay in any of these specifications. Thus, there does not appear to be any support for our first hypothesis. As we expect, increased patient complexity is associated with longer lengths of stay. Specifically, having three or more Elixhauser comorbidities is associated with an increase in the length of stay of more than 1.2 days relative to patients with no comorbidities.

As we hypothesize in Section 3, however, there could be a heterogenous impact of hospitalists based on patient complexity. Table 1.2 displays estimates from regression models where we examine the impact of hospitalists by patient complexity. We continue to find that more complex patients have longer risk-adjusted lengths of stay. Moreover, we now see that hospitalist use is associated with lower risk-adjusted lengths of stay. This effect is especially pronounced for more complex patients. Patients with no comorbidities are the reference group and the corresponding indicator variables are dropped from the specifications. The positive coefficient on the "hospitalist use" variable tells us that for patients with no comorbidities, hospitalist use is associated with an increase in risk-adjusted length of stay of approximately 0.07 days. Though this coefficient may imply that patients at hospitals with hospitalist programs are unobservably more complex in the year of hospitalist program adoption.[11] It is also possible that having a hospitalist program could entail more discontinuity of care on average and this disruption leads to longer lengths of

[11] These patients would be unobservable more complex relative to the mean complexity of patients at that hospital during the entire sample period.

Table 2.1: *Effect of Hospitalist Use on Risk-Adjusted Length of Stay*

Dependent Variable	Length of Stay		
Patient Population	All	Medical	Surgical
Hospitalist Use	-0.0246	-0.0284	-0.00490
	(-0.99)	(-1.00)	(-0.29)
Patient Complexity Indicator Variables			
1 comorbidity	0.177***	0.186***	0.175***
	(13.60)	(11.79)	(25.09)
2 comorbidities	0.484***	0.496***	0.465***
	(31.10)	(27.70)	(45.55)
3+ comorbdities	1.272***	1.257***	1.424***
	(65.79)	(60.14)	(67.36)
N	26719104	21997175	4721929

t statistics in parentheses, * $p < 0.05$,** $p < 0.01$,$^{***}p < 0.001$. Standard errors are clustered at the hospital-year level. All regressions include hospital and year fixed effects, as well as a set of hospital-level control variables including size, ownership status, teaching status, system membership, trauma center status, and teaching intensity. Patient-level characteristics include age, sex, zip code income quartile, and a set of diagnosis-related group (DRG) dummies.

stay. However, as we can see from the coefficients on the interaction terms, for patients who have comorbidities, hospitalists are associated with shorter lengths of stay. The magnitude of this effect is increasing in the number of comorbidities. On top of the baseline effect, having 1 comorbidity is associated with an additional reduction of almost 0.08 days, having 2 comorbidities is associated an additional reduction of 0.156 days and having 3 or more comorbidities is associated with an additional reduction of 0.223 days when the hospital has a hospitalist program. The magnitudes on these coefficients are similar when we restrict the sample to only medical patients.

The results in Table 2.2 support the contentions in our second hypothesis. As the complexity of each case increases, the benefits of hospitalist use start to outweigh the costs. One explanation for our findings could be that hospitalists engage in roles that become more important as the complexity of patients increases. For example, consider the coordination of care among multiple specialists. A particularly difficult patient with numerous comorbidities might require the consultation of several different specialists. Such patients persistently complain that there is no single individual who is *de facto* in charge at the hospital. To the extent that an attending hospitalist can act as the principal physician and patient advocate in such situations, we might observe improved outcomes. Complex patients require care coordination and since hospitalists, with their wealth of supply-side knowledge, are able to provide this service they become particularly helpful for complex patients.

Surprisingly, we also find statistically significant effects of hospitalist use on surgical patients and the magnitudes of the effects are, in fact, higher. While surgical patients are typically under the supervision of surgeons, it is possible that the benefits of hospitalists occur through a channel that could also affect surgical patients. For instance, post-surgical patients are often assigned to general medical/surgical wards where beds are also occupied by medical patents. if hospitalists institute better workflow processes in such wards, these initiatives could have a spillover benefit on the post-surgical patients. Another explanation is that patients whose primary diagnosis is a surgical DRG could be more complex patients who are also likely to have other medical issues and are likely to benefit from hospitalists.

Table 2.2: *Effect of Hospitalist Use on Risk-Adjusted Length of Stay*

Dependent Variable	Length of Stay		
Patient Population	All	Medical	Surgical
Hopitalist Use	0.0698*	0.0679*	0.114***
	(2.39)	(2.10)	(5.49)
Patient Complexity Indicator Variables			
1 comorbidity	0.229***	0.239***	0.239***
	(9.79)	(9.99)	(15.22)
2 comorbidities	0.588***	0.599***	0.598***
	(21.18)	(22.13)	(25.92)
3+ comorbidities	1.423***	1.398***	1.757***
	(40.60)	(41.27)	(42.70)
Interactions of Hospitalist Use with Patient Complexity			
1 comorbidity	-0.0778**	-0.0815**	-0.0921***
	(-3.08)	(-3.02)	(-5.00)
2 comorbidities	-0.156***	-0.159***	-0.185***
	(-5.18)	(-5.19)	(-6.90)
3+ comorbidities	-0.223***	-0.212***	-0.451***
	(-5.50)	(-5.29)	(-9.13)
N	26719104	21997175	4721929

t statistics in parentheses, * $p < 0.05$,** $p < 0.01$,$^{***}p < 0.001$. Standard errors are clustered at the hospital-year level. All regressions include hospital and year fixed effects, as well as a set of hospital-level control variables including size, ownership status, teaching status, system membership, trauma center status, and teaching intensity. Patient-level characteristics include age, sex, zip code income quartile, and a set of diagnosis-related group (DRG) dummies.

2.5.2 Effects on In-Hospital Mortality

While length of stay is a reasonable measure of resource use, it is a less robust measure of quality. If patients spend less time at the hospital that could be good if it means that they are getting better faster, not developing complications and having less exposure to hospital acquired infections. However, to the extent that they are being pushed out of the hospital it could also be interpreted as lower quality care.

Mortality is an unambiguous measure of quality but we only observe this outcome if patients die during the course of their hospital stay. In-hospital mortality is a relevant outcome only for certain conditions. We select three conditions where inpatient admission could lead to mortality with a reasonably high probability: pneumonia, congestive heart failure and chronic obstructive pulmonary disease (COPD).[12] We estimate our regression model for samples of patients that are restricted to these diseases, and we use an indicator variable for whether the patient died in the hospital as our outcome variable. Table 2.3 shows that hospitalist use is associated with a slight increase in mortality for pneumonia and heart failure patients (0.35 and 0.77 percentage points respectively). However, as the patients become more complex the association between hospitalist use and mortality becomes negative. The interaction term between having more than 2 comorbidities and hospitalist use is negative and statistically significant for all three of these conditions. The net effect is a 0.07 percentage point reduction in mortality for the most complex pneumonia patients, a 0.21 percentage point reduction for the most complex COPD patients and a 0.20 percentage point reduction for the most complex CHF patients.

2.6 Robustness Checks

2.6.1 Heterogeneous Impacts Based on Physician Employment

In our baseline results, we measure the use of hospitalists by the existence of a hospitalist program at the hospital to which the patients are admitted. If hospitalist programs help to achieve some of the same benefits that employment brings, we would expect hospitalists to have the biggest

[12]For a given admission, the in-hospital mortality rates for pneumonia, congestive heart failure and COPD are 3.7%, 3.6%, and 1.8% respectively, whereas the average in-hospital mortality rate is 1.6% for all patients in our sample.

Table 2.3: *Effect of Hospitalist Use on Risk-Adjusted Mortality*

Dependent Variable	Indicator for Death		
Patient Population	Pneumonia	COPD	CHF
Hospitalist Use	0.00350**	0.00180	0.00768**
	(2.81)	(1.25)	(3.03)
Patient Complexity Indicator Variables			
1 comorbidity	-0.00947***	-0.00226**	-0.00640***
	(-11.24)	(-2.64)	(-4.04)
2 comorbidities	-0.0147***	-0.000953	-0.00649***
	(-14.38)	(-1.06)	(-4.19)
3+ comorbidities	-0.0111***	0.00321***	-0.000322
	(-10.31)	(3.46)	(-0.21)
Interactions of Hospitalist Use with Patient Complexity			
1 comorbidity	0.000226	-0.00202	-0.00658**
	(0.22)	(-1.65)	(-2.66)
2 comorbidities	-0.00298*	-0.00248	-0.00844***
	(-2.43)	(-1.90)	(-3.40)
3+ comorbidities	-0.00421***	-0.00385**	-0.00972***
	(-3.37)	(-2.87)	(-3.83)
N	1087778	598701	969339

t statistics in parentheses * $p < 0.05$,** $p < 0.01$,*** $p < 0.001$ Standard errors are clustered at the hospital level. All regressions include hospital and year fixed effects, as well as a set of hospital-level control variables including size, ownership status, teaching status, system membership, trauma center status, and teaching intensity. Patient-level characteristics include age, sex, zip code income quartile, and a set of diagnosis-related group (DRG) dummies.

impact in hospitals where other physicians are not normally employed. In settings where all other physicians are likely to be employed by the hospital, we would expect to see a much smaller impact. Therefore, we dig deeper and explore whether the impact of hospitalists varies by the employment status of other physicians affiliated with the hospital.

Our data enable to us to identify hospital where we expect physicians in general to be employees. Following previous work (Cuellar and Gertler, 2006; Ciliberto and Dranove, 2006; Baker *et al.*, 2014), we consider fully-integrated organizations to be the most tightly vertically integrated form in which the hospital owns the physician practice. We conduct our previous analyses separately on patients admitted to hospitals that are fully integrated and those that are not. Table 2.4 shows our results for regressions that were estimated using patient discharges from these two categories of hospitals. The last column is the same as Column 1 in Table 2.2 and shows the results for the overall sample.

In comparing our results across the columns, we see that our overall results are driven by the impact of hospitalists in those hospitals which do not normally employ their doctors. In fact, when we restrict our sample to patients who were admitted to tightly integrated hospitals, we do not find statistically significant results. This finding supports the view that hospitalist programs are a vehicle for achieving some of the same efficiency gains that can be achieved through employing workers instead of contracting with them. This explanation makes sense in the context of health care because doctors who are not employed often face fee-for-service reimbursement schedules and do not have an incentive to engage in activities such as care-coordination that are not reimbursed. On the other hand, doctors who are salaried do not face incentives to focus more on tasks that are reimbursed. They can be more easily incented to focus on performance measures that are critical to the hospital such as reducing length of stay. Thus in an environment where the doctors are salaried, they are likely to be involved in the coordination of care even in the absence of hospitalist programs, which means that hospitalists are less likely to have a marginal impact. Of course, the effects could be driven by shared attributes of hospitalists and employed physicians other than their propensity to engage in care coordination. The evidence does not rule out such channels, but we believe given our baseline results, that similar incentives for care coordination is a likely explanation.

Table 2.4: *Effect of Hospitalist Use by Physician Employment Status*

Dependent Variable	Length of Stay		
Hospital Sample	Non-Integrated Hospitals	Integrated Hospitals	All Hospitals
Hospitalist Use	0.0474	0.0216	0.0698*
	(0.0391)	(0.0538)	(0.0292)
Patient Complexity Indicator Variables			
1 comorbidity	0.241***	0.176***	0.229***
	(0.0274)	(0.0414)	(0.0234)
2 comorbidities	0.607***	0.495***	0.588***
	(0.0324)	(0.0528)	(0.0278)
3+ comorbidities	1.452***	1.281***	1.423***
	(0.0401)	(0.0722)	(0.0351)
Interactions of Hospitalist Use with Patient Complexity			
1 comorbidity	-0.0855**	-0.0283	-0.0778**
	(0.0301)	(0.0459)	(0.0252)
2 comorbidities	-0.164***	-0.0746	-0.156***
	(0.0358)	(0.0587)	(0.0301)
3+ comorbidities	-0.235***	-0.100	-0.223***
	(0.0481)	(0.0810)	(0.0405)
N	17576787	9142317	26719104

t statistics in parentheses * $p < 0.05$,** $p < 0.01$,***$p < 0.001$ Standard errors are clustered at the hospital-year level. Integrated hospitals are those with a tight form of vertical integration in which the hospital is likely to own the physicians of the non-hospitalist physicians affiliated with the hospitals, and physicians are likely to be salaried employees. All regressions include hospital and year fixed effects, as well as a set of hospital-level control variables including size, ownership status, teaching status, system membership, trauma center status, and teaching intensity. Patient-level characteristics include age, sex, zip code income quartile, and a set of diagnosis-related group (DRG) dummies.

2.6.2 Is Hospitalist Use Associated with Changing Patient Complexity?

Given that we present results concerning the heterogeneous impact of hospitalists by patient complexity, one concern is that patient complexity could be positively associated with the use of hospitalist programs. Such a situation could arise either because hospitalists document complexity better or because more complex patients selectively sort into hospitals with hospitalist programs. This association could bias our results, but we can directly test this claim using our data. We test this by using our measure of complexity, the number of Elixahauser comorbidities as a dependent variable. Adoption of a hospitalist program is associated with an increase of 0.0249 in the number of comorbidities reported, a change that is not statistically significant. This result supports the view that admission patterns are not changing systematically as hospitals adopt hospitalist programs.

2.6.3 Placebo Test

The concern with our empirical strategy is that hospitals could be undertaking other initiatives that affect the length of stay at the same time as they are adopting hospitalist programs. One way to address this issue is to conduct some falsification tests to check whether hospitalists affect length of stay for patients for whom we would not expect them to have an impact. We perform falsification tests using pregnancies as a placebo. Hospitalists should not impact the length of stay for routine normal deliveries. Column 1 in Table 2.5 shows the results for women who are admitted to the hospital for childbirth and undergo normal delivery. We find that hospitalist use is not associated with length of stay. Since states often have regulations concerning the minimum length of stay requirements for vaginal or cesarian deliveries, one might expect that pregnancies would also be unaffected by any unobservable initiatives that we are trying to rule out. There is still variation, however, in the length of stay for normal deliveries with a mean of 2.05 days and a standard deviation of 1.76 days, indicating that there is scope for hospitalists to help. For cesarian deliveries, the mean length of stay is 3.69 days, with a standard deviation of 3.14 days.

Table 2.5: *Effect of Hospitalist Use on Risk-Adjusted Length of Stay*

Dependent Variable	Length of Stay
Patient Population	Pregnancy/Normal Delivery
Hospitalist Use	0.0321
	(1.74)
Patient Complexity Indicator Variables	
1 comorbidity	0.0568
	(0.31)
2 comorbidities	0.687
	(1.75)
3+ comorbidities	1.041
	(1.54)
Interactions of Hospitalist Use with Patient Complexity	
1 comorbidity	0.347
	(1.48)
2 comorbidities	-0.0544
	(-0.12)
3+ comorbidities	0.469
	(0.55)
N	277633

t statistics in parentheses * $p < 0.05$,** $p < 0.01$,$^{***}p < 0.001$ Standard errors are clustered at the hospital-year level. All regressions include hospital and year fixed effects, as well as a set of hospital-level control variables including size, ownership status, teaching status, system membership, trauma center status, and teaching intensity. Patient-level characteristics include age, sex, zip code income quartile, and a set of diagnosis-related group (DRG) dummies.

2.7 Discussion and Conclusion

As transactions get more complex, it is useful to have specialized workers who understand how to best serve customers. The dimension along which the complexity increases, however, is important to consider. Is it better to have a worker who is particularly familiar with the customer, having helped the customer with other services before? Or is it better to have a worker who is very familiar with the process, having helped to provide a similar service to other customers before. We investigate this tradeoff by studying the effect of a relatively novel process innovation, the adoption of hospitalist programs, on the management of inpatients at hospitals.

There are many theories as to why hospitalists could be beneficial for patients. We have presented a broad framework for two types of knowledge that hospitalists and PCPs have, and the comparative advantage of each type of physician. Further research is necessary to tease out the mechanisms via which hospitalists achieve productivity gains. In addition to risk-adjusted length of stay and mortality, it is possible to consider other dependent variables to the extent that they capture hospital productivity. Potential variables of interest include the readmissions rate, the frequency of hospital-acquired conditions, and the hospital-level adoption of process innovations such as electronic medical records.

Our analysis faces several limitations. First, the Nationwide Inpatient Sample does not contain data from every hospital in every year. Therefore, we do not have a complete panel of hospitals and even though our study period comprises 8 years, the typical hospital shows up only about 3 times in our sample.

