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The Trillion Dollar Conundrum: Complementarities and Health Information Technology†

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We examine the heterogeneous relationship between the adoption of EMR and hospital operating costs at thousands of US hospitals between 1996 and 2009. We first document a previously-identified puzzle: Adoption of EMR is associated with a slight cost increase. Drawing on the literature on IT and productivity, we analyze why this average effect arises. We find that: (i) EMR adoption is initially associated with a rise in costs; (ii) EMR adoption at hospitals in IT-intensive locations leads to a decrease in costs after three years; and (iii) Hospitals in other locations experience an increase in costs even after six years. (*JEL* D24, I11, M15)

More than a quarter century ago economists engaged in a vigorous debate about the benefits from investment in information technology (IT) in manufacturing and services. That debate was encapsulated in the Solow "Productivity Paradox"—"You can see the computer age everywhere but in the productivity statistics" (Solow 1987). That debate eventually faded from view, in part because the data began to reject it. Over time it was found that firms achieved productivity benefits from IT, just with a lag. Moreover, explanations for the lag emerged from considerable work on IT use in enterprises. The challenges to productivity benefits were due to the costly adaptations required for the successful implementation of new IT. In time, it was found that the firms realizing benefits from their IT investments were those that had made complementary investments in areas such as worker skills and organizational decision rights.[1]

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[1] See, for example, Bresnahan, Brynjolfsson, and Hitt (2002) and Bloom, Sadun, and Van Reenen (2012). Several other explanations have also been highlighted for these empirical findings, including mismeasurement of IT capital or output. For further details on these issues, see Triplett (1999).

A new manifestation of this debate has surfaced around the use of electronic medical records (EMR), and information technology specific to healthcare. A small sampling of research from the last half dozen years provides a sense of the uncertainty about the productivity benefits from these investments. The Congressional Budget Office states: "No aspect of health information technology (i.e., EMR) entails as much uncertainty as the magnitude of its potential benefits" (Congressional Budget Office 2008). A widely cited 2005 report by the RAND Corporation, published in the leading policy journal *Health Affairs*, estimates that widespread adoption of EMR by hospitals and doctors could reduce annual health spending by as much as $81 billion while simultaneously leading to better outcomes (Hillestad et al. 2005). Jaan Sidorov, a medical director with the Geisinger Health Plan, an early adopter of EMR, published a response to the RAND report in *Health Affairs*. Sidorov (2006) highlights the high cost of adoption and cites evidence that EMR leads to greater health spending and lower productivity. In 2013, RAND published a follow-up study in *Health Affairs* in which it fails to find consistent evidence of savings and deems the performance of EMR to be "disappointing" (Kellermann and Jones 2013). Other recent studies, cited below, also fail to find consistent evidence that EMR savings offset adoption costs.

What impact does EMR have on a key determinant of an existing organization's productivity, such as its operating costs? Like other types of enterprise IT, we view EMR as a type of business process innovation, one that involves not only investments in IT but also changes in the operational practices within the adopting organization. If EMR is viewed in this way, how does that change the understanding of EMR's impact? We argue that prior literature has missed important features of EMR by not building on research that has studied the adoption and productivity benefits of large scale enterprise IT and "insider econometrics" studies of IT adoption.[2]

Building on this prior research, we stress the complementary assets that increase the efficiency of "coinvention," which is the process of adapting an innovation to unique circumstances, thereby generating a net benefit to the enterprise. These complementary assets come from several sources. *Local* resources may be available as market services, such as expertise in the implementation of similar technologies, or widespread spillovers in how to use the IT. Resources available *internally to the enterprise*, such as experience with other business processes, may also help with implementation of the technology and often cannot be purchased from markets in the short run. To summarize, variance in local and internal resources provides an explanation for why the payoff from EMR may be delayed, and for why we observe variance in the returns to investments in enterprise IT across locations.

We conduct an empirical examination of the impact of EMR adoption on hospital operating costs during the period 1996 to 2009. The data come from several sources linking hospital costs to EMR adoption and the potential for complementarities. Our main analysis regresses logged operating costs on EMR adoption, hospital fixed effects, and a large number of controls. We focus on whether the relationship between

[2]For examples of multi-industry studies that examine the adoption of enterprise IT and the accompanying organizational adaptations, see for example Bresnahan and Greenstein (1996); Bresnahan, Brynjolfsson, and Hitt (2002); Forman, Goldfarb and Greenstein (2005); and Bloom et al. (2009). For examples of single-industry "insider econometrics" studies, see Ichniowski and Shaw (2003) and Bartel, Ichniowski, and Shaw (2007).

EMR and costs is greater for hospitals that are positioned to exploit available complementarities. Thus, our key independent variable is the interaction between EMR adoption and the presence of local complements, as measured by the IT-intensity of local industry. Our key identification assumption is that EMR adoption is not correlated with unobservable cost factors that are differentially trending in hospitals with locally available complementary inputs relative to hospitals that lack these inputs. We explain below why we believe our results suggest that this is a reasonable assumption.

We find the evidence consistent with our reframing: the timing of cost savings is consistent with what we would expect given the literature on the productivity paradox in IT. For the average hospital, the gains from EMR adoption appear with some delay. Moreover, there is significant heterogeneity in the gains achieved, depending on the local availability of complementary factors such as IT workers. We focus on costs because much of the political discussion has emphasized cost savings, and because the multi-product nature of hospitals makes it easier to measure the implications of EMR for costs than for productivity. However, our focus on costs means that we cannot use our data to rule out the possibility that our results are paralleled by opposing effects on clinical benefits, though much of the prior literature, including Agha (2012) and McCullough et al. (2010), have found clinical benefits to be small on average.[3] Important exceptions are Miller and Tucker (2011) and McCullough et al. (2011, 2012), who found some substantial clinical benefits, particularly for high mortality risk patients.

We find that hospitals that adopted EMR between 1996 and 2009 did not experience a statistically significant decrease in costs on average. In fact, under many specifications, costs rose after EMR adoption, particularly for the more advanced EMR systems. However, this effect is mediated by measures of the availability of technology skills in the local labor market. Specifically, in strong IT locations, costs can fall sharply after the first year of adoption to below pre-adoption levels. In weak IT locations, costs remain above pre-adoption levels indefinitely. Overall, hospitals in IT-intensive markets enjoyed a statistically significant 3.3 percent decrease in costs from three years after adoption of basic EMR and a marginally significant 2.1 percent decrease in costs from three years after adoption of advanced EMR. These results are significantly better than the up to 4 percent *increase* in costs after adoption by hospitals in other markets.

Figures 1A and 1B display these general patterns in the raw data, comparing hospitals that adopt basic and advanced EMR before the adoption period, during the adoption period, and after the adoption period. For basic EMR, costs for the average hospital rise initially and fall back three years after adoption. For non-IT-intensive locations, costs rise sharply in the year of adoption, and then fall back. For IT-intensive locations, costs fall with adoption, and are substantially lower three years after adoption. For advanced EMR, the patterns are similar: costs rise in the period of adoption for non-IT-intensive locations and fall over time for the other hospitals.

We provide evidence that the benefits of strong IT locations arise in part from an agglomeration of IT employment in (other) hospitals. Hospitals in locations with

[3] Agha looks at three quality measures—readmission rates, adverse drug reactions, and complications. McCullough et al. look at mortality.

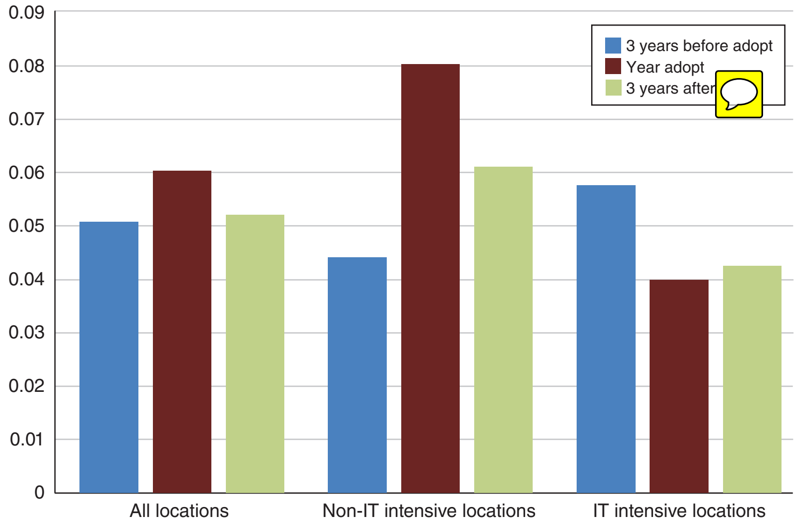

Figure 1A. Percent Rise in Costs per Admission from Year Earlier, by Timing of Basic EMR Adoption

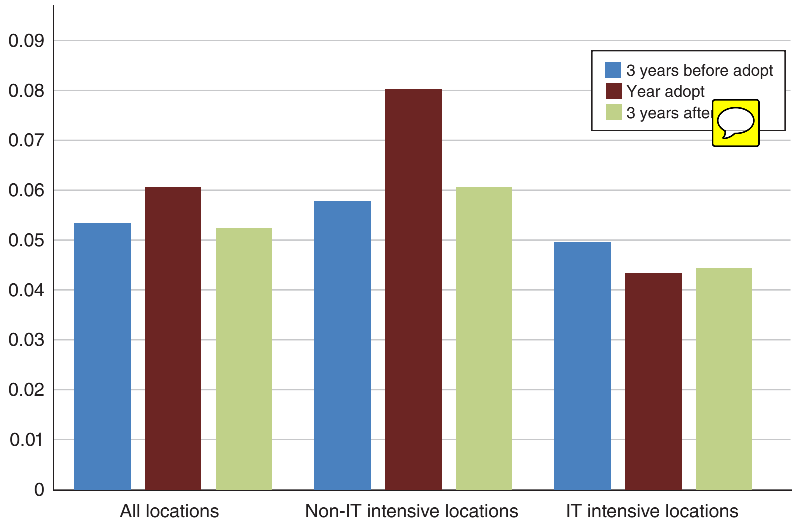

Figure 1B. Percent Rise in Costs per Admission from Year Earlier, by Timing of Advanced EMR Adoption

strong health IT (HIT) employment enjoyed a 3.9 percent decrease in costs from three years after adoption of basic EMR and a 1.8 percent decrease in costs from three years after adoption of advanced EMR. However, concentration of IT employment in other industries is not associated with greater benefits from adopting basic or advanced EMR. Controlling for strong HIT employment, costs still fall more rapidly in strong IT locations than in weak ones. In short, one benefit of strong IT locations is a thicker labor market for HIT workers, though other benefits persist as well.

We also show results suggesting that complementary skills can be found inside the hospital. For advanced EMR, the initial increase in costs is mitigated substantially if hospitals already have significant software experience. Hospitals without experience are hurt in the short run for the most sophisticated technologies. We do find, however, that within a short time inexperienced hospitals can make up the difference. Specifically, the difference in costs after adoption for hospitals with and without internal expertise disappears within three years. This suggests that, in contrast to complementary assets that depend on a location with favorable agglomeration economies, some assets complementary to EMR can be acquired relatively quickly.

These findings have several implications. As annual US healthcare expenditures climb towards $3 trillion and with spending forecast to exceed $4.5 trillion by 2020, many analysts hope that electronic medical records (EMR) can stem the tide (Centers for Medicare and Medicaid Services 2010). For example, David Cutler and Melinda Beeuwkes Buntin make EMR the centerpiece of their "Two Trillion Dollar" solution for modernizing the health care system (Buntin and Cutler 2009). While some are confident in EMR, others remain cautious, especially due to EMR's sluggish diffusion. As of 2009, only about 30 percent of America's hospitals had adopted any advanced elements of EMR.[4] This may have been due, in part, to the lack of consistent evidence of cost savings.

In order to spur EMR adoption, Congress in 2009 passed the Health Information Technology for Economic and Clinical Health Act (HITECH Act), which provides $20 billion in subsidies for providers who adopt EMR. Two-thirds of hospitals said they planned to enroll in the first stage of HITECH subsidy programs by the end of 2012 (US Department of Health and Human Services 2011). The 2010 Patient Protection and Affordable Care Act also contains provisions promoting EMR adoption. Despite these legislative actions, many remain unconvinced of the benefits of EMR. Our findings also may help resolve the ongoing debate. Supporters and detractors both seem to treat EMR as if its economic impact is independent of other environmental factors, as if it either works or it doesn't. This creates a conundrum for both sides. If EMR is going to save hundreds of billions of dollars or more, as its supporters claim, why isn't it working in obvious ways? If it costs more than it saves, as the skeptics argue, why are policymakers so keen to expand adoption?

Our results suggest that the debate about EMR should be reframed by drawing on the general literature on business adoption of IT, where it is very common for successful technology adoption to require complementary changes in business processes that rely on specific labor and information inputs. It is also common for new enterprise IT to be more productive when companies have access to these inputs in their local market. Using this experience, it is not surprising that EMR has the potential to generate substantial savings but demonstrates mixed results in practice.

This is not to say that these mixed results will be permanent. Complementary labor and information inputs that enhance IT effectiveness include worker experience with general IT and independent consulting firms with IT experience. These inputs naturally accumulate over time in all but the smallest markets, suggesting that the performance of EMR will likely improve nearly everywhere. Moreover, our results suggest there can be positive externalities to adoption. Thus, the HITECH Act may have been a valuable measure for encouraging hospitals to adopt EMR in markets that are not currently rich in complementary assets. With the majority

[4] Source: Authors' calculations based on data supplied by Healthcare Information and Management Systems Society (HIMSS).

of hospitals well on the way to EMR adoption, and with the inevitable growth of complementary assets, it is premature to dismiss the potential of EMR.

We proceed as follows. Sections II and III describe the institutional setting for EMR and some of the prior evidence about its effects on hospitals. This motivates a comparison in Section IV between EMR and the adoption of IT inside other organizations, which leads to a reframing of several key hypotheses. Sections V and VI present data
AQ2 and results. Section VI concludes.

I. What Is EMR?

EMR is a catchall expression used to characterize a wide range of information technologies used by hospitals to keep track of utilization, costs, outcomes, and billings. In practice, EMR includes, but is not limited to, the following:

- A *Clinical Data Repository* (*CDR*) is a real time database that combines disparate information about patients into a single file. This information may include test results, drug utilization, pathology reports, patient demographics, and discharge summaries.
- *Clinical Decision Support Systems* (*CDSS*) use clinical information to help providers diagnose patients and develop treatment plans.
- *Order Entry* provides electronic forms to streamline hospital operations (replacing paper and faxes).
- *Computerized Provider Order Entry* (*CPOE*) is a more sophisticated type of electronic order entry and involves physician entry of orders into the computer network. CPOE systems typically include patient information and clinical guidelines, and can flag potential adverse drug reactions.
- *Physician Documentation* helps physicians use clinical information to generate diagnostic codes that are meaningful for other practitioners and valid for reimbursement.