Second, hospitalists do not take care of all inpatients. The most agnostic approach is to measure average outcomes for all patients, which is what we show in the tables, in addition to separating the sample by medical and surgical DRGs. However, our estimates might be less noisy if we narrow our scope to the most relevant patient population - those exhibiting a set of conditions most commonly encountered by hospitalists. But given the limitations of our data, we do not actually know which patients were cared for by hospitalists. It is true that the mere existence of a hospitalist program could bring benefits for all patients in the hospital to the extent that the benefits of any process improvements spill over to patients who are not under the direct supervision of hospitalists. To tease out this effect from the direct impact of patient contact with hospitals, however, one would need to identify a setting patients who were cared for by hospitalists.

A third potential critique of our findings is that the larger effects of hospitalists on complex patients (relative to simpler patients) is due to the fact that conditional on diagnosis, hospitalists are more likely to be used for complex than simple patients. Such an assignment could lead to the pattern of results we see and would be an alternative to our interpretation of hospitalists having more of an impact of LOS for complex patients than for simple patients. However, this explanation does not explain why we see higher lengths of stay for the simplest patients. If such patients were taken care of by PCPs both before and after the adoption of hospitalist programs, then we should not expect to see the changes in length of stay that we observe for them.

Finally, hospitals do not adopt hospitalist programs randomly, creating concerns about the endogeneity of the key explanatory variable. We have attempted to address this with several approaches. First, we use hospital fixed effects to control for those characteristics of hospitals that are both time invariant and potentially correlated with both hospitalist use and our dependent variables of interest (i.e. length of stay and mortality). This captures factors such as hospital size, teaching status, location, and many demographic characteristics that tend to stay stable over time. Second, while one might expect hospitalist adoption to be endogenous, which might impact the *average* effect of hospitalist use on length of stay, it is not clear that that possibility should generate the differential effects by patient complexity that lie at the heart of our findings.

Another issue is that our results do not clearly generalize to all contexts. That is, it is not clear that process specialization is *always* beneficial as complexity increases. It may depend on whether the complexity is created primarily due to process factors or customer factors.

The association of greater cumulative experience with improved performance is a well-documented phenomenon in the study of organizations (Yelle, 1979; Argote, 2013; Lapré, 2011). Despite the importance of the volume of cumulative experience, recent work suggests that the specific traits of experience need to be considered (Mishina, 1999; Lapré *et al.*, 2000; Argote and Miron-Spektor, 2011). In this paper, we investigate the trade-off between two such traits: customer-specific experience and organization-specific experience.

The hospital is a setting where supply-side knowledge and demand-side knowledge are both important. We shed light on the productivity implications of a recent process innovation in this setting - the emergence of hospitalists. Compared to traditional primary care physicians, hospitalists have more process familiarity at the expense of customer familiarity.

We find that the impact of hospitalist programs on resource use and the quality of care depends on patient complexity, with hospitalists being especially helpful for more complex patients. A possible explanation for this result could be that complex patients require more care coordination, which is a particular strength of hospitalists. We also find that hospitalists do not have a significant impact for routine conditions such as pregnancies where the protocol-driven approach to treatment might be a substitute for hospitalists.

We thus provide insight into the importance of different types of management experience. Our results support the view that process familiarity might be quite important relative to customer familiarity.

Chapter 3

Technology Adoption and Organizational Change: Recent Trends in the Health Care Delivery Sector

3.1 Introduction

The health care sector has experienced a vast amount of consolidation over the previous two decades. This consolidation has taken the form of hospital mergers, hospitals employing more physicians, and hospitals buying up physician practices. This period has also seen the rapid diffusion of electronic medical records (EMRs) as well as other kinds of technologies. My goal is to document the extent to which these phenomena are related to each other.

The bulk of this chapter is an empirical analysis of recent trends among health care delivery organizations. There has been an acceleration in the uptake of EMRs over the last decade, especially following the passage of the HITECH Act, which set aside billions of dollars in subsidies for the adoption of certified electronic medical records. Jha *et al.* (2009) document the rapid diffusion of electronic medical records in the last few years. I use data from the American Hospital Association to find the link between EMR adoption and hospitalist use. Taking advantage of a rich new dataset, the AHA Health IT Supplement, to obtain data on the adoption and use of EMRs, I show that the correlation between organizational integration in health care delivery and technology adoption has increased over time.

I document two distinct kinds of integration in the health care delivery sector. One type of integration is the closer association between hospitals and physicians as evidenced by the emergence of the salaried physician model and the adoption of hospitalist programs. The second type of integration is the consolidation of ownership. This trend can be measured by increasing concentration in health care markets. It is also evidenced by the gradual disappearance of stand-alone hospitals, as more and more hospitals become part of bigger health systems that operate multiple hospitals under common ownership.

I find that EMR adoption is positively correlated with hospitalist use and the tendency of hospitals to employ their physicians. In particular, I find that the likelihood of having a hospitalist program goes up to around 60% from around 40% if the hospital has a basic EMR system, while the probability of employing the physicians on the medical staff increases by 8 percentage points. This finding, however, does not provide evidence of a causal relationship because there might be time varying unobservable factors that predict both closer hospital-physician integration and greater EMR adoption. Therefore, I next attempt to understand what factors predict the adoption of EMR and hospitalist programs. I find that both EMR adoption and hospitalist use are associated with the hospital being part of a system and using other sophisticated technological equipment.

For a limited set of hospitals, I investigate the relationship between management quality and the adoption of process innovations using data on US hospitals from the World Management Survey. I find that well-managed hospitals are more likely to have electronic medical records and to use hospitalists. However, I do not find any link between physician employment and management quality or between local market concentration and management quality.

There are several plausible mechanisms through which technology adoption could be related to organizational structure in health care. First, information technology could result in greater fragmentation of providers because it reduces the cost of transferring information between different silos. Information technology, however, could also be associated with greater consolidation in the hospital industry. The upfront cost of investing in new technology is invariably high in health care. Larger organizations find it easier to invest in technology since there are economies of scale and, therefore, diffusion of technology could follow consolidation in the health care sector. Electronic medical records could further lead to better monitoring, which might favor the employment model over the traditional independent contractor model as far as the relationship between hospitals and physicians is concerned. The relationship between the market structure of hospital markets and technology adoption is also not clear. Markets that are more competitive might have reason to engage in a medical arms race by spending on sophisticated equipment. However, hospitals in competitive markets have less free cash flow and so may be limited in their ability to invest in the latest technology.

A strand of the management literature predicts that product innovations and process innovations have different models of diffusion (Damanpour and Gopalakrishnan, 2001). Since both electronic medical records and new organizational relationships between hospitals and physicians fall into the category of process innovations, they might have similar diffusion patterns that are different from the diffusion of product innovations at hospitals such as high-end diagnostic and therapeutic technologies. Given this difference, it is not clear whether we even necessarily expect organizational process innovation to be occurring simultaneously with the adoption of new products. This chapter, however, provides evidence that the use of hospitalists and good management quality is correlated with the adoption of high-end technology.

In fact, the set of results presented in this paper suggests some theories for what is happening in the US health care delivery sector during this period. One potential narrative is that as hospitals increased in size by merging with other hospitals or buying up physician practices, they also spent more on technology such as sophisticated diagnostic equipment and electronic medical records. These technologies in turn made it possible for hospitals to attract more physicians and thus led to further absorption of physician practices into hospitals. Some hospitals are better managed than others and these hospitals were more likely to adopt process innovations in particular. The increasing correlation between various kinds of technological innovation as well as between different measures of consolidation suggests that hospitals are sorting into 'haves' – organizations that are part of large systems at the forefront of technological and organizational innovation, and 'have-nots' – technological laggards that are not very well integrated with physicians or other organizations.

The rest of this chapter is organized as follows. Section 3.2 provides some background on hospital physician relationships. Section 3.3 introduces the data and presents some trends in the diffusion of different kinds of innovations at hospitals. Section 3.4 describes changes in the correlation between these innovations over time. Section 3.5 discusses the role of management in the diffusion of innovations and presents an analysis using data on management quality at a limited set of hospitals. Section 3.6 discusses some potential mechanisms. Section 3.7 concludes.

3.2 Background on Hospital Physician Relationships

The hospital industry is particularly interesting from an organizational economics perspective because the key decision-makers, physicians, are neither employees nor owners (Rebitzer and Votruba, 2011). In the production of inpatient care, hospitals and physicians combine their services to create a single product that is sold to the patient and insurer. Physicians traditionally have been relatively independent of hospitals and have used them as workshops in which to carry out their professional services (Berenson *et al.*, 2007). In the prevailing medical staff model, physicians and hospitals did not have a typical market relationship: they neither bought services from nor competed with each other. Rather, they informally exchanged physicians' use of the hospital's facilities for carrying out responsibilities, such as serving on quality and utilization review committees and taking emergency department call, as obligations for having medical staff privileges (Berenson *et al.*, 2007; Robinson, 2001).

The fragmented nature of the U.S. health care system has contributed to this independence. A hospital stay entails treatment by multiple physicians who are each paid a fee for services that is separate from the other physicians and from the fees the hospital receives for providing support. Even when a hospital receives flat payments from Medicare for a diagnosis-related group, those fees cover only hospital support services and not physician fees (Elhauge, 2010). Moreover, Cebul *et al.* (2008) claim that despite the crucial role played by physicians in resource allocation and care processes in the hospital, integrating physicians more tightly into process improvement efforts is made difficult by the sociology of the medical profession and also by legal doctrines that have historically supported arms-length physician-hospital relationships.

However, the historical tides are turning. According to the American Hospital Association (AHA), affiliations involving independent groups of physicians have been declining in prevalence, while arrangements in which physicians are salaried employees have been increasing. An AHA survey finds a 32% increase in hospital employment of doctors from 2000 to 2010. [1] According to Congressional testimony, Merritt Hawkins, the physician search and consulting firm, conducted more than 2,700 physician search assignments for hospitals, medical groups, and small physician practices from April 1, 2011, to March 31, 2012. Only 2% of those physician searches were on behalf of entities seeking doctors to start a practice in an area or to join a solo practitioner as a partner, compared with 42% in 2004. Overall, 63% of the group's physician search assignments were carried out for hospitals that wanted to hire doctors, compared with 11% in 2004.[2]

The closer integration between physicians and hospitals has advantages for both parties. For physicians, selling a practice to a hospital or entering into a close financial agreement can reduce overhead, while providing predictable schedules and compensation. For hospitals, buying or affiliating with practices allows development of areas of excellence, ensures staff, provides a network of referrals from physicians, and can give the combined entity more leverage with insurers (Kirchhoff, 2013).

Nevertheless, Robinson (2001) notes that while a long tradition in health care management, research, and policy analysis, interprets the organizational integration of physicians and hospitals as a step toward enhanced efficiency, accountability and quality improvement, an equally long tradition views this integration in a skeptical light, as evidenced in statutes prohibiting the "corporate practice of medicine", bans on patient referrals to facilities in which the physician has a financial interest, and antitrust enforcement directed at physician-hospital organizations. It is clear that vertical integration can be used in ways that are not necessarily beneficial to consumers. While legal restrictions forbid hospitals from directly paying physicians for referrals, hospitals could employ or contract with physicians to increase admissions, diagnostic testing, and outpatient services at their facilities. Closer integration could also allow hospitals and doctors to bundle their services and charge higher prices.

Existing literature has considered the increasing integration and its on effect on the industry. Cutler and Scott Morton (2013) document the rapid consolidation in the hospital industry over the

[1] American Hospital Association, AHA Hospital Statistics, 2012 Edition, p. vii

[2] Testimony of Mark Smith, President, Merritt Hawkins, Before the House Committee on Small Business, Subcommittee on Investigations, Oversight, and Regulations, "The Decline of Solo and Small Medical Practices," July 19, 2012.

last decade: sixty percent of hospitals are part of health systems and the average local system has 3.2 independent hospitals; 432 hospital merger and acquisition deals were announced between 2007 and 2012, involving 835 hospitals. Using hospital claims from Truven Analytics MarketScan for the non-elderly privately insured in the period 2001 to 2007, Baker *et al.* (2014) investigate the impact of vertical integration on hospital prices, volumes, and spending. They find that an increase in the market share of hospitals with the tightest vertically integrated relationship with physicians – ownership of physician practices – is associated with higher hospital prices and spending. In this chapter, I am primarily interested in understanding the interaction between technology adoption and hospital-physician integration. I turn to this issue in the next section.

3.3 Data and Preliminary Patterns

3.3.1 Data Sources

The main source of the data in this chapter is the American Hospital Association (AHA) Annual Survey, which contains information on all short-term non-federal acute-care hospitals in the US. From the AHA Annual Survey, I obtain data on hospital characteristics including number of admissions, number of beds, ownership status, system membership, trauma center status, residency programs, medical school affiliation, hospitalist programs, and teaching intensity. The dataset contains more than 5000 hospitals each year from 2001 to 2012. Appendix C shows summary statistics of the variables used in my analysis.

I also measure hospital physician integration using data from the American Hospital Association. In particular, I am able to distinguish between different forms of contractual arrangements that physicians have with hospitals. I measure the prevalence of the following forms of contractual arrangements: hospital ownership of physician practices, physician-hospital organizations, and independent practice associations. Starting in 2003, I am also able to see whether a hospital had a hospitalist program. I also use data from the AHA Annual Surveys to construct a technology index for hospitals in this time period. Appendix C shows the list of technologies used to construct the index, ranging from relatively established diagnostic machinery such as CT-Scan to cutting edge technology such as robotic surgery.

I use data on the adoption of electronic medical records from the AHA Health IT Supplement.

This survey has been conducted as a supplement to the AHA annual survey since 2008 and asks detailed questions about EMR adoption so that we know whether a hospital has each of the twenty-four functionalities listed in Table 1.1. Since this survey was designed with input from the Office of the National Coordinator of Health IT, one major advantage of this dataset is that there is a strong correlation between the measured EMR functionalities and the meaningful use criteria outlined in regulations that followed the HITECH Act.

Data on hospital management quality is from the World Management Survey.[3] This data set contains only about 285 hospitals in the US, therefore I perform a limited analysis concerning the relationship of management quality at these hospitals and the other outcomes that I am interested in this paper. Section 3.6 presents this analysis and describes the data in further detail.

3.3.2 Trends in Diffusion

The last decade has been a period of rapid technology adoption in hospitals. Electronic medical records are a prime example. As Figure 1.1 shows, the fraction of hospitals with a basic EMR system has gone up from under 10% in 2008 to almost 60% in 2013. An EMR has four functionalities, which are laid out in Table 1.1 in Chapter 1. The first is storing information about the patient, including patient demographics, physician notes, problem lists and medication lists. The second functionality is storing results such as lab reports, radiology reports and diagnostic test results. Advanced EMRs can also store images. The third functionality is computerized provider order entry (CPOE), which allows physicians to order lab tests, radiology tests, medications and consultations electronically. CPOE prevents the fulfillment of prescriptions that do not meet dosage requirements. The last category is clinical decision support (CDS), which provides clinical guidance, reminders, and various kinds of interaction alerts such as drug-drug interactions and drug-allergy interactions.

If EMRs are so helpful, why has adoption lagged behind? Providers typically cite the prohibitive cost of health IT as the key barrier to adoption. A complete EMR costs about $20 million in addition to annual operating costs of about $3 million (Laflamme *et al.*, 2010). There are several components to adopting a new EMR system: the initial fixed cost of the hardware,

[3] I thank John Van Reenen, Nick Bloom and Rafaella Sadun for sharing the World Management Survey data on US hospitals.

software, and technical assistance necessary to install the system; licensing fees; the expense of maintaining the system; and the opportunity cost of the time that health care providers could have spent seeing patients but instead must devote to learning how to use the new system and how to adjust their work practices accordingly (Orszag, 2008). Moreover, the kind of quality improvement delivered by EMRs does not lead to financial benefits because payers do not generally reimburse providers more for using EMRs and because patients or doctors rarely choose hospitals based on their EMR system (Cutler, 2014). Over the last few years, there have been several policy changes that make this a particularly interesting time to study EMRs. The Health Information Technology for Economic and Clinical Health (HITECH) Act of 2009 authorized nearly $30 billion to increase the adoption of electronic health record systems, with much of this money in the form of incentive payments to hospitals and eligible providers for meeting specific *meaningful use*. Hospitals have until the end of 2015 to deploy certified electronic health records or face fines starting at $2,000 a bed in the first year and up to $35,000 a bed by 2019 (Laflamme *et al.*, 2010).