As this list shows, there is no single technology associated with EMR, and different EMR technologies may perform overlapping tasks.

Nearly all of the information collected by EMR already resides in hospital billing and medical records departments and in physicians' offices. EMR automates the collection and reporting of this information, including all diagnostic information, test results, and services and medications received by the patient. EMR can also link this information to administrative data such as insurance information, billing, and basic demographics. EMR can reduce the costs and improve the accuracy of this data collection. Two components of EMR, Clinical Decision Support Systems and Computerized Provider Order Entry, use clinical data to support clinical decision making (Agha 2012 refers to this as a distinct category labeled Clinical Decision Support or CDS). If implemented in ideal conditions and executed according to the highest standards, EMR can reduce personnel costs while facilitating more accurate diagnoses, fewer unnecessary and duplicative tests, and superior outcomes with fewer costly complications.

Despite these potential savings, EMR adoption has been uneven. Table 1A reports hospital adoption rates for the five components of EMR described above. The data is

Table 1A—Types of EMR and Hospital Adoption Rates

EMR	Description	Percent of hospitals adopting 1996	2009
Clinical data repository	Real time database that consolidates clinical data to create a unified patient medical record	0.134	0.809
Clinical decision support	Uses patient data to generate diagnostic and/or treatment advice	0.136	0.752
Order entry	Provides electronic forms to streamline hospital operations (replacing faxes and paper forms)	0.196	0.851
Computerized physician order entry	Electronic entry of physician treatment orders that can be communicated to the pharmacy, lab, and other departments	0.007	0.242
Physician documentation	Allows physicians to transition from written to electronic notes	0.033	0.227

Notes: The unit of observation is a hospital-year. Includes all hospitals in baseline sample that report total cost data.

Source: Authors' calculations from HIMSS Analytics data.

Table 1B—Number of Hospitals Adopting by Year

Year	Basic EMR adoption	Advanced EMR adoption
By 1996	587	186
1997	128	10
1998	73	13
1999	52	12
2000	57	23
2001	71	36
2002	111	66
2003	102	87
2004	161	118
2005	182	133
2006	124	81
2007	114	99
2008	64	65
2009	44	49
Not adopted by 2009	279	2,220
Total Hospitals in our EMR adoption data	2,149	3,198

Note: Sample includes all hospitals in baseline EMR adoption data.

Source: Authors' calculations from HIMSS Analytics data.

taken from HIMSS Analytics, which we describe in more detail in Section V. Clinical Data Repository, Clinical Decision Support, and Order Entry are older technologies that were present in many hospitals in the 1990s. Even for these older technologies, adoption rates range from 75 to 85 percent in 2009. The remaining applications emerge in the early to mid-2000s. Adoption rates for these are below 25 percent.

While informative, our dataset lacks several crucial pieces of information. For example, it lacks comparable data on physician adoption of EMR, which is much lower than hospital adoption (Callaway and Ghosal 2012). Our data do not tell us about intensity of use by physicians and staff within hospitals, about the details of the installation, or on how close operations come to ideal conditions. Interviews with hospital administrators suggest that adoption can be uneven within hospitals, with some departments enthusiastically embracing change while others do not. Although beyond the scope of this study, compatibility issues may shape the success of EMR at a regional level, and this too is missing from our data. There are many different EMR vendors and their systems do not easily interoperate. As a result, independent providers cannot always exchange information, which defeats some of the purpose of EMR adoption (Miller and Tucker 2009).

II. Evidence on the Potential Savings from EMR

Has adoption of EMR reduced hospital costs? This section reviews prior evidence, stressing the absence of work focusing on operational savings, lack of emphasis on complementarities with the labor market, and the absence of accounting for the functional heterogeneity of EMR's components. This discussion will motivate our concerns and our approach to framing the study of EMR's impact on productivity using past research that emphasized enterprise IT as a business process innovation.

Nearly every EMR study remarks on the expense. One prominent estimate, from the Congressional Budget Office (CBO 2008), estimates that the cost of adopting EMR for office-based physicians is between \$25,000 and \$45,000 per physician, with annual maintenance costs of \$3,000 to \$9,000. For a typical urban hospital, these figures range from \$3–\$9 million for adoption and \$700,000–\$1.35 million for maintenance. These costs are substantial: If the adoption costs are amortized over ten years, EMR can account for about 1 percent of total provider costs. It would be no surprise, therefore, if research suggested that EMR does not pay for itself, let alone generate hundreds of millions of dollars in savings.

In their review of 257 studies of EMR effectiveness, Chaudry et al. (2006) note that few studies focus on cost savings, providing, at best, indirect evidence of productivity gains. Most of the studies they review focus on quality of care. Ten studies examine the effects of EMR on utilization of various services. Eight studies show significant reductions of 8.5–24 percent, mainly in laboratory and radiology testing. While fifteen studies contained some data on costs, none offered reliable estimates of cost savings.

Hillestad et al. (2005), the widely cited RAND study mentioned in our introduction, uses results from prior studies of EMR and medical utilization and extrapolates the potential cost savings net of adoption costs. They estimate that if 90 percent of US hospitals were to adopt EMR, total savings in the first year would equal \$41.8 billion, rising to \$77.4 billion after 15 years. They also predict that EMR adoption could eliminate several million adverse drug events annually, and save tens of thousands of lives through improved chronic disease management.

Sidorov (2006) challenges these findings, arguing that the projected savings are based on unrealistic assumptions. For example, the RAND study appears to assume that EMR would entirely replace a physician's clerical staff. Sidorov argues that providers who adopt EMR tend to reassign staff rather than replace them. To take another example, EMR is supposed to eliminate duplicate tests, while it is just as likely that EMR may allow providers to justify ordering additional tests.[5] Buntin et al. (2011) review 73 studies of the impact of EMR on medical utilization. EMR is

[5] McCormick et al. (2012) document that physicians with EMR tend to order more diagnostic tests, though they do not address the potential role of omitted variables in driving this result.

associated with a significant reduction in utilization in 51 (70 percent) of these studies. They do not identify any studies of EMR and costs.

Indeed, we have identified only three focused cost studies. Borzekowski (2009) uses fixed effects regression to examine whether early versions of financial and clinical IT systems generated significant savings between 1987 and 1994. He finds that hospitals adopting the most thoroughly automated versions of EMR realize up to 5 percent savings within five years of adoption. He also finds that hospitals that adopt less automated versions of EMR experience an increase in costs. His conclusions mirror the popular discussion: there appears to be the potential for savings but there is little understanding of the drivers of the heterogeneity across hospitals. Furukawa, Raghu, and Shao (2010) study the effect of EMR adoption on overall costs among hospitals in California for the period 1998–2007. Also using fixed effects regression, they find that EMR adoption is associated with 6–10 percent higher costs per discharge in medical-surgical acute units, in large part because nursing hours per patient day increased by 15–26 percent. This is plausible because nurse use of EMR can be very time consuming. Agha (2012) is another panel data study that exploits variation in hospitals' adoption status over time. She analyzes 2.5 million Medicare inpatient admissions across 3,900 hospitals between the years 1998–2005 and considers both costs and benefits, potentially allowing for welfare considerations. Health IT is associated with an initial 1.3 percent increase in billed charges. Although this increase is reversed after five years, we explain below that such a pattern may be an artifact of accounting practices rather than reflective of genuine savings. Agha finds that this general pattern of increased initial spending, followed by a slow decline, occurs for specific cost items including diagnostic and pharmacy but not physician and outpatient services. Agha also looks at outcomes finding that adoption appears to have little impact on the quality of care, measured by patient mortality, medical complication rates, adverse drug events, and readmission rates. This is not a comprehensive list of outcomes, so it is difficult to draw any definitive welfare conclusions from Agha's study. While not directly about costs, Lee, McCullough, and Town (2012) document small positive effects of hospital IT on productivity.

None of the studies frame EMR in the context of the prior literature on enterprise IT. In other words, there is no examination of factors that shape availability of complementary components such as local expertise or prior experience with related technology, nor is there a theoretical framework that would suggest such differential effects. In the next section, we offer such a framework, based on research on the productivity of large scale IT projects in enterprises, and develop some specific implications for the deployment of EMR.

III. Information Technology and Complementarities

The existing literature on effective implementation of IT within businesses has emphasized the view of IT as a business process innovation.[6] Such innovations alter

[6]Specifically, Attewell (1992); Bresnahan and Greenstein (1996); Black and Lynch (2001); Bresnahan, Brynjolfsson, and Hitt (2002); Brynjolfsson and Hitt (2003); Hubbard (2003); Forman, Goldfarb, and Greenstein (2005); Bloom et al. (2009); and Bloom, Sadun, and Van Reenen (2012). Forman and Goldfarb (2006) summarize

organizational practices, generally with the intent of improving services, reducing operational costs, and taking advantage of new opportunities to match new services to new operational practices. Typically this type of innovation involves changes in the discretion given to employees, changes to the knowledge and information that employees are expected to retain and employ, and changes to the patterns of communications between employees and administrators within an organization. Because important innovation in enterprise IT occurs on a large scale, it typically involves a range of investments, both in computing hardware and software, and in communications hardware and software. Several insights from this literature shape our approach:

Adaptation Expenses Play a Key Role.—Initial investment often does not generate a substantial productivity gain until after complementary investments, adaptations, and organizational changes (e.g., David 1990; Bresnahan and Greenstein 1996; Bresnahan, Brynjolfsson, and Hitt 2002; Bartel, Ichniowski, and Shaw 2007; Bloom, Sadun, and Van Reenen 2012). Many of these necessary changes coincide with initial adoption, or are incurred after the initial adoption. For example, CPOE generates many changes to routine processes, and their productivity gains come after the initial rollout, and after doctors and nurses and hospital administrators tailor the software to their specific needs and preferences.

Coinvention Costs Determine Post-Adoption Expenses.—Productivity gains often depend on whether the employees of the adopting organization—the administrative staff, doctors, and nurses—find new uses to take advantage of the new capabilities, and/or invent new processes for many unanticipated problems. These inventions change complementary business processes and often aim to make new IT useful (Bresnahan and Greenstein 1996). For example, implementing EMR alters many formats for stored information, but the preferences of users become apparent only after users experience the new process.

Adoption Generates Substantial Risks of Nonmonetary Costs.—Interruptions to ongoing operations can generate large opportunity costs in foregone services, and for which there may be no market price or, relatedly, no potential for insurance.[7] These costs have many sources: non-convexities in investment, the technical necessity of investing in one stage of a project only after another is completed, lack of interoperability during upgrades, and cognitive limits in anticipating difficulties with a new process. Sometimes these costs can be reduced with internal resources—for example, development of middleware by in-house IT staff.

the earlier literature. The literature on "insider econometrics" has touched on related themes, particularly stressing channels of communication, the influence of hierarchy on communications, and changes in hierarchy as a result of the deployment of new information technology (e.g., Ichniowski and Shaw 2003; Bartel, Ichniowski, and Shaw 2007).

[7] Private communication with David Artz, Medical Director of Information Systems, Memorial Sloan-Kettering Cancer Center, in August 2012.

Local and Market-Wide Scale Economies May Shape the Costs of Adaptation and Coinvention.—While some aspects of adaptation costs and coinvention expenses are idiosyncratic to each organization, many determinants of these costs can be shared. For example, as workers gain experience they can share lessons with others in the same organization or other organizations (as employees move). As hospitals gain experience, lessons can be shared with other hospitals. For example, lead software vendors improve designs, third-party software vendors create middleware and applications, and independent IT consulting firms share experiences with new clients. These local scale economies not only influence the costs of implementing the system, but may also increase the benefits achieved after adoption.

Two key empirical implications arise from this discussion. First, if the productivity impact of EMR follows patterns seen with other enterprise IT, then it should come with a lag. Second, the productivity impact of EMR should depend on factors that shape the supply conditions for complements, such as the experience of a hospital's IT staff, as well as third-party software and support and the local labor market for skilled labor.

We expect to observe a visible relationship between investment in health IT and local conditions in a limited metropolitan geographic area. Prior research has found considerable heterogeneity across US locations in the availability of complementary factors, such as skilled labor, and in the prevalence of knowledge spillovers (Forman, Goldfarb, and Greenstein 2005, 2012), third-party software support and service (Arora and Forman 2007), and infrastructure (Greenstein 2005, Greenstein and McDevitt 2011). Similarly, we expect that thicker markets lowered the (quality-adjusted) price of obtaining IT services such as contract programming and of hiring workers to develop in-house functions.[8]

We also expect to observe a visible relationship between adaptation and coinvention expenses and experience with IT. Prior IT projects may reduce development costs and increase the benefits achieved from the system if on-staff programmers are able to transfer lessons learned from one project to another.[9] Prior work on other IT projects may create learning economies and spillovers that decrease the costs of adapting general purpose IT to organizational needs, reducing the importance of external consultants and local spillovers. For example, many major medical centers in the US—such as Duke, Vanderbilt, Hopkins, UPMC, Yale, or Washington University in St. Louis—invested in advanced IT in order to remain competitive, and those centers initially built their EMR with in-house software instead of packages, using internal expertise during every additional investment. That internal expertise

[8] For example, see this quote: "There's a lot of dedicated health care professionals out there in the universe," said Josh Lee, a doctor at and chief medical information officer for the University of California San Diego Medical Center. "There's a lot of dedicated IT professionals. But it's a much narrower band where you have people that can live in both of those worlds." http://www.pcworld.com/businesscenter/article/229071/hospitals_compete_for_it_talent_with_funding_at_stake.html, accessed September 16, 2012.

[9] For example, software developers may be able to share common tools for design, development, and testing (Banker and Slaughter 1997), or they may be able to reuse code (Barnes and Bollinger 1991). Software development may also have learning economies (Attewell 1992) that through experience reduce the unit costs of new IT projects. Much prior research in the costs of innovative activity has also presumed experience with related projects lowers the costs of innovation (Cohen and Levinthal 1990).

proved valuable when the hospitals later adopted commercial packages and customized them to their organizations.

IV. Data

We use a variety of data sources to examine the relationship between EMR adoption and costs. In particular, we match data on EMR adoption from a well-known private data source on health IT investments (HIMSS Analytics) with cost data from the Medicare Hospital Cost Report. We add data from the American Hospital Association's (AHA) Annual Survey of Hospitals. We obtain regional controls and information on local complementary factors from the decennial US Census and from US County Business Patterns data. We supplement the sources above with information on lagged hospital-level IT experience and the local IT workforce from another private source on IT investment, the Harte Hanks Market Intelligence Computer Intelligence Database (hereafter CI database).[10] Our data are organized as an unbalanced panel, with data available every year from 1996 to 2009. Table 2 provides descriptive statistics.[11]

EMR Adoption.—Information about EMR adoption comes from the Healthcare Information and Management Systems Society (HIMSS) Analytics database. The HIMSS Annual Study collects information systems data related to software and hardware inventory and reports the current status of EMR implementation in more than 5,300 healthcare providers nationwide, including well over 3,000 community hospitals.[12] Because most organizations tend to participate for a long period of time, the HIMSS Analytics data closely approximates panel data and can be used for fixed effects regression.