In addition to the spread of EMRs, this period has also experienced the diffusion of expensive diagnostic and therapeutic equipment. I construct a technology index using a list of technologies that the AHA annual surveys ask about. The technology index has risen steadily over this time period as shown in Figure 3.1. Figure 3.2 shows the histogram of the technology index, showing there is quite a bit of variation in how close hospitals are to the technological frontier. On one extreme of the spectrum of technologies, most hospitals have basic equipment such as an ultrasound machine and CT scan. On the other end, innovations such as proton beam therapy and robotic surgery are just starting to diffuse during this period and very few hospitals have adopted them.

This period also experienced a rapid increase in consolidation of health care providers. To measure the competitive environment in the hospital industry, I calculate the Herfindahl-Hirschman Index (HHI) for each of the 306 hospital referral regions in the country. The market share for a given hospital is the share of the HRR's total admissions that can be attributed to that hospital. Figure 3.3 shows the increase in HHI between 2001 and 2011. There has been a steady increase in the average HHI across hospital referral regions in this period from about 0.24 to 0.26.

In addition to ownership consolidation driven by hospital mergers, there is also operational consolidation that has been going on over this period. This operational consolidation includes the

Figure 3.1: *Trend in Technology Index*

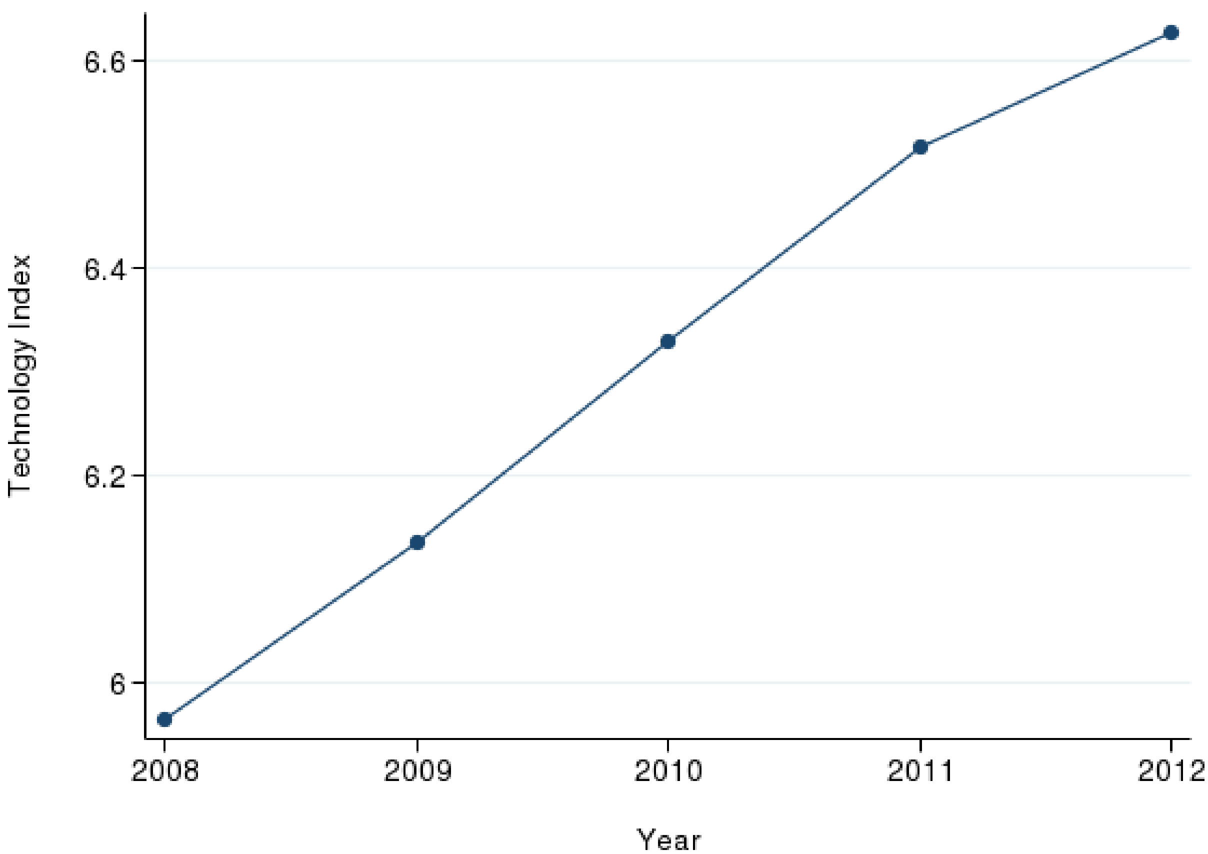


Figure 3.2: *Distribution of Hospitals by Technology*

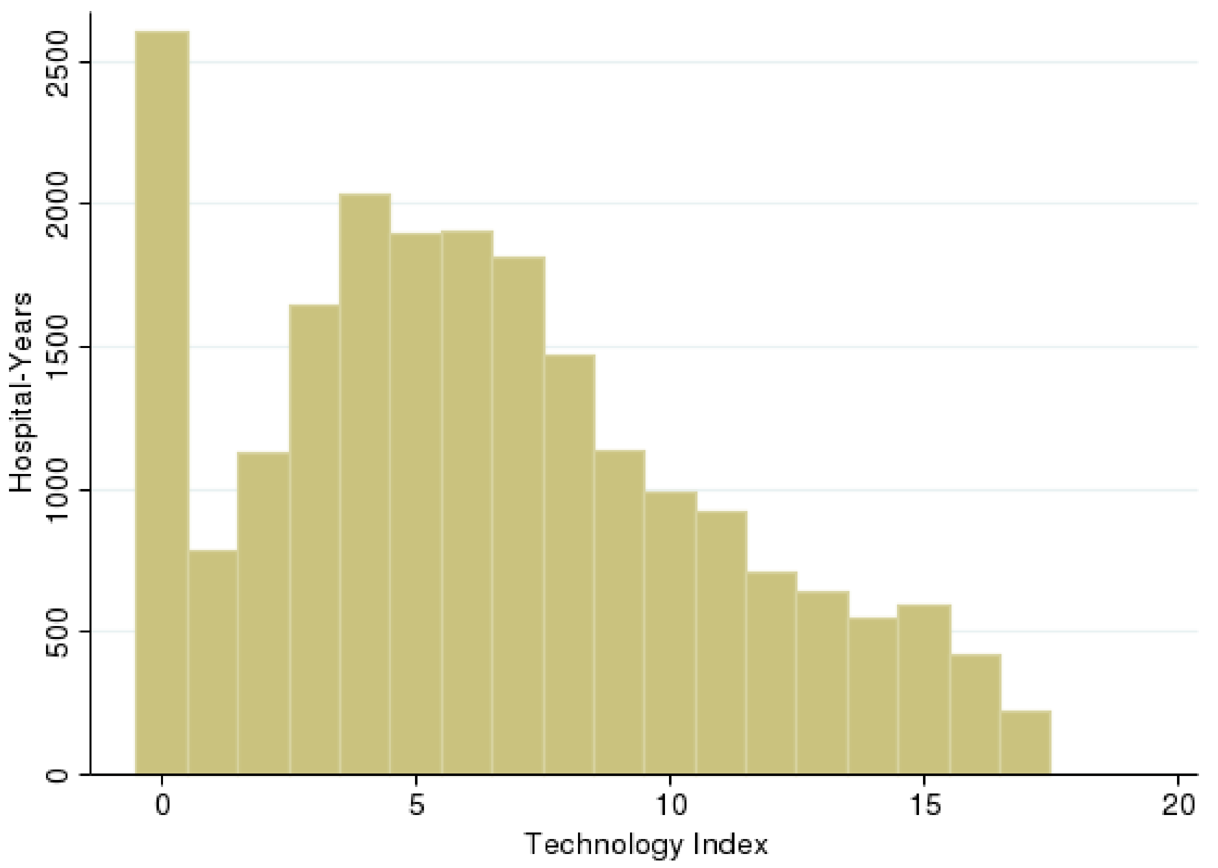


Figure 3.3: *Trends in Mean HHI at HRR Level*

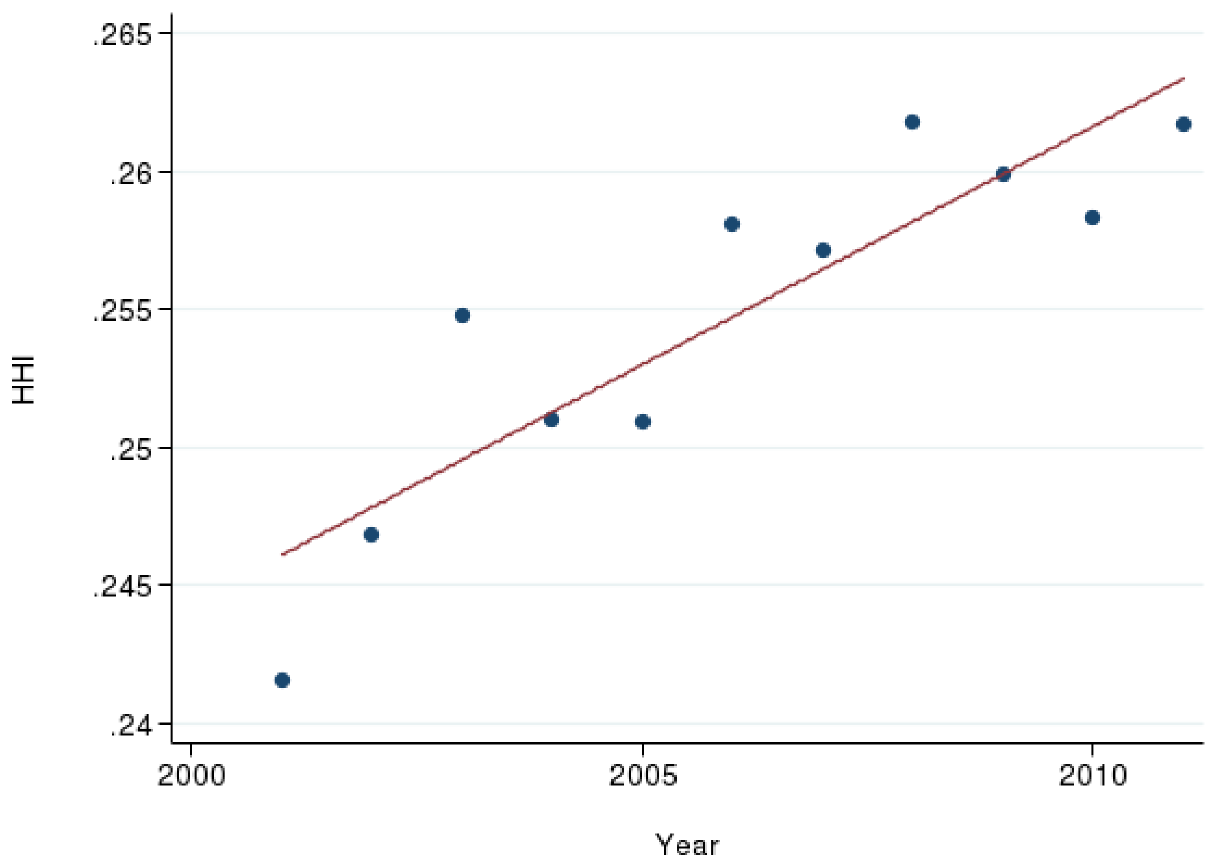
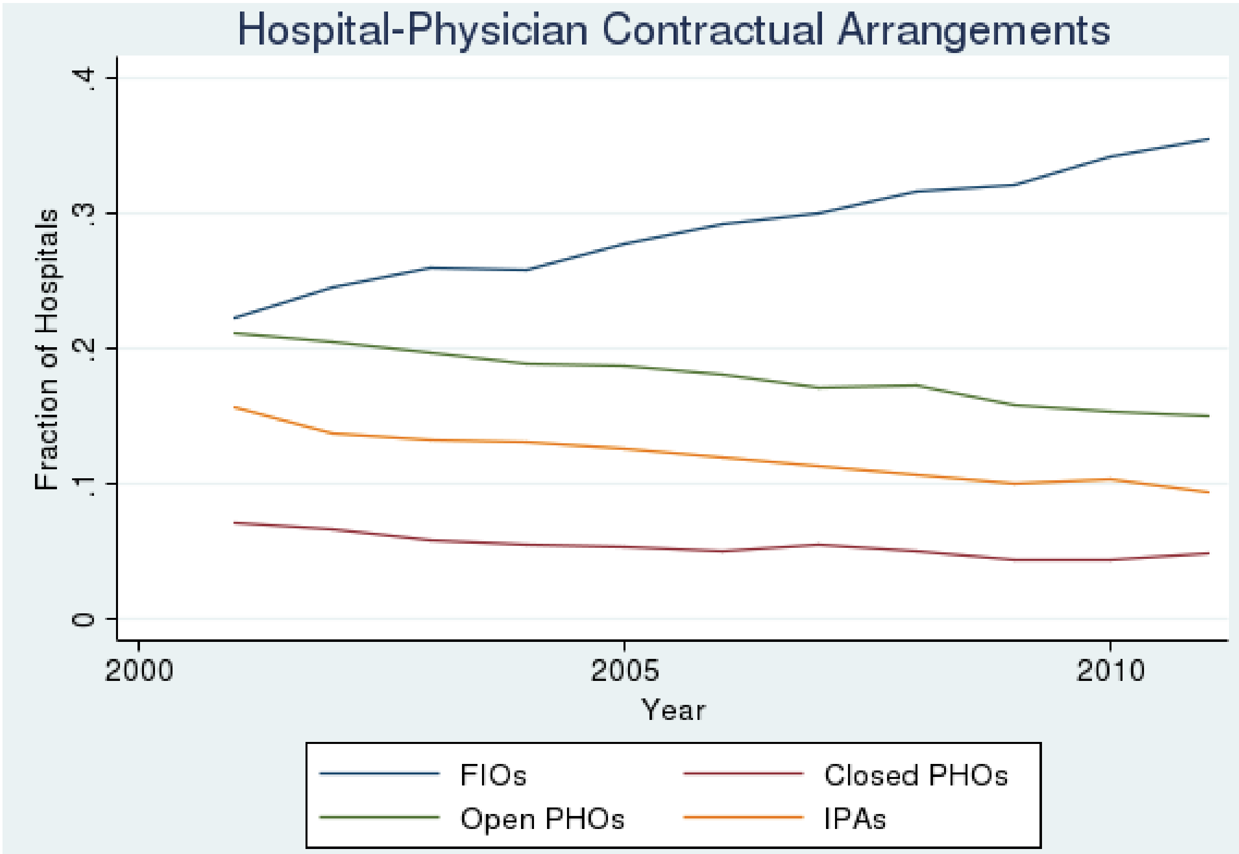


Figure 3.4: *Trends in Hospital-Physician Integration*



employment of physicians and the use of hospitalist programs. This type of integration is often described as vertical integration but it is not necessarily clear who are the upstream producers and who are the downstream producers amongst hospitals and physicians. The share of hospitals with a hospitalist program has gone from under 20% in 2003 to almost 50% in 2011. Figure 2.3 shows the trend in the adoption of hospitalist programs. The emergence of hospitalist programs is emblematic of the broader phenomenon of increased hospital-physician integration during this period. Appendix C shows the employment arrangement of hospitalists over this time.

Figure 3.4 shows how the contractual arrangements between hospitals and physicians evolved between 2001 and 2011. The share of hospitals that are fully-integrated organizations (FIOs) has increase from just over 20% to almost 40%. FIOs are the closest form of integration between hospitals and physicians (Baker *et al.*, 2014) and doctors are typically salaried employees of the hospital. Figure 3.4 also shows trends in other kinds of arrangements that represent looser integration between physicians and hospitals. The share of hospitals that contract with their physicians as physician-hospital organizations (PHOs) has gone down over this time period. A PHO is a separate business entity whose main purpose is to act a vehicle for hospitals and physicians to negotiate with third-party payers. A closed PHO means the physicians sign an exclusive contract with the hospital whereas in an open PHO any member of the medical staff is free to participate. Independent practice associations (IPAs) are the least tightly integrated contractual arrangement and as shown in the figure, their prevalence has been declining steadily during this period.

There have been relevant policy changes over this period that have supported this trend of closer integration. The Affordable Care Act has promoted the formation of Accountable Care Organizations (ACOs), groups of doctors and hospitals who coordinate with each other to provide care. More integrated providers such as ACOs could increase the scope for IT use. There has also been a move from volume-based payment to value-based payment. These complementary changes could facilitate technology use in organizations. Given the policy incentives in place, these patterns of technology adoption and provider consolidation are likely to continue in the coming years. It is therefore important to understand the relationship between them. I turn to this issue in the next section.

3.4 Trends in Correlation and Factor Analysis

In this section, I investigate the co-movements of the variables that were introduced earlier. I consider the following variables: basic EMR adoption, hospitalist program, technological product innovations, system membership of a hospital, and the hospital referral region's HHI. The technological product innovations include a set of technologies that were being steadily adopted over this time period: MRI, multi-slice CT scan, and robotic surgery. Table 3.1 shows the correlation between these variables at various points in time. I measure correlation at three points in time: 2005, 2008 and 2012.

Most of these variables are positively correlated with each other, consistent with the earlier evidence. Moreover, the positive correlation between the various factors increases over time.

For instance, when we compare 2012 with 2008, we see that almost every pairwise correlation has become more positive. The positive correlation between hospitalist use and EMR adoption increases from 0.113 in 2008 to 0.201 in 2012. The strongest pairwise correlations are between the adoption of high-end technologies. Multi-slice CT scan and robotic surgery have a correlation of 0.458 in 2012.

Hospitalist use also appears to be correlated with the adoption of advanced technologies. In 2005, the correlation coefficients between hospitalist use and MRI adoption, multi-slice CT scan, and robotic surgery are 0.33, 0.22 and 0.25 respectively. By 2012, these numbers have all increased to around 0.40. This co-movement is in line with evidence from the literature. For instance, David *et al.* (2009) find a strong positive association between the likelihood of using hospitalists and access to expensive medical equipment.[4]

In 2005, there is no data on EMR adoption, therefore the correlation table omits that variable. The pairwise correlation coefficients between all the other variables are systematically lower in 2005 than in the later years, confirming the trend of increasing co-movement over time.

Table 3.1a: *Correlation Table for 2012*

	EMR	Hospitalist Program	Robotic Surgery	Multi-Slice CT Scan	MRI	Salaried Physicians	System Member	HHI
EMR	1.0000							
Hospitalist Program	0.2013	1.0000						
Robotic Surgery	0.1896	0.3906	1.0000					
Multi-Slice CT Scan	0.2002	0.4141	0.4584	1.0000				
MRI	0.1994	0.4396	0.3272	0.4545	1.0000			
Salaried Physicians	0.1119	0.1178	0.1191	0.0949	0.1068	1.0000		
System Member	0.0755	0.1516	0.1401	0.0740	0.1040	-0.0512	1.0000	
Market HHI	-0.0029	-0.0497	-0.0636	-0.0472	-0.0717	0.0245	-0.0468	1.0000

3.4.1 EMR Adoption and Hospital-Physician Integration

In the previous section, I find that the spread of EMRs and the closer integration of hospitals and physicians has taken place concurrently. I merge data from the AHA Health IT supplement with the AHA data to further investigate the link between EMR adoption and hospital consolidation.

[4]But using technology-specific Certificate of Need laws to predict technology use, they find no causal link between access to technology and hospitalist use.

Table 3.1b: *Correlation Table for 2008*

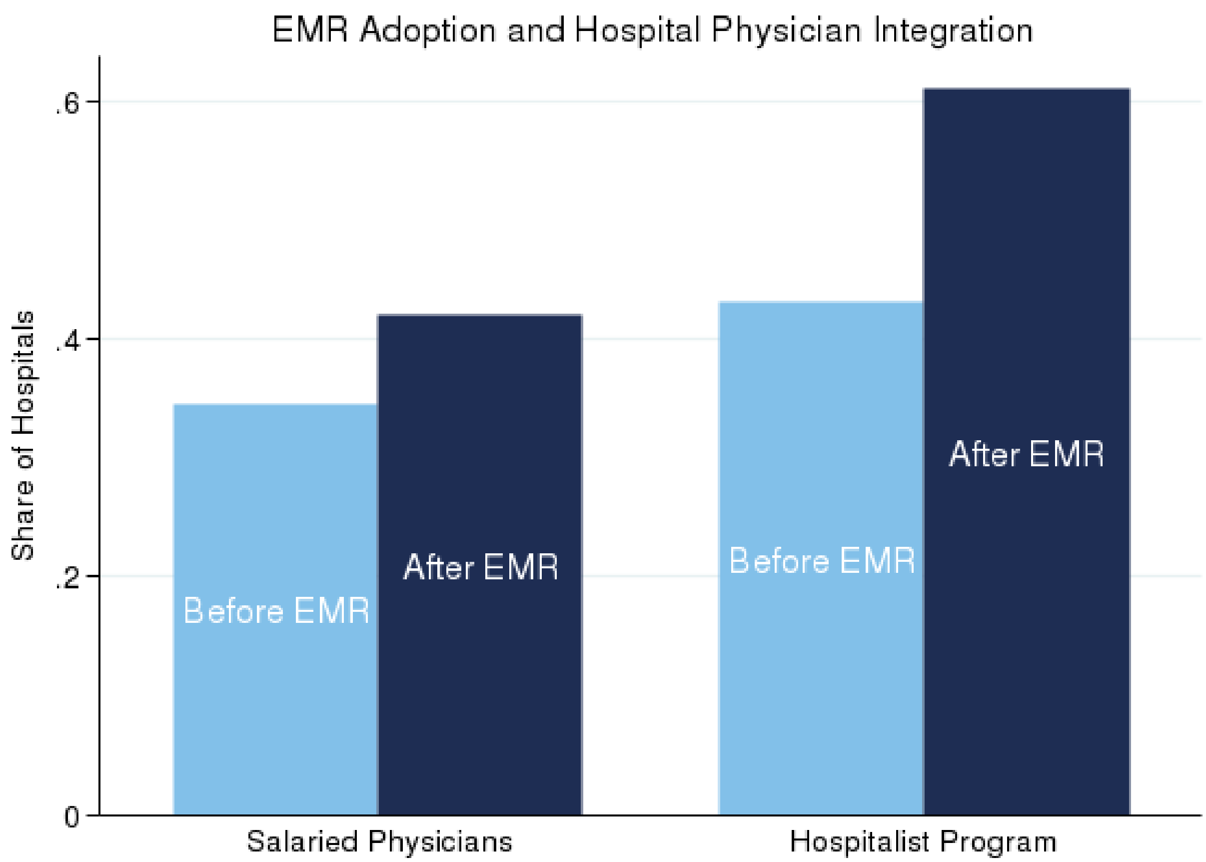
	EMR	Hospitalist Program	Robotic Surgery	Multi-Slice CT Scan	MRI	Salaried Physicians	System Member	HHI
EMR	1.0000							
Hospitalist Program	0.1128	1.0000						
Robotic Surgery	0.1334	0.3388	1.0000					
Multi-Slice CT Scan	0.1035	0.3766	0.3951	1.0000				
MRI	0.0957	0.3646	0.2426	0.3816	1.0000			
Salaried Physicians	0.0384	0.0874	0.0862	0.0954	0.0406	1.0000		
System Member	0.0480	0.1181	0.0991	0.0412	0.0589	-0.0715	1.0000	
HHI	-0.0283	-0.0290	-0.0482	-0.0282	-0.0683	0.0080	-0.0379	1.0000

Table 3.1c: *Correlation Table for 2005*

	Hospitalist Program	Robotic Surgery	Multi-Slice CT Scan	MRI	Salaried Physicians	System Member	HHI
Hospitalist Program	1.0000						
Robotic Surgery	0.2473	1.0000					
Multi-Slice CT Scan	0.2208	0.2692	1.0000				
MRI	0.3267	0.1801	0.2360	1.0000			
Salaried Physicians	0.0868	0.0639	0.0530	0.0336	1.0000		
System Member	0.1191	0.0512	0.0438	0.0971	-0.0631	1.0000	
HHI	-0.0637	-0.0355	-0.0308	-0.0571	0.0167	-0.0341	1.0000

Figure 3.5 shows that the share of hospitals that are fully integrated organizations (FIOs) - the closest arrangement between physicians and hospitals - is about 35% before EMR adoption, and rises to more than 40% after EMR adoption. Physicians who are part of FIOs are most likely to be salaried employees of the hospital. The adoption of hospitalist programs is further evidence of the closer integration between hospitals and physicians. Hospitalists are typically employees of the hospital, but they could be employed by an independent physician group. Around 40% of hospitals without a basic EMR have hospitalist programs whereas more than 60% of hospitals with a basic EMR have hospitalist programs.

Figure 3.5: *EMR Adoption and Hospital-Physician Integration*



There is thus a positive correlation between the adoption of EMRs and hospitalist use. Table 3.2 shows the trend in this correlation. It appears that the positive association between basic EMR adoption and hospitalist use is increasing over time. The correlation coefficient rises steadily

Table 3.2: *Correlations over Time*

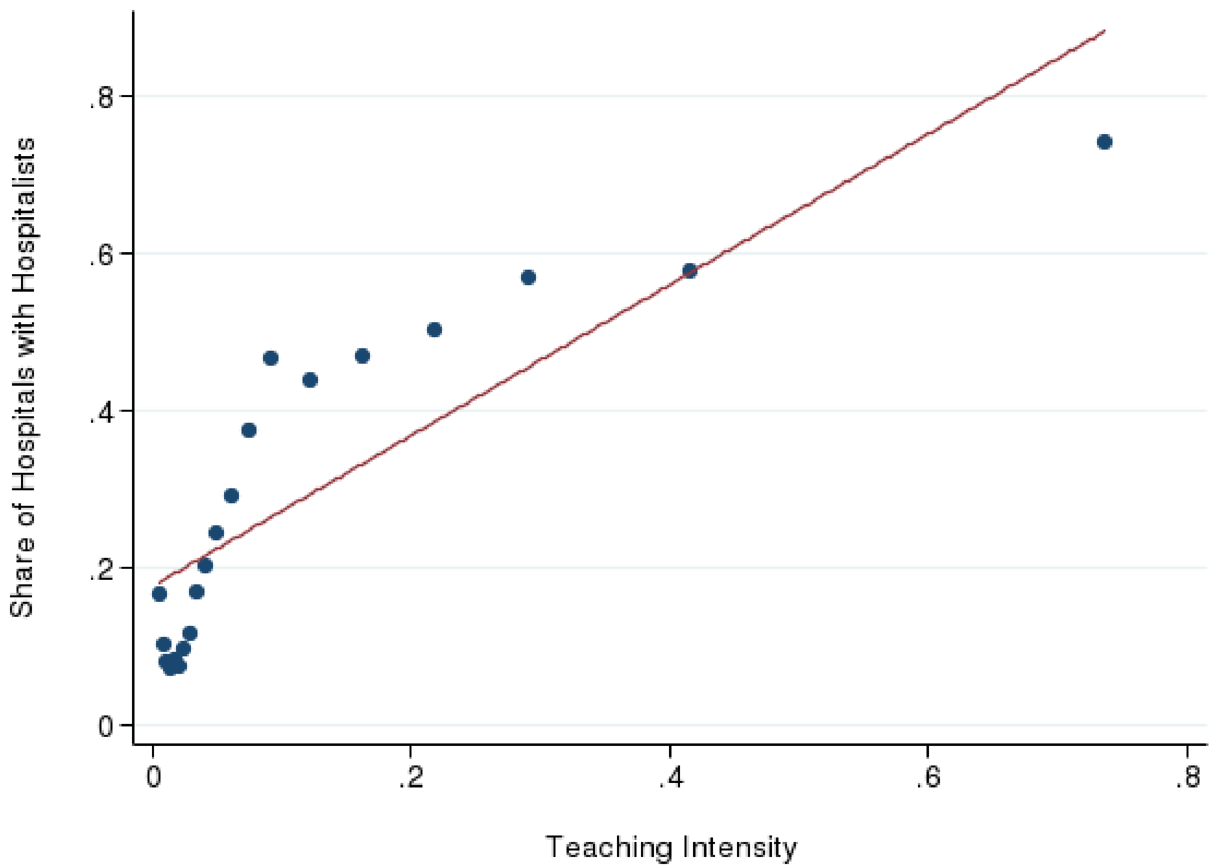
Correlation Between EMR Adoption and Hospitalist Use	
Year	**Correlation Coefficient**
2008	0.1069
2009	0.1553
2010	0.1307
2011	0.1896
2012	0.1788
Correlation Between EMR Adoption and HHI	
Year	**Correlation Coefficient**
2008	-0.022
2009	-0.0354
2010	-0.0173
2011	-0.0064
2012	0.014
Correlation Between Hospitalist Use and HHI	
Year	**Correlation Coefficient**
2008	-0.0185
2009	-0.0078
2010	-0.0166
2011	-0.0255
2012	-0.0245
Correlation Between Hospitalist Use and Technology Index	
Year	**Correlation Coefficient**
2008	0.5135
2009	0.5232
2010	0.5526
2011	0.5401
2012	0.5645

from 0.1128 in 2008 to 0.2013 in 2012. While EMR adoption and hospital-physician integration are correlated, they are most likely explained by some general trend that is affecting all hospitals during this period. I next attempt to understand the determinants of the adoption of organizational innovations and how they relate to the determinants of the adoption of product innovations.

3.4.2 Determinants of the Adoption of Innovations

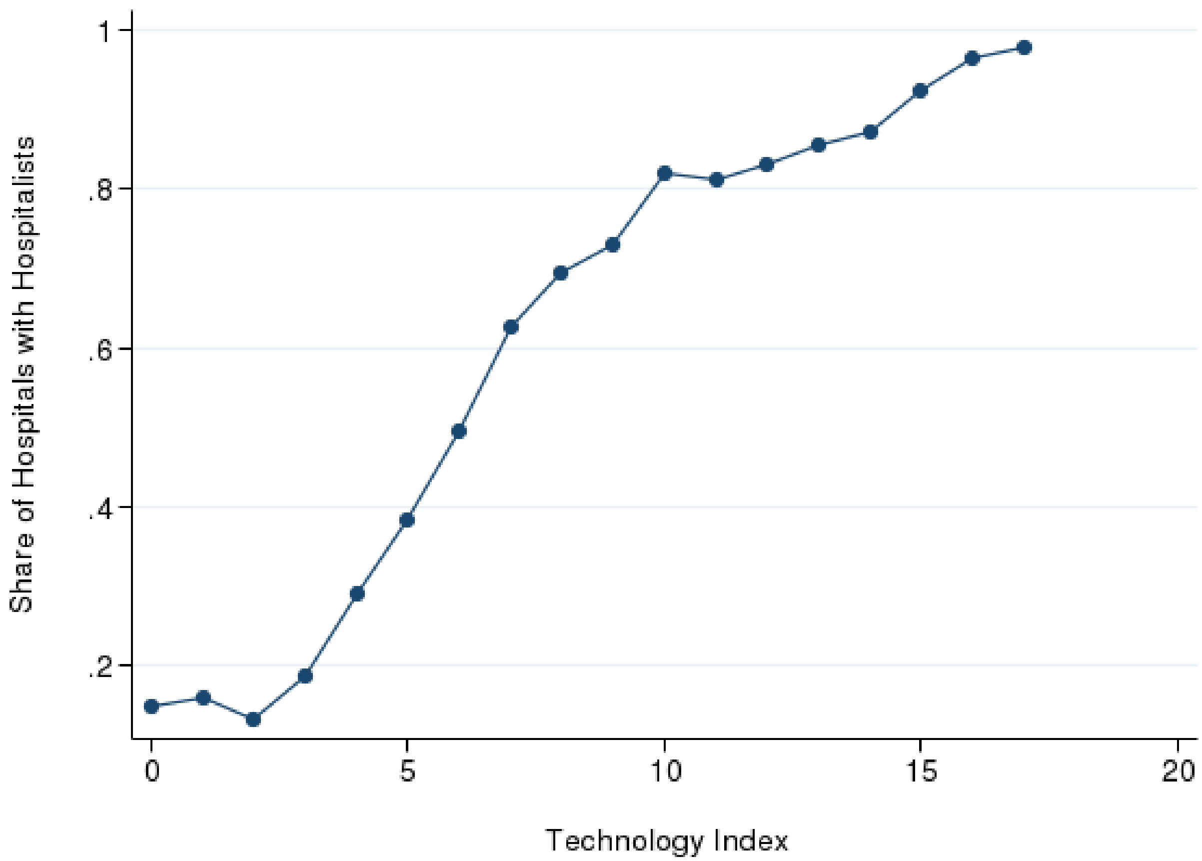
It is clear that there is some correlation in the adoption of process innovations. What are the determinants of their adoption? I observe the following patterns with regard to the adoption of EMRs. As shown in Table 3.2, there is no correlation between EMR adoption and HHI at the hospital-referral region level. Similarly, there is no correlation between hospitalist use and HHI at the hospital-referral region level. However, hospitals with a high teaching intensity, defined as the number of residents per bed are more likely to have hospitalists. This correlation, which is captured in Figure 3.6, is surprising because we think of hospitalists as substitutes for residents since both types of doctors perform similar duties, spending all their time at the hospital.