HIMSS reports adoption of 99 different technologies in 18 categories. Examples include Emergency Department Information Systems, Financial Modeling for Financial Decision Support, and a Laboratory Information System. Following most other studies, we restrict attention to five applications in the category Electronic Medical Records, which we listed above. These closely represent the kind of EMR applications that the RAND study and others believe will lead to dramatic cost savings and quality enhancements.

[10] The CI database contains establishment- and firm-level data on characteristics such as the number of employees, personal computers per employee, number of programmers, and the use of specific software applications. A number of researchers have used this data previously to study adoption of IT (e.g., Bresnahan and Greenstein 1996) and the productivity implications of IT investment (e.g., Bresnahan, Brynjolfsson, and Hitt 2002; Brynjolfsson and Hitt 2003; Bloom, Sadun, and Van Reenen 2012). As has been discussed elsewhere (e.g., Forman, Goldfarb, and Greenstein 2005), this dataset represents one of the most comprehensive sources of information on the IT investments of private firms available: for example, as of 2000, it comprised roughly one-half of all US establishments over 100 employees.

[11] The number of observations column in Table 2 shows a key challenge within and across data sources: missing data. There is considerable variation across hospitals and years for each of the variables. We simply drop observations with any missing data from our main specifications.

[12] Community hospitals provide treatments for a wide range of diseases and have relatively short (less than 30 day) average lengths of stay. There are approximately 5,000 community hospitals in the United States. HIMSS hospitals are more likely than average to be privately owned and tend to be larger than non-reporting hospitals.

Table 2—Summary Statistics

Variable	Mean	SD	Min.	Max.	Obs.
EMR measures (2009 values)					
CDR	0.809	0.393	0	1	2,856
CDSS	0.752	0.432	0	1	2,587
Order entry	0.851	0.357	0	1	3,046
Basic EMR adoption (CDR, CDSS, or order entry)	0.870	0.336	0	1	2,149
CPOE	0.242	0.428	0	1	3,527
Physician documentation	0.227	0.420	0	1	3,479
Advanced EMR adoption (CPOE or Physician documentation)	0.306	0.461	0	1	3,198
Cost measures (2009 values)					
log total costs	17.987	1.326	14.015	21.950	4,231
log total costs per admission	9.885	0.511	5.902	15.977	4,231
log labor costs	8.933	0.540	5.293	14.897	4,231
log direct costs	9.840	0.512	5.902	15.946	4,231
Hospital-level controls (2009 values)					
log inpatient days	9.833	1.405	1.792	13.194	4,196
log outpatient visits	11.113	1.408	0.000	15.124	4,202
Fixed hospital-level controls (1996 data)					
log total costs per admission	9.065	0.388	7.232	11.928	4,016
log total hospital beds	4.807	0.904	1.792	7.233	4,016
Independent practice association hospital	0.250	0.433	0	1	4,016
Management service organization hospital	0.200	0.400	0	1	4,016
Equity model hospital	0.079	0.270	0	1	4,016
Foundation hospital	0.156	0.363	0	1	4,016
log admissions	8.214	1.188	2.773	10.931	4,016
Births (000s)	0.810	1.119	0.000	13.614	4,016
For-profit ownership	0.146	0.353	0	1	4,016
Non-secular nonprofit ownership	0.483	0.500	0	1	4,016
Nonprofit church ownership	0.124	0.330	0	1	4,016
Number of discharges Medicare (000s)	3.554	1.899	1.001	17.876	4,016
Number of discharges Medicaid (000s)	2.798	1.228	1.001	21.184	4,016
Residency or Member of Council Teaching Hospitals	0.189	0.392	0	1	4,016
Location-level controls					
log population in 2000 census	11.840	1.781	7.643	16.069	4,016
Percent Black in 2000 census	0.113	0.144	0.000	0.843	4,016
Percent age 65+ in 2000 census	0.136	0.038	0.028	0.347	4,016
Percent age 25–64 in 2000 census	0.853	0.046	0.455	1.047	4,016
Percent university education in 2000 census	0.137	0.059	0.037	0.402	4,016
log median household income in 2000 census	10.552	0.243	9.697	11.303	4,016
Other variables used					
Top quartile county IT-intensive industry	0.424	0.494	0	1	4,231
Top county in IT-intensity, education, income, and pop.	0.234	0.423	0	1	4,231
County is in an MSA	0.544	0.498	0	1	4,231
Number of programmers in all hospitals in county in 1996	11.301	34.802	0	229.593	4,020
Number of programmers total in county in 1996	1,775.648	4,509.823	0	24,611.010	4,020
Number of programmers at hospital in 1996	1.238	6.284	0	101	1,469
Number of business applications at hospital in 1996	4.204	3.736	0	36	1,461
Number of clinical applications at hospital in 1996	2.019	2.117	0	14	1,461

Notes: The unit of observation is a hospital-year. Includes all hospitals in baseline sample that report total cost data. Top panel (EMR measures) reports EMR adoption rates calculated from HIMSS Analytics data. Cost measures are computed using data from Medicare Cost Reports. Hospital-level controls are derived from American Hospital Association's Annual Survey of Hospitals. IT-intensity of county, number of programmers, and presence of business and clinical applications are computed using the Harte Hanks Computer Intelligence database.

We aggregate the five EMR applications into two broad categories that we label "basic" and "advanced" EMR, similar to our prior framework for enterprise IT (e.g., Forman, Goldfarb, and Greenstein 2012). Applications within each of these categories involve similar costs of adoption and require similar types of coinvention to be used successfully. We say that a hospital has basic EMR if it has adopted a clinical data repository (CDR), clinical decision support systems (CDSS), or order entry/communication. We say that a hospital has advanced EMR if it has adopted either computerized practitioner order entry (CPOE) or physician documentation, applications that are more difficult to implement and more difficult to operate successfully due to the need for physician training and involvement. Analyses of health IT adoption, such as the HIMSS Forecasting Model, consider advanced EMR applications to represent the final stage of EMR adoption (HIMSS Analytics 2011). As with other types of information technology, early adopters are larger and tend to be in more urban areas. Similarly, relative to non-adopters and basic EMR adopters, advanced EMR adopters are larger and more urban. These patterns are documented in the online Appendix. Table 1B shows adoption by year for basic and advanced EMR over the sample period. Adoption rose sharply. By 2009, 87.0 percent of hospitals had basic EMR and 30.6 percent had advanced EMR.

Our estimation sample is based on the set of hospitals that replied to the HIMSS survey. Thus, we may exclude hospitals that systematically invest little in information systems and have little incentive to reply to the HIMSS survey. Further, hospitals responding to the HIMSS survey may not respond to all questions. We identify the date of EMR adoption based upon the date when the hospital signed a software contract with the EMR vendor. Thus, missing data on either the presence or absence of an application or the software contract date will create missing observations in our analysis sample. This will create differences in sample sizes across regressions that document the implications of different EMR applications. In the online Appendix we document the number of data points for CMS cost, HIMSS advanced adoption, and HIMSS basic adoption by year after the sample restrictions described above. While the number of cost data points ranges between 3,523 and 4,422 per year, the number of data points for advanced EMR adoption ranges between 1,959 and 3,208 and the number for basic adoption ranges between 1,337 and 2,164.[13] In 1996 the response rate for basic EMR adoption is 58 percent.