Figure 3.6: *Hospitalist Use and Teaching Intensity*



In addition to the diffusion of process innovations, the adoption of production innovations has continued apace over this period. I perform a similar exercise to understand what factors make a hospital likely to adopt high end technologies. I find that hospitals with hospitalists programs are more likely to adopt these technologies. Fig 3.7 plots the fraction of hospitals with a hospitalist program, for any given level of the technology index and it is clear that hospitals that score high

Figure 3.7: *Hospitalist Use and Technology Index*



on the index are significantly more likely to have a hospitalist program. As shown in Table 3.2 the correlation between hospitalist use and the technology index is strong and increasing over time. David *et al.* (2009) find a similar positive association and argue that the hospitalist's role of utilization management could be viewed as complementary to sophisticated medical equipment in the production of inpatient care services.

3.4.3 Factor Analysis

Since these variables are all positively correlated, I perform a factor analysis to investigate whether the variation among hospitals can be reduced to fewer principal components. Table 3.3 shows the results of the factor analysis at four points in time: 2001, 2005, 2008 and 2012. By the usual criterion of eigenvalues greater than 1, there are two significant factors in each of these years. In 2001, these two factors account for 55% of the cumulative variation in the data. In 2012, these two factors account for 44.2% of the variation in the data. In 2008, the two factors account for 40.5% of the variation in the data. Thus between 2008 and 2012, there was a reduction in the different types of hospitals.[5] After rotating the factors to reduce the correlations between them, the first factor loads mainly on hospitalist use and high-end technologies. The second factor loads on salaried physicians and HHI.

I have documented that there is a positive correlation between the adoption of basic EMR systems and the adoption of hospitalist programs. There could be some geographic patterns that explain the adoption of both process innovations and product innovations. However, in addition to location-specific factors that could influence the diffusion of these innovations, there might also be organization-specific factors. In particular, does the quality of a hospital's management matter? I explore this issue in the next section.

[5]Comparing the 2008 and 2012 results is the most appropriate approach since these two years contained exactly the same variables.

Table 3.3: *Factor Analysis Results*

	Eigenvalue	Proportion	Cumulative
		2012	
1	2.44722	0.3059	0.3059
2	1.08886	0.1361	0.442
3	0.9688	0.1211	0.5631
4	0.91183	0.114	0.6771
5	0.84312	0.1054	0.7825
6	0.68223	0.0853	0.8678
7	0.57347	0.0717	0.9394
8	0.48447	0.0606	1
		2008	
1	2.14889	0.2686	0.2686
2	1.08908	0.1361	0.4047
3	0.98594	0.1232	0.528
4	0.96323	0.1204	0.6484
5	0.89341	0.1117	0.7601
6	0.74898	0.0936	0.8537
7	0.62	0.0775	0.9312
8	0.55047	0.0688	1
		2005	
1	1.79925	0.257	0.257
2	1.08434	0.1549	0.4119
3	0.97713	0.1396	0.5515
4	0.9154	0.1308	0.6823
5	0.83412	0.1192	0.8015
6	0.74259	0.1061	0.9075
7	0.64717	0.0925	1
		2001	
1	1.16458	0.2911	0.2911
2	1.02431	0.2561	0.5472
3	0.99909	0.2498	0.797
4	0.81201	0.203	1

3.5 The Role of Management

Given that organization specific variables might explain the diffusion of innovations, it is interesting to explore if the adoption of process innovations is related to the management quality at hospitals. I explore this using survey data for U.S. hospitals from Bloom *et al.* (2014) who collect data on management practices for operations, targets and human resources in 2,000 hospitals in Brazil, Canada, France, Germany, India, Italy, Sweden, UK and the US. These management practices are strongly associated with better clinical outcomes, such as heart attack survival rates, and financial outcomes like profits. They also show that hospitals with more clinically trained managers, that are larger, that operate in more competitive markets, and that are not government owned appear to have significantly higher management scores.

The analysis in this section is limited to only about 300 hospitals and therefore, the results in this section should not be directly compared to the earlier results. We can nevertheless gain a better understanding of the role of management in the adoption of innovations. qManagement practices are measured using the methodology developed in Bloom and Van Reenen (2007). This interview-based tool scores a set of 20 basic management practices on a grid from 1 ("worst practice") to 5 ("best practice"). Twenty questions about management quality were asked which fell into one of four main categories : operations management, performance monitoring, target setting, and talent management. Appendix C contains a description of each of these categories.

The main measure of management quality is the average of the 20 scores. Figure 3.8 shows the distribution of management scores at the hospitals. Among this sample of hospitals, management quality is normally distributed, with a mean of 3 and a standard deviation of 0.55. I consider how this measure of management is related to the trends that I document earlier in this paper. As Figure 3.9 indicates, there is a very small correlation between hospital concentration and management quality. In line with the findings of Bloom *et al.* (2014), management quality is slightly higher in more competitive hospital markets. On the other hand, as Figure 3.10 shows, there appears to be a strong positive relationship between management quality and the technology index. As far as product innovations are concerned, well-managed hospitals are at the cutting edge of technology adoption.

Table 3.4, as well as Appendix C, shows the results of some further analysis into the relationship

Figure 3.8: *Distribution of Management Quality*

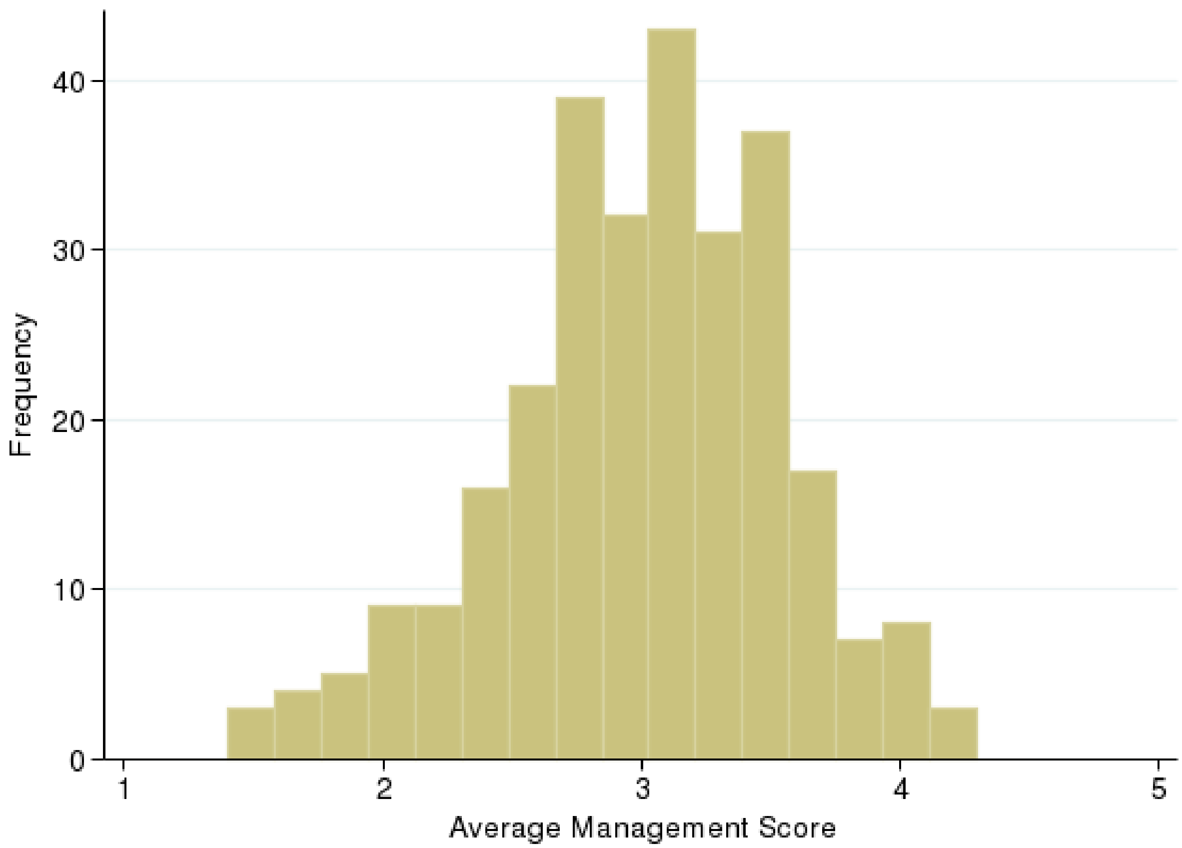


Figure 3.9: *Hospital Concentration and Management Quality*

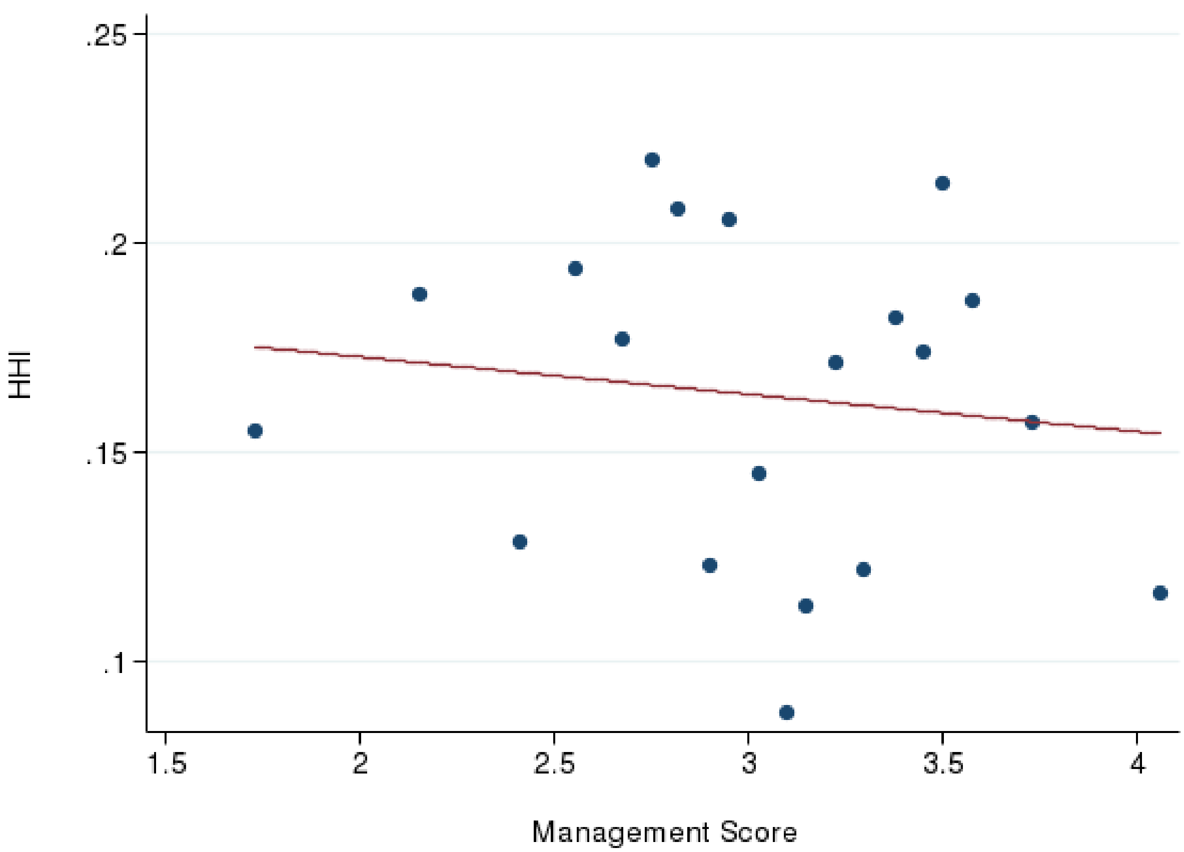


Figure 3.10: *Technology Adoption and Management Quality*

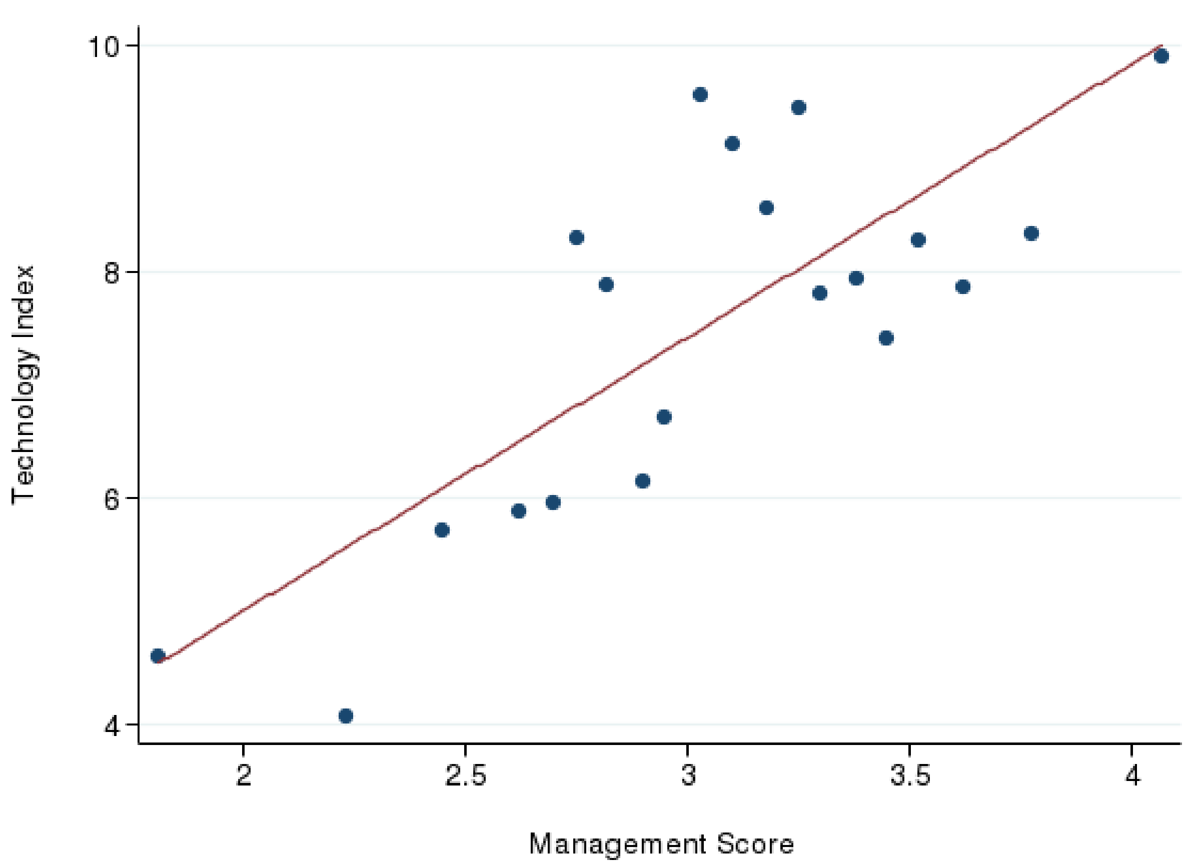


Table 3.4: *Management Quality and Process Innovations*

		Average Management Score
Basic EMR	No	2.988178
	Yes	3.107298
Hospitalist Program	No	2.821398
	Yes	3.171229
Salaried Physicians	No	2.995536
	Yes	3.002687

between management quality and the adoption of process innovations. From Figure 15, it appears that there is a positive association between good management and the adoption of a basic EMR system. Hospitals with a basic EMR have an average management score of 3.11 compared to 2.99 for hospitals without a basic EMR. The relationship between good management and hospitalist use is even stronger. Hospitals without a hospitalist program have an average score of 2.82, whereas those with a hospitalist program have an average score of 3.17. However, there does not appear to be any association between good management and tighter hospital-physician integration as measured by the likelihood of physicians to be salaried employees of the hospital. The average management scores is approximately 3.0, both for hospitals that are fully-integrated organizations and those that are not.

3.6 Potential Mechanisms

In this section, I highlight a few plausible mechanisms that could explain the co-movement of the innovation adoption trends I present in this chapter.

It is possible that IT leads to greater consolidation among health care delivery organizations. Adopting an electronic medical record system necessitates substantial capital investment. For an average hospital with two hundred beds, the initial cost of adoption is \$20 million in addition to \$3 million annually in licensing and operating expenses. For a physician practice, the upfront cost is in the \$8,000 -\$16,000 range per physician while the annual cost is about 20% of the upfront cost. The HITECH Act, which was passed as part of the stimulus package in 2009, set aside billions of dollars in subsidies for the adoption and use of certified electronic medical records by eligible hospitals and physicians. The incentive payments in the HITECH Act help but do not cover the full cost of adopting an EMR. Therefore, physicians and smaller hospitals who do not want to deal with the hassle of buying and installing an EMR system might have an incentive to become part of a larger hospital system. It would then be the parent organization's responsibility to make the necessary upfront investment. Information technology can also help to lower monitoring costs. The organizational economics literature documents that such a change in monitoring costs favors the ownership model (Baker and Hubbard, 2004) and we could see this change play out in the health care delivery system as well.

IT could also lead to decentralization of organizations, because of lower information acquisition costs as in Garicano (2000). One of the barriers to the hospitalist model is the potential information loss when responsibility for the patient is transferred from the primary care physician to the hospital. An electronic medical record could reduce the cost of acquiring information about patients. This technology, therefore, removes one of the barriers to the hospitalist model. The empirical evidence in this chapter shows that EMR adoption is positively associated with hospitalist use.

I have also presented evidence of variation in the adoption of innovations across hospitals. What prevents hospitals from adopting some of these innovations that have documented benefits? Since the benefits are not always visible, not all stakeholders might be on board. There is scope for good management as evidenced by the successful rollout of process innovations in isolated organizations (Cutler, 2014). The fee-for-service reimbursement system does not reward physicians who figure out a way to deliver care most efficiently. Phelps (2000) claims that this is a property rights issue because when doctors learn how to treat patients better they have little way to reap the benefits of the innovation. Large manufacturing firms and service delivery chains have internal mechanisms through which they can exploit the gains from process innovation. Physician offices and single hospitals do not have this capability, blunting the incentives to invest in process improvement.

There is evidence that process innovations diffuse differently from product innovations. The management literature defines product innovation as new products and services introduced to meet an external user or market need, and process innovation as new elements introduced into an organization's production or service operations (e.g., input materials, task specifications, work and information flow mechanisms, and equipment) to produce a product or render a service (Ettlie and Reza, 1992; Knight, 1967; Utterback and Abernathy, 1975). Product innovations can often diffuse through pioneering early adopters. Agha and Molitor (2015) analyze the influence of physician investigators who lead pivotal clinical trials for new cancer drugs and find that patients in the lead investigator's region are initially 36% more likely to receive the new drug. Damanpour and Gopalakrishnan (2001) argue that product innovations are adopted more because they are more observable, increase market shares and profits, are more appropriable and have a higher chance of institutional imitation. The last point is true because organizations imitate other organizations in their institutional environment and adopt product innovations that have been adopted by elite organizations or industry leaders (Hage and Dewar, 1973; Rogers Everett, 1995). Thus, technical and product innovations are more industry-specific, i.e., they are more standardized across industry, while administrative and process innovations are more organization-specific, i.e., they are generally unique to the unit of adoption. Organization-specific innovations cannot be imitated without significant modifications to make them compatible with the structure, culture, and systems of the adopting organization; thus, they are less likely to be replicated (Damanpour, 1996). The evidence in this chapter does not support the theory that process innovations and product innovations diffuse differently among health care delivery organizations. At various points in time, process innovations such as hospitalist use or new information systems are positively correlated with the adoption of high-end technological equipment.

The role of management may be particularly important for organization-specific innovations. Therefore, one goal of this paper is to study the relationship between good management and the adoption of process innovations. Indeed, I find that better managed hospitals are more likely to have EMRs and hospitalist programs. To the extent that more competitive areas have better management, we might expect hospitals in those areas to be pioneers in the adoption of process innovations. On the other hand, areas that are more concentrated have hospitals in larger systems, and with more free cash flow to invest in new technologies. Therefore, one might also expect hospitals in these locations to lead in the adoption of new technologies such as electronic medical records. I find that while good management is correlated with the adoption of new technologies, the competitiveness of a hospital's market is weakly correlated with both management quality and technology adoption.

3.7 Conclusion

The health care delivery system is undergoing rapid change and I document some important facts surrounding the diffusion of innovations in this industry. I find that three distinct upward trends that are positively correlated. Electronic medical records are diffusing rapidly, there has been an increase in the integration of hospitals and physicians, and the adoption of expensive new diagnostic and therapeutic technologies has continued at hospitals. In this chapter, I have explored the relationship between these phenomena, focusing on organizational outcomes rather than health outcomes, which were the main focus of chapters 1 and 2.

I find that closer hospital-physician integration is positively associated with the adoption of new technology, and that this positive correlation is increasing over time. I highlight some potential mechanisms that could explain the co-movement of these trends and I find some preliminary evidence. In particular, hospitals are more likely to use hospitalists and enter employment contracts with physicians at the same time as they adopt EMRs. While I cannot provide any evidence of a causal relationship, I believe that the general tendency over time to adopt EMRs and use hospitalists explains this positive correlation. EMR adoption could be complementary to the use of hospitalists because these hospital-based physicians can access information about their patients more easily when records are digitized. Similarly, the benefits of sharing information within a organization are larger in the presence of EMRs leading to closer hospital-physician integration.

Since it is expensive to invest in new technology, smaller hospitals might want to join big systems who can afford to buy such equipment. I find that hospitals that are part of a larger health system are more likely to have adopted electronic medical records as well as product innovations such as MRI, multi-slice CT scan and surgical robots. I also find that good management is correlated with the adoption of electronic medical records and the use of hospitalists. It would be interesting to conduct more detailed studies to understand why certain hospitals are able to achieve rapid uptake of these innovations while others are not.

It is important to explore this issue further to understand what determines the adoption of new innovations. To the extent that there are well-documented benefits to some of these innovations, it will be important to understand why certain organizations adopt them while others do not. Identifying the barriers to adoption will help both hospital managers and policymakers in their roles.

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Appendix A

Appendix to Chapter 1

A.1 Supplementary Tables

Table A.1: *Effect of EMR Adoption on No. of Admissions*

	Dependent Variable: Total Admissions			
	CHF	Pneumonia	Hip Fracture	AMI
EMR	-24.36	-24.87	-28.49	-20.22
	(85.13)	(85.21)	(86.03)	(89.15)
N	7366	7340	7222	6884
adj. R^2	0.991	0.991	0.991	0.991

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Standard errors are in parentheses and are clustered at the hospital level. Each coefficient represents the effect of EMR adoption on the number of admissions for the given disease, based on regressions of total admissions on EMR adoption. All regressions include hospital and year fixed effects, as well as a set of hospital-level control variables including size, ownership status, teaching status, hospitalist use, system membership, trauma center status, and Medicare/Medicaid discharges.

Table A.2: *Effect of EMR on Length of Stay - dropping top 5%*

	Dependent Variable: Log Length of Stay			
	Pneumonia	CHF	AMI	Hip Fracture
EMR	-0.0285***	-0.0235*	-0.000777	-0.000233
	(0.00576)	(0.00914)	(0.00802)	(0.00513)
EMR*Complex	0.0251***	0.0313***	0.00137	0.00329
	(0.00525)	(0.00904)	(0.00791)	(0.00379)
N	818522	1013460	480347	412434
adj. R^2	0.132	0.080	0.140	0.124
F-Test	0.422	0.0828	0.920	0.501

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Standard errors are in parentheses and are clustered at the hospital level. All regressions include hospital and year fixed effects, as well as a set of hospital-level control variables including size, ownership status, teaching status, hospitalist use, system membership, trauma center status, and Medicare/Medicaid discharges. Patient-level characteristics include age, sex, race, and the interactions of these demographic variables, past admission, and a set of diagnosis-related group (DRG) dummies.

Table A.3: *Effect of EMR on Thirty-Day Mortality and Readmission*

Dependent Variable: Thirty Day Mortality or Readmission				
	Pneumonia	CHF	AMI	Hip Fracture
EMR	-0.0162***	-0.0141***	-0.0217***	-0.00635
	(0.00339)	(0.00401)	(0.00556)	(0.00530)
EMR*Complex	0.0185***	0.0160***	0.0253***	0.0126**
	(0.00269)	(0.00341)	(0.00554)	(0.00440)
N	870084	1070108	526359	428363
adj. R^2	0.032	0.016	0.074	0.117
F-Test	0.404	0.444	0.336	0.172

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Standard errors are in parentheses and are clustered at the hospital level. All regressions include hospital and year fixed effects, as well as a set of hospital-level control variables including size, ownership status, teaching status, hospitalist use, system membership, trauma center status, and Medicare/Medicaid discharges. Patient-level characteristics include age, sex, race, and the interactions of these demographic variables, past admission, and a set of diagnosis-related group (DRG) dummies.

Table A.4: *Effect of EMR on Upcoding*

	Dependent Variable: High No. of Secondary Diagnoses							
	Pneumonia		**CHF**		**AMI**		**Hip Fracture**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EMR	0.00405	0.00505	-0.000315	0.00230	0.00198	0.00387	0.00386	0.00625
	(0.00403)	(0.00424)	(0.00341)	(0.00357)	(0.00407)	(0.00439)	(0.00538)	(0.00554)
EMR*Readmission		-0.00351		-0.00301		-0.000938		-0.0137^{**}
		(0.00342)		(0.00247)		(0.00427)		(0.00477)
EMR*Readmission*SameHospital		0.00202		-0.000845		-0.00620		0.00984^{*}
		(0.00312)		(0.00224)		(0.00468)		(0.00501)
N	870084	870084	1070108	1070108	526359	526359	428546	428546
adj. R^2	0.215	0.215	0.170	0.171	0.245	0.247	0.193	0.194
F-Test (p value) (EMR + EMR*Repeat = 0)		0.750		0.858		0.573		0.279
F-Test (p value) ($\sum$ All 3 Coefficients = 0)		0.407		0.657		0.469		0.676

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Standard errors are in parentheses and are clustered at the hospital level. All regressions include hospital and year fixed effects, as well as a set of hospital-level control variables including size, ownership status, teaching status, hospitalist use, system membership, trauma center status, and Medicare/Medicaid discharges. Patient-level characteristics include age, sex, race, and the interactions of these demographic variables, past admission, and a set of diagnosis-related group (DRG) dummies.

A.2 Legislative Background

This section provides some background information on the HITECH Act [1], which provided incentives for adoption of certified EMRs via the Medicare and Medicaid programs. Eligible acute care inpatient hospitals are defined as "subsection (d) hospitals" which are hospitals that are paid under the hospital inpatient prospective payment system (IPPS) and are located in one of the 50 states or the District of Columbia. Penalties are supposed to start in 2015. Actual payments in 2011 included $1.38 billion through Medicare to 604 hospitals and $1.5 billion through Medicaid to 1,043 hospitals. Hospitals are eligible for payments through both Medicare and Medicaid.

The formula for the Medicare payment in the first year is:

[2,000,000 + Discharge Related Amount] * Medicare Share of Inpatient Days

The formula for the Medicaid payment in the first year is:

[2,000,000 + Discharge Related Amount] * Medicaid Share of Inpatient Days

Only hospitals which have at least 10% *of discharges on Medicaid are eligible.*

The "Discharge Related Amount" for a 12 month period is:

- 0 for the first 1,149 discharges
- $200 per discharge for discharges between 1,150 and 23,000
- 0 for discharges in excess of 23,000

The formula for calculating the Medicare/Medicaid share includes an adjustment for charity care charges as a proportion of total charges. This effectively increases the Medicare/Medicaid share resulting in higher incentive payments for hospitals that provide a greater proportion of charity care.

Hospitals that demonstrate that they are meaningful users of certified EHR technology in FYs 2011, 2012, or 2013 could receive up to four years of financial incentive payments. Hospitals that begin receiving incentive payments later than FY 2013 will receive no more than three years of incentive payments.

Data on acute care hospital discharges from the hospital's most recently filed 12-month cost report at the time of the calculation is used as the basis for making preliminary incentive payments. Eligible hospitals can receive payments for attesting to the meaningful use of certified EHRs by reporting on 13 required core objectives and 5 of 10 menu set objectives. These objectives are detailed in Table A5.

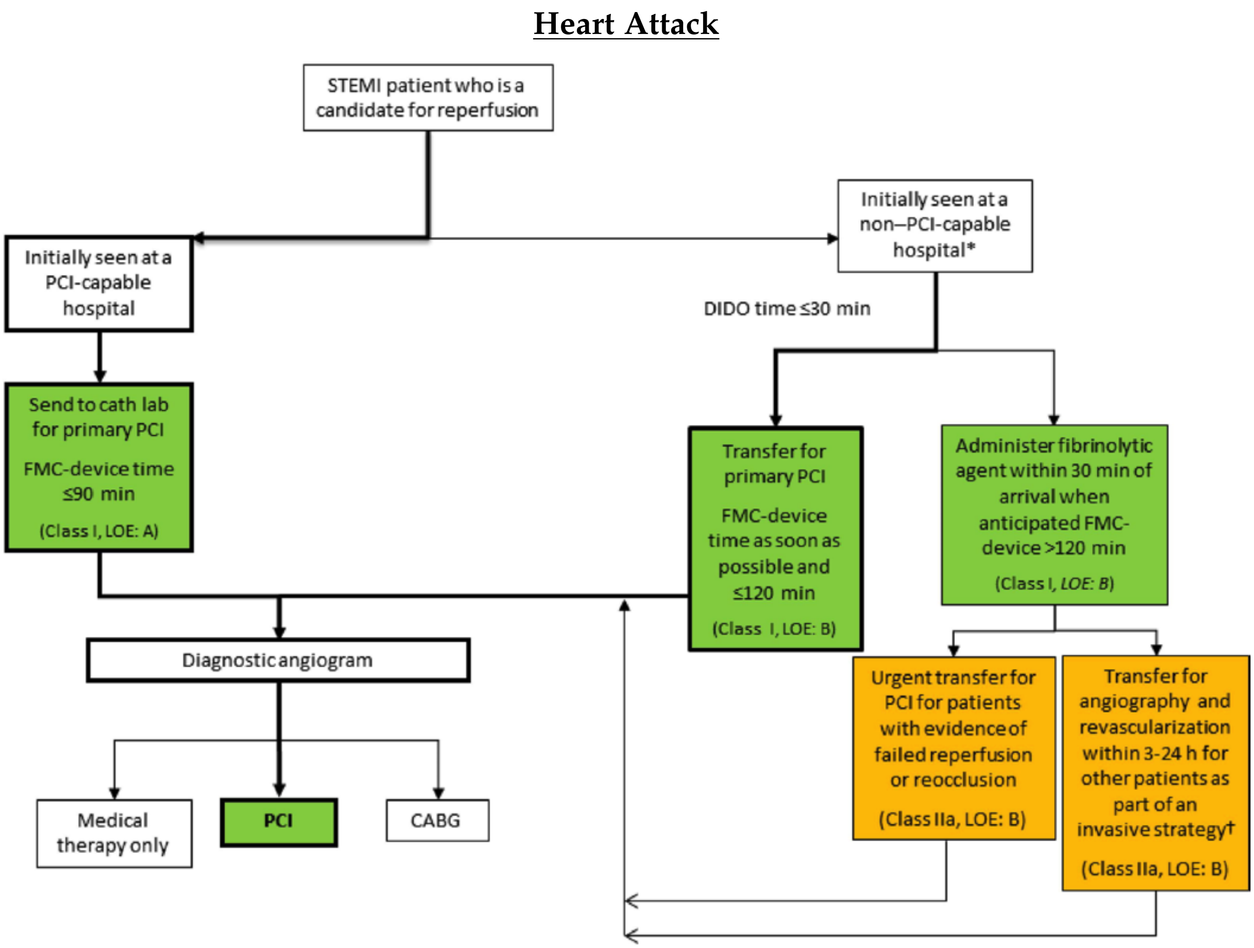
[1] Source: Centers for Medicare and Medicaid Services

Table A.5: *Stage 1 Meaningful Use Criteria*

	Core Objectives
1	Use for medication orders directly entered by any licensed healthcare professional who can enter orders into the medical record per State, local, and professional guidelines.
2	Implement drug-drug and drug-allergy interaction checks.
3	Maintain an up-to-date problem list of current and active diagnoses.
4	Maintain active medication list.
5	Maintain active medication allergy list.
6	Record all of the following demographics: preferred language; gender; race; ethnicity; date of birth; date and preliminary cause of death in the event of in-hospital mortality.
7	Record and chart changes in the following vital signs: height, weight, blood pressure, BMI, growth charts for children 2-20 years
8	Record smoking for patients 13 years old or older.
9	Report hospital clinical quality measures to CMS. (No longer core objective but still required.)
10	Implement one clinical decision support rule related to a high priority hospital condition along with the ability to track compliance with that rule.
11	Provide patients with an electronic copy of their health information upon request.
12	Provide patients with an electronic copy of their discharge instructions at time of discharge, upon request.
13	Protect electronic health information created or maintained by the certified EHR technology through the implementation of appropriate technical capabilities.
	Menu Set Objectives
1	Implement drug formulary checks.
2	Record advance directives for patients 65 years old or older.
3	Implement clinical lab-test results into EHR as structured data.
4	Generate lists of patients by specific conditions to use for quality improvement, reduction of disparities, research, or outreach.
5	Use certified EHR technology to identify patient-specific education resources and provide those resources to the patient if appropriate.
6	The eligible hospital or CAH who receives a patient from another setting of care or provider of care or believes an encounter is relevant should perform medication reconciliation.
7	The eligible hospital or CAH that transitions their patient to another setting of care or provider of care or refers their patient to another provider of care should provide summary care record for each transition of care or referral.
8	Capability to submit electronic data to immunization registries or immunization information systems and actual submission according to applicable law and practice.
9	Capability to submit electronic data on reportable lab results to public health agencies and actual submission according to applicable law and practice.
10	Capability to submit electronic syndromic surveillance data to public health agencies and actual submission according to applicable law and practice.