Missing data about specific technologies (and to a lesser extent about covariates) mean that our regressions involve 2,214 to 3,653 hospitals observed an average of 10 to 13 years. A comparison of hospitals that report and do not report data on adoption of basic EMR in 1996 reveals that hospitals who report basic EMR have similar costs per admission ($9,138 versus $9,497 for non-reporters) but are substantially larger, with 47.2 percent more beds. Furthermore, while ownership structures are similar, hospitals that do not report data are less likely to be located in metropolitan statistical areas and are less likely to be teaching hospitals. The online Appendix provides further details on the comparison.

Hospital Costs.—Our primary dependent variable is equal to total hospital operating expenses per admission.[14] There are several reasons why we study the impact of EMR on costs and not productivity. From a policy perspective, the debate on EMR focuses on two dimensions: costs and outcomes. From an econometric perspective,

[13] These numbers for basic and advanced adoption are lower than for the individual applications that make up the aggregates, because missing data for any one application will lead to missing data for the aggregate. Basic adoption has more missing data than advanced in part because of missing contract years for basic EMR adopters.

[14] This is derived by CMS by multiplying charges by the hospital's cost to charge ratio. However, because the cost to charge ratio is computed directly from actual accounting costs, this is, in effect, the actual cost figure.

hospitals are multi-product firms. It may be easier to specify cost as the dependent variable and include ad hoc controls for product mix than to try to define output on a uniform scale. This may explain why there are many published studies of hospital cost functions but few published studies of hospital production functions.

We collect data on hospital costs from Medicare Cost Reports. Hospitals are required to report costs to Medicare so that Medicare can compute national reimbursement rates. While these cost data are not audited, hospitals have little incentive to report inaccurately. The cost measure that we use, operating expenses per admission, includes all direct and indirect costs of providing patient services, including the costs of property, plant, and equipment depreciation, but exclude costs of ancillary services such as parking garages and public cafeterias.[15]

There are two distinct cost components of EMR that appear in operating expenses in distinct ways. Initial and ongoing labor and outsourced services are fully expensed in the year they are incurred. Hospitals choose how they wish to amortize fixed capital expenditures. This choice can mechanically affect cost patterns. For example, many hospitals choose the five year Modified Accelerated Cost Recovery System (MACRS). The MACRS schedule is accelerated so that the fixed cost of EMR decline gradually over the five year span and are then zeroed out. Because fixed capital expenses can account for half or more of total EMR costs, and labor costs associated with EMR implementation are typically highest in the first few years, the mechanics of cost allocation will generate increases in expenses per admission followed by a decline towards baseline levels. After five years, we may observe a discrete reduction in expenses. We are not interested in documenting this pattern; prior studies such as Agha (2012) have already done so. Rather, we are interested in whether this pattern depends on the hospital's IT capabilities and predict that initial cost increases will be smaller, and subsequent declines steeper, for hospitals in IT-rich environments. We do not expect any such mechanical bump in costs to be correlated with the local IT environment.

While our primary measure is total operating expenses per admission, we also show robustness to using total expenses and a case-mix weight on admissions.[16] In some years Cost Report data are missing; in our estimation sample 11 percent of hospital observations are missing cost data. We interpolate values for these missing cost data using the geometric mean of adjacent year costs though results are robust to excluding these observations. Table 2 shows that, on average, costs rise

[15] Many hospitals acquired physician practices during the period we study. Amortized acquisition costs, as well as physician salaries, are included in operating expenses. If hospitals embark on a physician acquisition spree at the same time that they acquire EMR, then there will be a positive correlation between EMR and operating costs. However, unless physician acquisition is correlated with the presence of complementary IT assets, our conclusions about the interactive role of IT assets are unchanged. Indeed, this is our identification assumption throughout—that unobservable cost trends are not correlated with IT-richness. We are able to check this assumption in the case of physician salaries. Salaries (but not acquisition costs) are reported separately in the cost reports. In the online Appendix, we show that removing physician salaries does not change the qualitative results.

[16] We obtained annual data on the case mix of Medicare patients for 87 percent of the sample available from the CMS website (https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/AcuteInpatientPPS/Historical-Impact-Files-for-FY-1994-through-Present.html). While Medicare case mix does not match actual case mix, we still document that our results are robust to (i) including the Medicare case mix as a control, and (ii) normalizing the cost per admission by the Medicare case mix index. Our main specification assumes that the case mix does not change simultaneously with EMR adoption for reasons other than EMR adoption.

considerably over the sample period (from 9.065 to 9.885 in logged values) but there is a great deal of variation across hospitals.

We emphasize results on aggregate costs to the hospital, and show robustness to labor costs. While the Cost Report does provide a breakdown of costs by department (e.g., diagnostic radiology, housekeeping, pharmacy), we do not believe these data are reliable reflections of the costs in those areas. In particular, there appears to be substantial accounting discretion in how costs are allocated within the hospital. For example, housekeeping costs range from −$16 per admission to $70,000 per admission with a mean of $196 and a standard deviation of $523. Thus, our understanding of these data is that the aggregate costs (and aggregate labor costs) are reliable, but the cost breakdown by department is subject to substantial variation in accounting norms across hospitals.

Hospital Characteristics.—We obtain hospital characteristics from the American Hospital Association Annual Survey. The survey contains details about hospital ownership, service offerings, and financials. We match AHA, Cost Report, and HIMSS data using the hospital Medicare ID and retain only matching hospitals. Specifically, we start with 4,915 hospitals in the HIMSS data, drop to 4,819 when merging with the Cost Report, and drop to 4,493 when merging with the AHA data. Following the health economics literature, we restrict attention to nonfederal short-term general hospitals—these are the "community" hospitals (including teaching hospitals) that provide the vast majority of acute inpatient services. Finally, we dropped a small number of hospitals that report very low total costs (less than $100,000) over one or more years in our sample period. After dropping these, the minimum cost is $1.2 million and the average cost is $61 million. We observe 58 percent of hospitals in all 14 years of the data and 93 percent of hospitals in seven or more years.

We use the AHA data to compute the following covariates:[17]

- Hospital size: We include number of outpatient visits and number of inpatient days. We also include 1996 values of number of beds and total number of admissions.
- Integration with physicians: We include indicators of whether the hospital operates an independent practice association or a management service organization hospital (as of 1996).
- Hospital ownership: We include for-profit ownership, non-secular nonprofit ownership, nonprofit church ownership, equity model hospital, or foundation hospital (in 1996).
- Other characteristics: We include whether the hospital is a teaching hospital (defined as having a residency program or being a member of the Council of Teaching Hospitals), number of births, total costs per admission (to control for different trends on the base level of the dependent variable), and the number of Medicare and Medicaid discharges (all values are from 1996).

[17] In a small number of cases, specific pieces of the AHA data are missing for a hospital in a given year but available in other years. In these cases, we impute the missing value using the other years though results are robust to dropping these observations.

In our regressions, we interact the 1996 values with a time trend. We emphasize the 1996 baseline to avoid potential changes in hospital characteristics that are driven by the EMR adoption. Results are robust to allowing the characteristics to change over time, but we prefer the simpler specification as a baseline.

Local Features.—We use US Census data to identify location-level factors that might affect costs independent of IT and to measure complementary factors that might facilitate process innovation. We focus on cross-sectional values to facilitate interpretation (so that locations do not switch status), though results are robust to allowing these values to change over time. For controls, we obtain the following variables from the 2000 decennial US Census and match on county: population, percent black, percent age 65+ and percent age 25–64, percent university education, and median household income. In our regressions, these are interacted with a time trend to allow different location characteristics to generate different cost trends.

To measure the availability of local complementary factors, we use three measures from the census and two measures based on the CI database.