Source: http://www.cms.gov/Regulations-and-Guidance/Legislation/EHRIncentivePrograms/Downloads/Hosp CAH MU-toc.pdf.
Hospitals are required to implement all of the core objectives in at least one unit, as well as 5 of the 10 menu set objectives.

A.3 Clinical Pathways



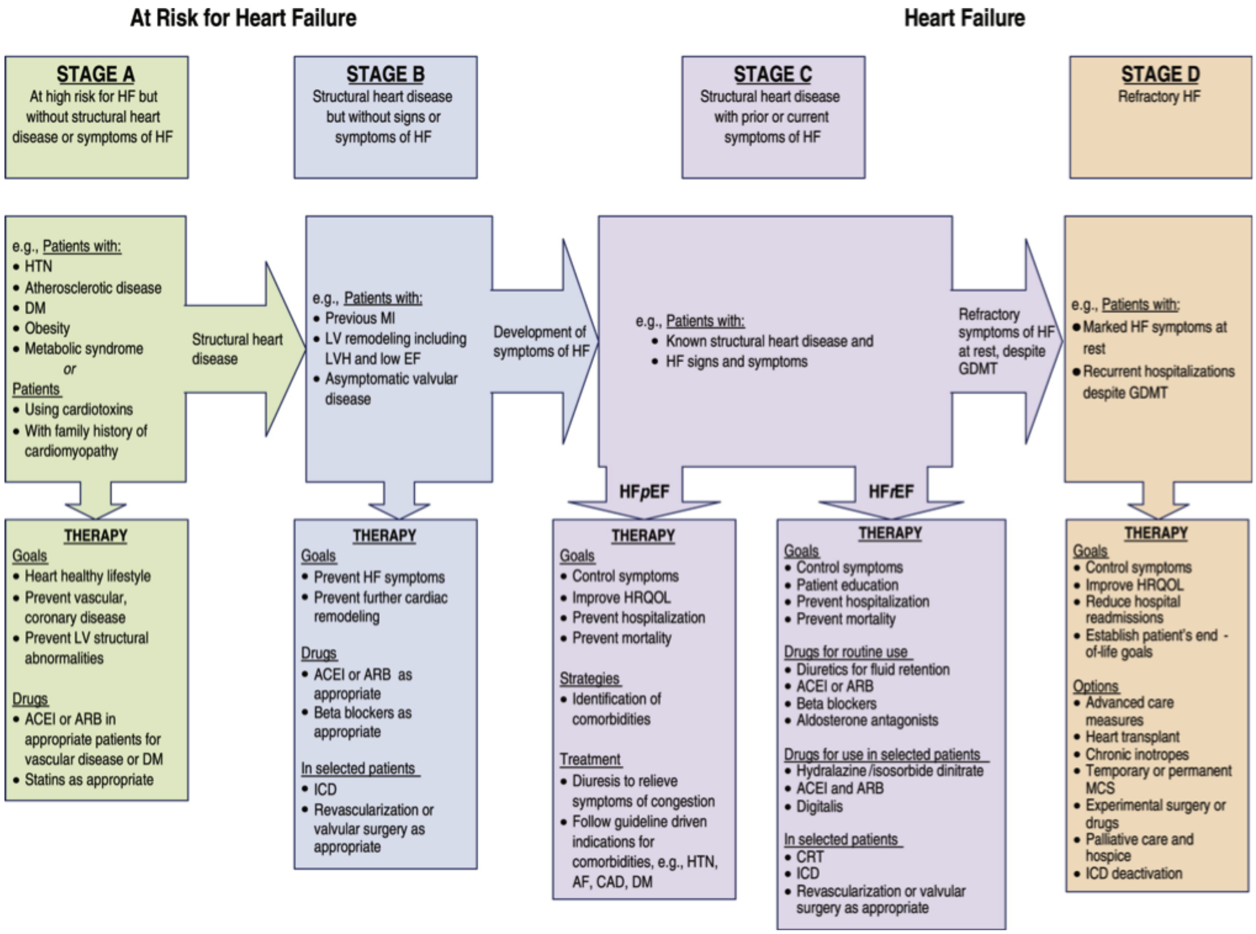
Source

2013 ACCF/AHA Guideline for the Management of ST-Elevation Myocardial Infarction: A Report of the American College of Cardiology Foundation/American Heart Association Task Force on Practice Guidelines

Notes

Reperfusion therapy for patients with STEMI. The bold arrows and boxes are the preferred strategies. Performance of PCI is dictated by an anatomically appropriate culprit stenosis. Patients with cardiogenic shock or severe heart failure initially seen at a non-PCI-capable hospital should be transferred for cardiac catheterization and revascularization as soon as possible, irrespective of time delay from MI onset (Class I, LOE: B). Angiography and revascularization should not be performed within the first 2 to 3 hours after administration of fibrinolytic therapy. CABG indicates coronary artery bypass graft; DIDO, door-in-door-out; FMC, first medical contact; LOE, Level of Evidence; MI, myocardial infarction; PCI, percutaneous coronary intervention; and STEMI, ST-elevation myocardial infarction

Congestive Heart Failure



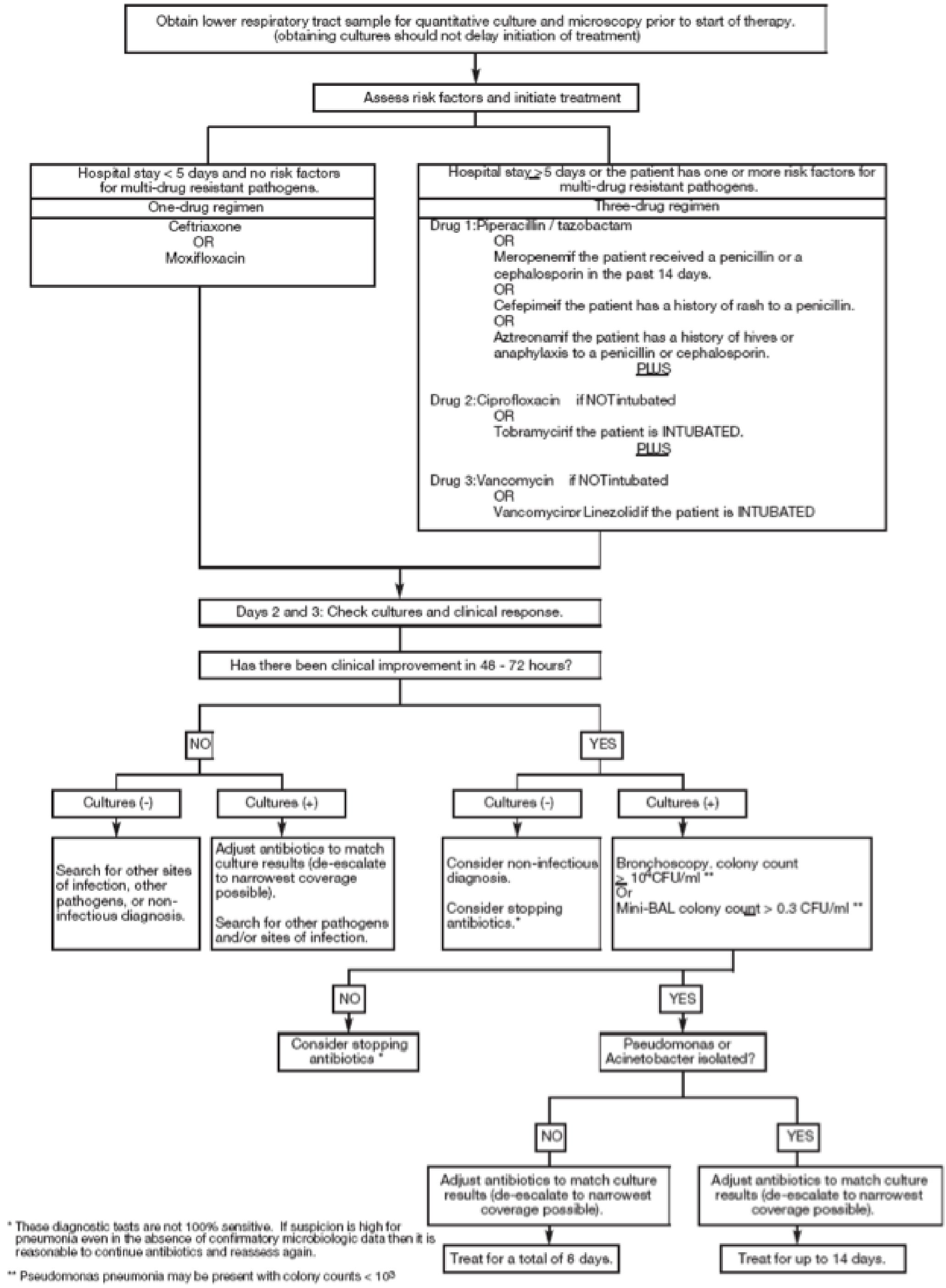
Source

2013 ACCF/AHA Guideline for the Management of Heart Failure: A Report of the American College of Cardiology Foundation/American Heart Association Task Force on Practice Guidelines

Notes

Stages in the development of HF and recommended therapy by stage. ACEI indicates angiotensin-converting enzyme inhibitor; AF, atrial fibrillation; ARB, angiotensin-receptor blocker; CAD, coronary artery disease; CRT, cardiac resynchronization therapy; DM, diabetes mellitus; EF, ejection fraction; GDMT, guideline-directed medical therapy; HF, heart failure; HFpEF, heart failure with preserved ejection fraction; HFrEF, heart failure with reduced ejection fraction; HRQOL, health-related quality of life; HTN, hypertension; ICD, implantable cardioverter-defibrillator; LV, left ventricular; LVH, left ventricular hypertrophy; MCS, mechanical circulator support; and MI, myocardial infarction.

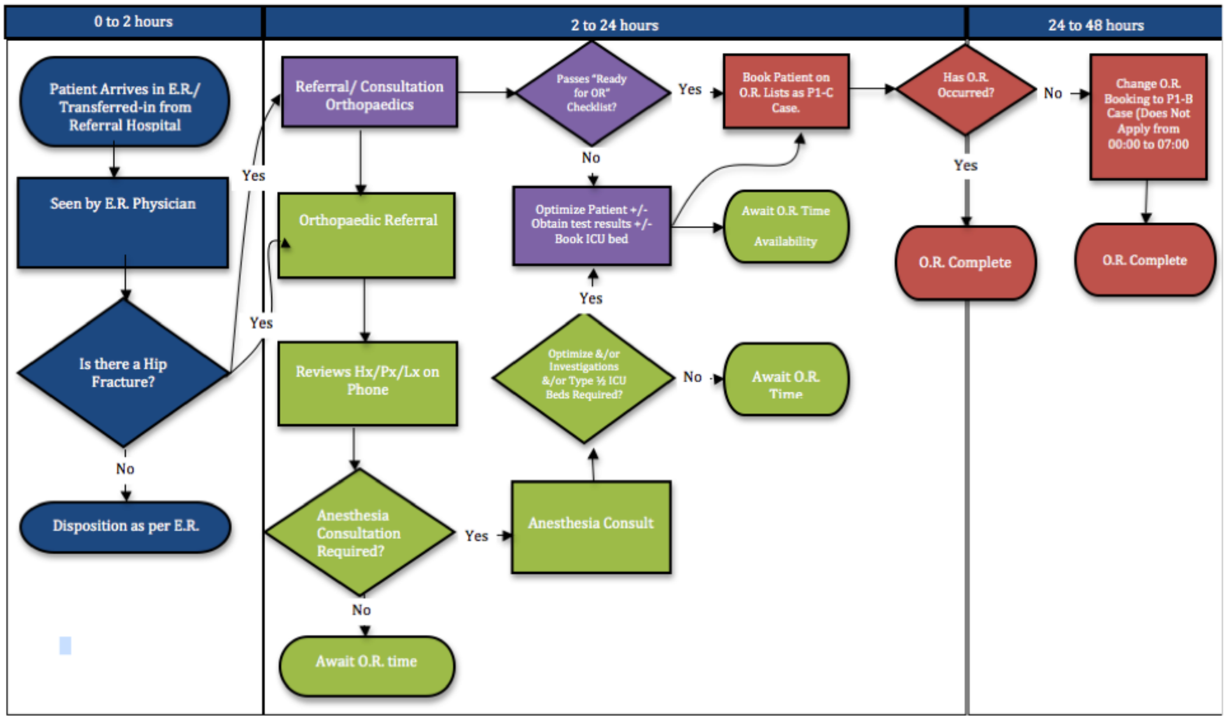
Pneumonia



Source

Tufts Medical Center: http://img.medscape.com/fullsize/migrated/578/701/lancaster.app1.gif

Hip Fracture



Source

The Ontario Orthopaedic Expert Panel through the Bone and Joint Health Network has developed a Provincial Hip Fracture Model of Care. This model flows patients across the health care continuum and provides best practice standardized guidelines for care. Integrated into this model is the target for 90% of hip fracture patients to receive surgery within 48 hrs of ER admission. http://www.gtarehabnetwork.ca/uploads/File/tools/Clinical-Care-Guidelines-for-Hip-Fracture-Acute-Care.pdf

Appendix B

Appendix to Chapter 2

B.1 Supplementary Tables

Table B.1: *Fraction of Patients in Each Complexity Category by Year*

	No. of Comorbidities			
Year	0	1	2	> 2
2003	.47	.17	.16	.20
2004	.41	.19	.17	.23
2005	.39	.18	.18	.25
2006	.39	.18	.17	.26
2007	.41	.17	.16	.26
2008	.41	.17	.16	.26
2009	.40	.17	.16	.27
2010	.39	.17	.16	.28
Average	.41	.17	.17	.25

Table B.2: *Hospital-Years by Paired Number of Years*

Paired Years	Hospital-Years	Percent	Cum.
1	853	18.01	18.01
2	1,362	28.76	46.77
3	1,350	28.51	75.27
4	736	15.54	90.82
5	315	6.65	97.47
6	84	1.77	99.24
7	28	0.59	99.83
8	8	0.17	100.00
Total	4,736	100.00	

Table B.3: *Number of Hospitals and Discharges by Year*

Year	Hospitals	Percent	Discharges	Percent
2003	590	12.46	3,555,810	12.8
2004	603	12.73	3,717,402	13.38
2005	604	12.75	3,695,665	13.3
2006	600	12.67	3,497,243	12.59
2007	591	12.48	3,536,855	12.73
2008	590	12.46	3,320,077	11.95
2009	544	11.49	3,075,882	11.07
2010	614	12.96	3,381,262	12.17
Total	4,736	100	27,780,196	100

Table B.4: *Summary Statistics for Hospital Characteristics*

Variable	Mean	Std. Dev.	Min	Max
No. of Admissions	8426.576	9512.732	23.67742	109915
No. of Beds	183.3025	187.5306	3	1966
For-Profit Hospital	.1541554	.3563539	0	1
Non-Profit Hospital	.670033	.4655929	0	1
Trauma Center	.3120357	.4457961	0	1
System Membership	.5531142	.481507	0	1
Medical School	.2484267	.4249765	0	1
Residency Program	.196779	.3885079	0	1
Teaching Intensity	.0538864	.2302604	0	7.78
System Membership	.5531142	.481507	0	1

Medical school is an indicator variable for whether the hospital is affiliated with a medical school. Teaching intensity is measured by the number of FTE residents per bed.