Our main measure of complementary factors is the percentage of local firms that are in IT-using and IT-producing industries. We measure the fraction of firms in IT-using and IT-producing industries in the county as of 1995 from the US census County Business Patterns data. National aggregate data shows that such industries have unusually high returns from investment in IT in the 1990s. We define these industries using the classification reported in Jorgenson, Ho, and Stiroh (2005, p. 93).[18] Table 2 shows that 42 percent of the hospitals in our data are in counties in the top quartile in IT intensity. While this measure correlates strongly with population (the median population in the top quartile is over double the median population of counties not in the top quartile in IT intensity), it is more than simply an urban/rural split. For example, Las Vegas, suburban Detroit (Macomb county), and Gary, Indiana are in counties with low IT intensity while many small and rural counties have high IT intensity. In our regressions, we use a dummy variable for whether the county ranks within the top quartile in the country.

Our second measure of local complementary factors combines county-level income, education, population, and IT intensity. This measure, also used in Forman, Goldfarb, and Greenstein (2012), defines "high all factors" counties as those with a population of over 150,000 that are in the top quartile in income, education, and IT intensity; 23 percent of the hospitals in our sample fit this criteria.

Third, we include a dummy for whether the hospital is located in an MSA. Urban locations will benefit from additional supply of complementary factors, including thicker labor markets, third party services firms, and better infrastructure. In particular, urban location has been shown to be correlated with lower costs for enterprise IT adoption in a variety of industries (Forman, Goldfarb, and Greenstein 2005, 2008). To measure local availability of IT skills, we create two measures of

[18] These industries are Communications (SIC 48), Business Services (73), Wholesale Trade (50–51), Finance (60–62, 67), Printing and Publishing (27), Legal Services (81), Instruments and Miscellaneous Manufacturing (38–39), Insurance (63–64), Industrial Machinery and Computing Equipment (35), Gas Utilities (492, 496, and parts of 493), Professional and Social Services (832–839), Other Transportation Equipment (372–379), Other Electrical Machinery (36, ex. 366–267), Communications Equipment (SIC 366), and Electronic Components (367).

the thickness for local employment of programmers. One measures the locations with the thickest labor markets for IT, while the other measures the thickest labor markets for health IT.

We use data from the 1996 and 2002 data releases of the CI database for the number of programmers working in hospitals and the number of programmers working outside of hospitals. For each establishment in the CI database, we take the midpoint of the (categorical) measure of the number of programmers. For each county-industry, we add up the number of programmers.[19] We weight these by comparing the county-industry employment in our sample to total county-industry employment, where the latter is estimated from the US census County Business Patterns data. Our measure of total non-health programmers is the weighted sum across all non-health industries.[20] For our measure of health programmers, we simply compute the (weighted) employment for hospitals, differencing out the focal hospital. We show results using both the 1996 and 2002 CI databases (and the County Business Patterns from the same year). As we do for strong IT locations, we compute the top quartile for both health and non-health programmers.

IT Capabilities.—We also use the CI database to obtain measures of historical hospital-level internal IT capabilities. For capabilities of hospitals, we gather data from 1996 on the number of computer programmers and the numbers of business and clinical software applications at the hospital, which we interpret as measures of hospital experience with IT. We merge this information into our main dataset using hospital names. Unfortunately, because the CI database is itself a sample from a broader population of establishments, there is a significant loss of data from merging these two sources: the number of hospitals in our sample falls by more than half in the regressions that use the CI database to measure internal hospital experience in software in 1996.

V. Empirical Strategy and Results

We perform linear regression with hospital and year fixed effects on an unbalanced panel of hospitals observed annually from 1996 to 2009. We proceed in four stages. First, we regress logged costs per patient on different measures of EMR adoption. We show that costs rise on average after adoption. Second, we decompose the rise in costs by years since adoption and document that the rise is largest in the first years after adoption. Third, we examine different margins of complementarity, and show that the results are much stronger for location than for internal IT experience. In particular, we show that the results are strongest in locations with a large number of HIT workers. These results provide suggestive evidence of

[19] Industries are defined by SIC in 1996 and NAICS in 2002. For both years, we use 2-digit industries (SIC in 1996, NAICS in 2002) plus a separate industry for hospitals (SIC 806 in 1996, NAICS 622 in 2002). In the online Appendix, we show that results are generally robust (though somewhat weaker) if we define programmers in insurance companies as health programmers.

[20] The county-industry weights are equal to (total county-industry employment in Country Business Patterns Data)/(total county-industry employment in the CI database). That is, if our data undersamples a given two-digit industry related to the census it is given more weight in our estimates. We define health industries as described in the previous footnote.

a difference between complementarities related to available internal expertise and complementarities related to agglomeration economies. Finally, we examine robustness, identification, and plausibility with a variety of further tests.

Overall Effects.—We begin by examining the relationship between (the log of) total operating costs per admission of hospital i in county c in time t $(cost^c_{it})$ and EMR:

$$\log(cost^c_{it}) = \boldsymbol{\alpha}\mathbf{X}_{it} + \boldsymbol{\beta}t\mathbf{X}_i + \boldsymbol{\gamma}t\mathbf{Z}^c_i + \theta EMR_{it} + \tau_t + \mu_i + \varepsilon^c_{it}. \tag{1}$$

Here, τ_t captures average changes to costs over time; μ_i is a hospital-specific fixed effect that gets differenced out by subtracting the hospital average values over time from each of the variables; and EMR_{it} is a discrete variable for whether hospital i had adopted a particular EMR technology by time t. Thus, θ identifies our main effect of interest. We assume that ε^c_{it} is a normal i.i.d. variable and calculate heteroskedasticity-robust standard errors that are clustered by hospital.

We include three categories of controls. First, X_{it} are controls for hospital characteristics that change over time: inpatient days and outpatient visits. We choose to allow inpatient days and outpatient visits to vary over time to be consistent with prior work on hospital costs that specified these with a translog function (e.g., Dranove and Lindrooth 2003). Furthermore, these help control for any trends to increased outpatient visits and decreased inpatient days. Second, X_i are all other controls for hospital characteristics. These include beds, type of hospital, ownership status, and discharges. We are concerned that EMR adoption may drive changes in these variables, so including contemporaneous values would be an error. We take their 1996 values and interact them with a linear time trend. Third, Z^c_i are controls for county-specific characteristics (such as population and income) that do not vary sufficiently over time for changes in their values to have much identifying power. However, the location-level characteristics do have power to identify cost trends. Therefore, we interact these local characteristics with a linear time trend.

For this part of our analysis, our identification relies on the assumption that any systematic changes in hospital costs after EMR adoption are captured by the changes in the hospital-level controls over time and the time trends for the locations.[21] Put another way, adoption of EMR is uncorrelated with unobservable cost trends (for example in physician acquisition programs) that were experienced differentially by adopting hospitals.

Table 3 shows the results of this regression. The dependent variable is total operating costs per admission, as defined in the AHA data. Columns 1 to 3 use the specific EMR technologies that together we label "basic EMR"; column 4 uses the aggregated basic EMR measure (which is equal to one when the hospital has adopted any of the three technologies); columns 5 and 6 use the EMR technologies that make up "advanced EMR"; column 7 uses the aggregated advanced EMR measure.

[21] As in Athey and Stern (2002); Hubbard (2003); Bloom et al (2009); Agha (2012); and Forman, Goldfarb, and Greenstein (2012) we initially treat the diffusion of a new technology as an exogenous factor that leads to a change in economic outcomes, and then examine the consequences of the exogeneity assumption.