Appendix C

Appendix to Chapter 3

C.1 Supplementary Figures

Figure C.1: *EMR Adoption and HHI*

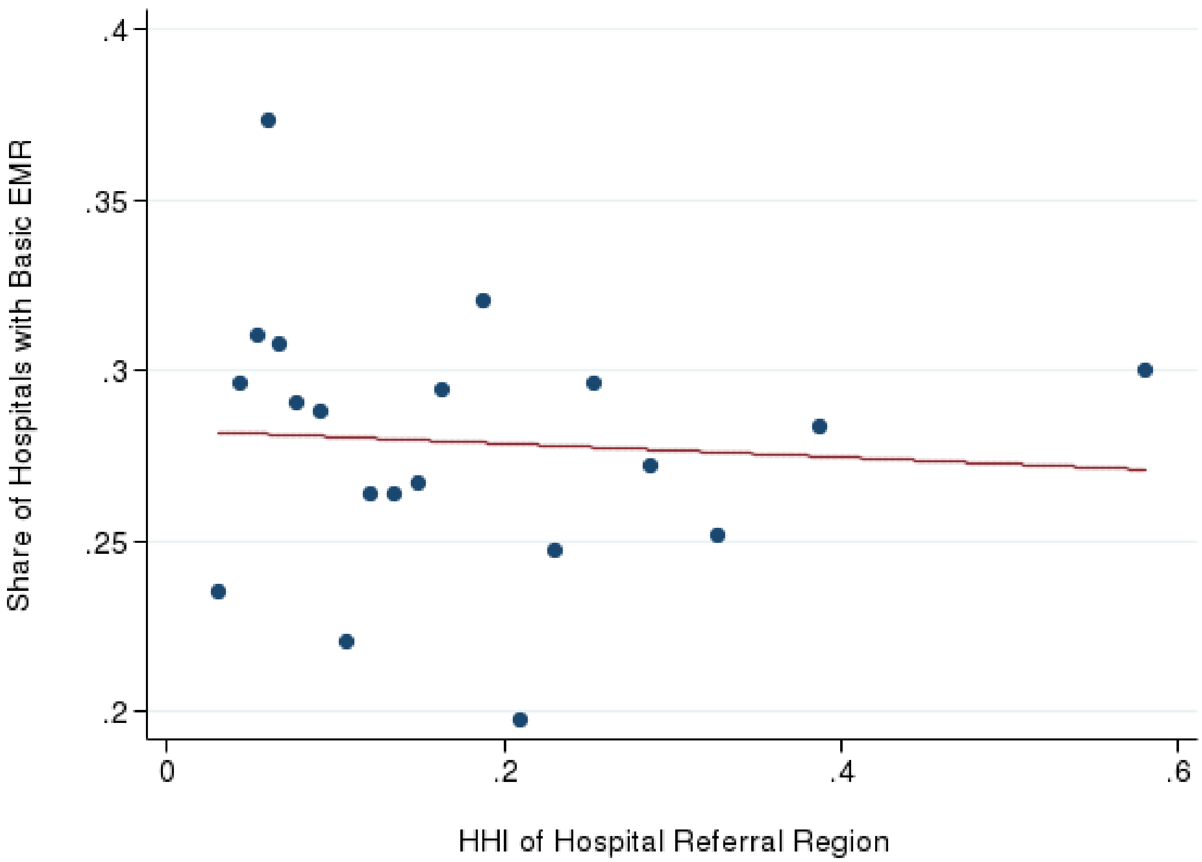


Figure C.2: *EMR Adoption and Management Quality*

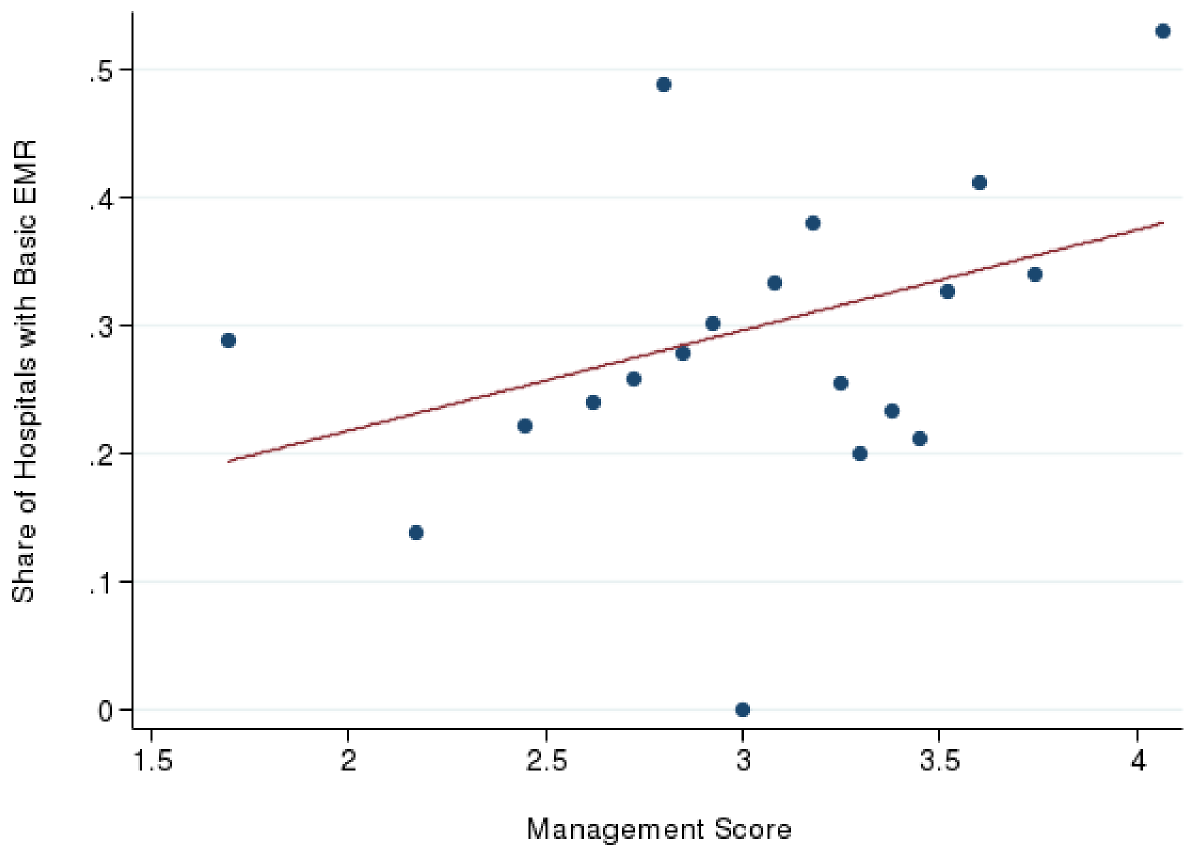


Figure C.3: *Hospitalist Use and Management Quality*

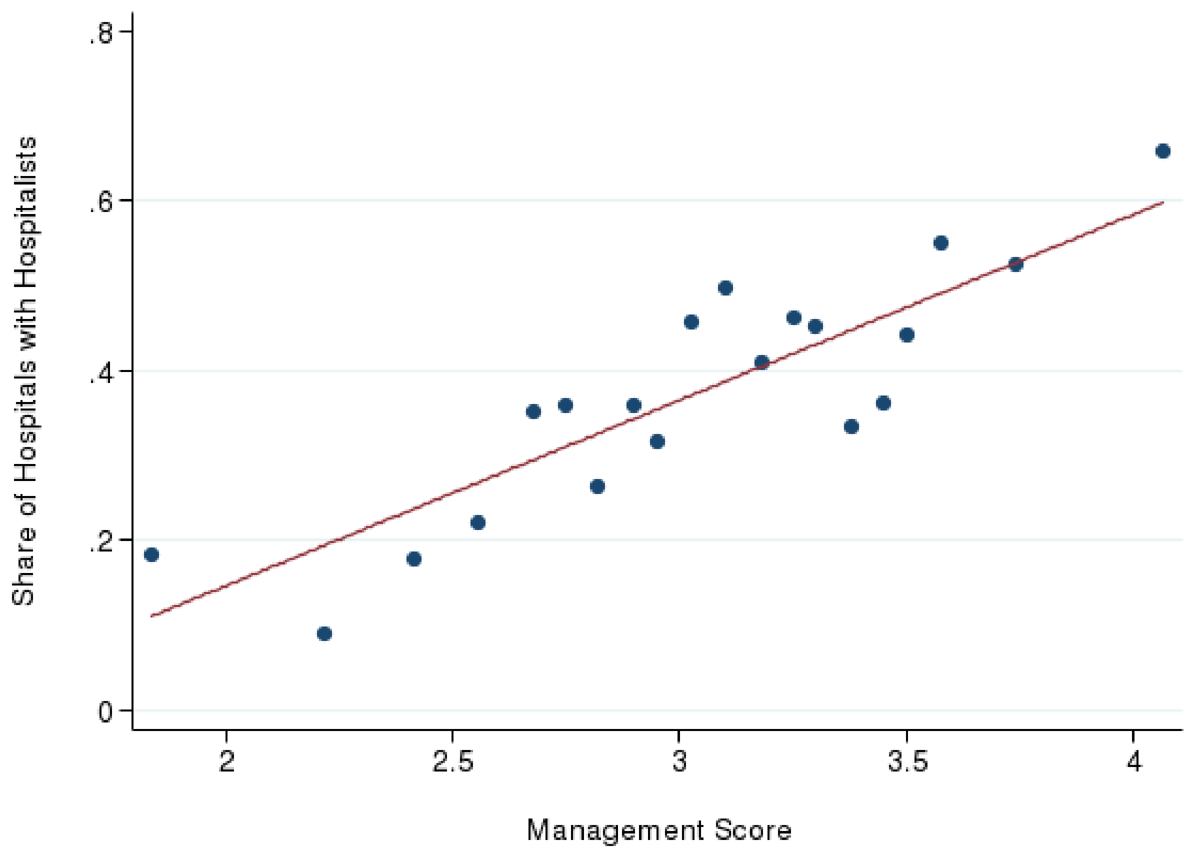
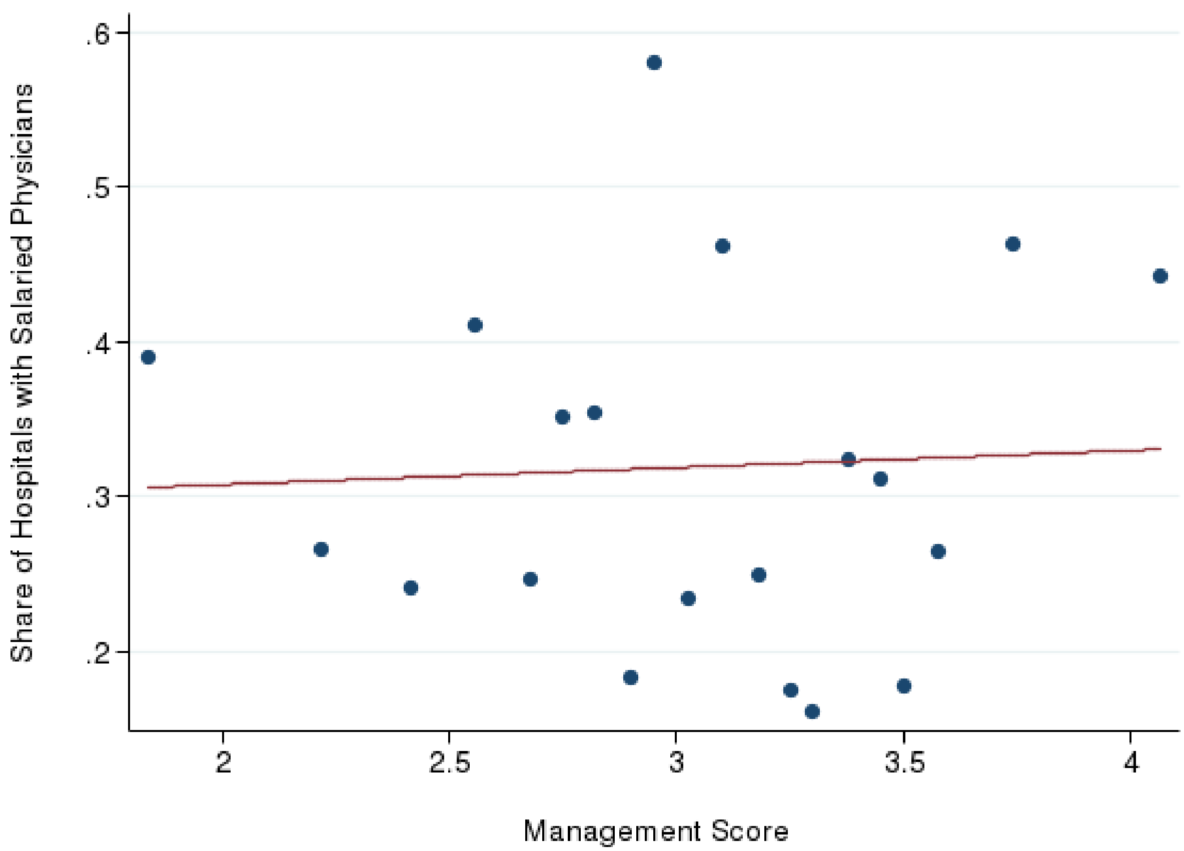


Figure C.4: *Hospital-Physician Integration and Management Quality*



C.2 Supplementary Tables

Table C.1: *Summary Statistics*

Variable	Mean	Std. Dev.
Hospitalist Program	.430315	.4951298
Teaching Intensity	.0411374	.1612652
Total Admissions	6605.6	9246.604
Total Beds	159.657	187.7349
Trauma Center	.2912937	.4543674
For-profit Hospital	.2148088	.4106976
Non-profit Hospital	.5521717	.4972803
Medical School Affiliation	.2406137	.4274644
Residency Program	.1766438	.3813744
System Member	.5632531	.4959925

Table C.2: *Technology Index*

	2003	2004	2005	2006	2007	2008	2009
Diagnostic Radiology							
CT Scanner	.816	.823	.826	.840	.848	.857	.856
Diagnostic radioisotope facility	0.576	.563	.570	.571	.563	.567	.571
Electron beam computed tomography	0.043	.057	.062	.066	.069	.065	.068
Magnetic resonance imaging	.554	.560	.583	.606	.621	.642	.649
Multi-slice spiral computed tomography	.274	.365	.482	.546	.565	.589	.594
Positron emission tomography	.150	.168	.147	.148	.148	.150	.155
Single photon emission CT	.351	.357	.367	.374	.377	.391	.385
Ultrasound	.814	.813	.817	.827	.831	.834	.830
Full-field digital mammography			.139	.180	.235	.322	.390
MSCT (64+ slice CT)			.123	.199	.275	.333	.373
Positron emission tomography/CT			.115	.142	.157	.174	.183
Intraoperative MRI					.0382	.0428	.0436
Therapeutic Radiology							
Intensity-modulated radiation therapy	.120	.167	.182	.203	.208	.219	.228
Shaped beam radiation system		.121	.148	.166	.175	.177	.180
Image-guided radiation therapy			.0852	.1046	.1342	.1552	.1769
Stereotactic radiosurgery			.138	.142	.151	.160	.164
Proton beam therapy					.0175	.0195	.0219
Robotic Surgery							
Robotic Surgery			.058	.074	.092	.124	.155

Table C.3: *The Employment Arrangement of Hospitalists over Time*

	Year						
Employment Relationship	2003	2004	2005	2006	2007	2008	2009
Independent Provider Group	326	376	475	537	625	639	704
Physician Group	282	364	464	532	569	591	622
Hospital Employee	421	423	142	606	646	663	760
University Employee	53	55	66	66	80	77	85
Other	105	114	142	153	160	166	0
Total	1187	1332	1289	1894	2080	2136	2171

Table C.4: *Hospital Operations Management Questions from Health Care Survey*

Dimension	Description
Operations Management	Operations Management is all about how effectively the patient journey and pathway management is configured: what is the motivation behind changes to operations, how standardized and integrated are clinical pathways, and are staff deployed to do what they are best qualified for?
Performance Monitoring	Performance Monitoring is all about how well your performance monitoring system informs your and your employees' day-to-day operations of your hospital: how do processes and attitudes are screened, how meaningful are your metrics in relation to how frequently they measured and reviewed, to what degree the detection of different levels of process-based performance leads to adequate and consequential process improvements?
Target Setting	Target Setting is all about how tightly your targets are linked to the hospital's wider objectives: are your targets covering a sufficiently broad set of metrics, how strongly are your short and long term targets connected, how well are they cascaded down and clarified to your employees?
Talent Management	Talent Management is all about how you manage your people: to what degree is people management emphasized within your hospital, how careful are your hiring policies, how closely are pay and promotions linked to the ability and effort of your employees, how do you deal with under-performers, and how do you retain your best-performers?

Source: www.worldmanagementsurvey.com