Table 3—Main Effects by Technology

Technology	log total costs per admission CDR (1)	log total costs per admission CDSS (2)	log total costs per admission Order entry (3)	log total costs per admission Basic EMR adoption (4)	log total costs per admission CPOE (5)	log total costs per admission Physician documentation (6)	log total costs per admission Advanced EMR adoption (7)
Adopted EMR	0.0123	0.0114	0.0018	0.0045	0.0103	0.0248	0.0195
	(0.0055)**	(0.0059)*	(0.0053)	(0.0064)	(0.0068)	(0.0075)***	(0.0070)***
Observations	31,175	27,849	33,388	23,418	38,167	37,519	34,407
Number of hospitals	2,964	2,679	3,161	2,228	3,653	3,597	3,306
R^2	0.58	0.57	0.58	0.58	0.56	0.56	0.56
Controls							
log inpatient days	−0.5061	−0.4917	−0.5331	−0.4476	−0.5564	−0.6086	−0.6094
	(0.1476)***	(0.1688)***	(0.1736)***	(0.1873)**	(0.1433)***	(0.1380)***	(0.1433)***
log outpatient visits	−0.0493	−0.0386	−0.0561	−0.0605	−0.0545	−0.0572	−0.0581
	(0.0960)	(0.0977)	(0.0987)	(0.1190)	(0.0878)	(0.0878)	(0.0903)
log inpatient days × log inpatient days	0.0280	0.0257	0.0317	0.0298	0.0276	0.0309	0.0299
	(0.0079)***	(0.0080)***	(0.0073)***	(0.0086)***	(0.0071)***	(0.0067)***	(0.0070)***
log outpatient visits × log outpatient visits	0.0123	0.0102	0.0150	0.0171	0.0105	0.0112	0.0104
	(0.0059)**	(0.0054)*	(0.0056)***	(0.0067)**	(0.0050)**	(0.0050)**	(0.0050)**
log inpatient days × log outpatient visits	−0.0211	−0.0180	−0.0267	−0.0306	−0.0173	−0.0181	−0.0165
	(0.0129)	(0.0127)	(0.0120)**	(0.0143)**	(0.0115)	(0.0115)	(0.0118)
Other controls (coefficient values not shown)	log total costs per admission × year, log total hospital beds × year, Independent practice association hospital × year, Management service organization hospital × year, Equity model hospital × year, Foundation hospital × year, log admissions × year, Births (000s) × year, For-profit ownership × year, Non-secular nonprofit ownership × year, Nonprofit church ownership × year, Number of discharges Medicare (000s) × year, Number of discharges Medicaid (000s) × year, Residency/Member Council Teaching Hospitals × year, log local population × year, % Black × year, % age 65+ × year, % age 25–64 × year, % university education × year						

Notes: Unit of observation is a hospital-year. Sample includes annual data from 1996 to 2009. Regressions include hospital-specific fixed effects, differenced out at means, and year fixed effects. Robust standard errors, clustered by hospital, in parentheses. Full set of coefficients shown in the online Appendix. Other hospital controls are 1996 values and other census controls are 2000 values.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

The results suggest that, on average, EMR does not reduce costs per admission. Instead, in many specifications, EMR is associated with a positive and significant increase in costs of about 1 to 2 percent.

Effects by Time Since Adoption.—As discussed above, a rich literature on IT productivity has documented that IT adoption affects productivity with a lag. Table 4 examines the timing of cost changes with EMR adoption. Specifically, Table 4 splits the *EMR* variable into two pieces, based on time since adoption:

$$(2)\ \log(cost_{it}^{c}) = \boldsymbol{\alpha}\mathbf{X}_{it} + \boldsymbol{\beta}t\mathbf{X}_i + \boldsymbol{\gamma}t\mathbf{Z}_i^{c} + \theta_1 EMR_{it} + \theta_2 EMR_{it-3} + \tau_t + \mu_i + \varepsilon_{it}^{c},$$

where EMR_{it-3} is a dummy variable for whether the hospital adopted EMR at least three years earlier. We therefore identify separate coefficients for the first three years observed after adoption and for the subsequent years. In the online Appendix, we show results for each technology and each year after adoption. The hospital fixed effects mean these coefficients should be interpreted relative to the period

Table 4—Main Effects by Technology, by Years Since Adoption

Technology	log total costs per admission Basic EMR adoption (1)	log total costs per admission Advanced EMR adoption (2)	log total costs per admission Basic EMR adoption (3)	log total costs per admission Advanced EMR adoption (4)	log total costs Basic EMR adoption (5)	log total costs Advanced EMR adoption (6)
Adopt in previous three year period	0.0072 (0.0074)	0.0230 (0.0083)***	0.0053 (0.0063)	0.0253 (0.0069)***	0.0195 (0.0061)***	0.0410 (0.0066)***
Adopt at least three years earlier	−0.0195 (0.0103)*	0.0066 (0.0109)	−0.0077 (0.0089)	0.0065 (0.0097)	0.0115 (0.0087)	0.0340 (0.0099)***
Controls	No	No	Yes	Yes	Yes	Yes
Observations	24,284	35,733	23,418	34,407	23,418	34,407
Number of hospitals	2,247	3,334	2,228	3,306	2,228	3,306
R^2	0.50	0.47	0.58	0.56	0.74	0.71

Notes: Unit of observation is a hospital-year. Sample includes annual data from 1996 to 2009. Regressions include hospital-specific fixed effects, differenced out at means, and year fixed effects. Robust standard errors, clustered by hospital, in parentheses. Columns 3–6 include the same set of controls as in Table 3.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

before adoption. Columns 1 and 2 regress log total costs per admission on basic and advanced EMR adoption but do not include any controls beyond hospital and year fixed effects. Columns 3 and 4 add the full set of controls included in Table 3. The coefficient estimates change very little with the addition of a large number of controls. Columns 5 and 6 use log total costs, rather than log total costs per admission, as the dependent variable.

The results show that costs can rise significantly immediately after adoption, with costs per admission increasing 2.6 percent in the first three years following adoption of advanced EMR. After this initial period, costs per admission return to the pre-adoption levels. As discussed earlier, this may be an artifact of depreciation rules. For basic EMR, in the specification with controls for hospital characteristics, there is no significant impact on costs. This is consistent with the prior literature on enterprise IT: initial adoption costs are high because of disruptions to established processes, over time these disruptions diminish, and more complicated technologies take more time to be effectively implemented. It is also consistent with Agha (2012) who finds a transitory increase in total medical expenditures upon adoption but that this increase goes away over time to yield no essentially no change in costs.

Effects by Location.—The literature on enterprise IT has emphasized that efficient use of IT requires the availability of complementary factors such as skilled labor, third-party software support and service, and infrastructure. To explore this hypothesis, we interact EMR adoption measures with the IT-intensity of a location:

$$(3)\qquad \log(cost_{it}^{c}) = \boldsymbol{\alpha}\mathbf{X}_{it} + \boldsymbol{\beta}t\mathbf{X}_{i} + \boldsymbol{\gamma}t\mathbf{Z}_{i}^{c} + \theta_1 EMR_{it} + \theta_2 EMR_{it-3}$$
$$+ \varphi_1 IT\_INTENSE_{i}^{c} \times EMR_{it}$$
$$+ \varphi_2 IT\_INTENSE_{i}^{c} \times EMR_{it-3} + \tau_t + \mu_i + \varepsilon_{it}^{c},$$

Table 5—Interactions with IT-Intensive Location

Definition of IT-intensive location	Top quartile county IT-intensive industries				High all factors: County pop. over 150k and top quartile county in IT-intensive industry, education, and income		MSA	
Technology	Basic EMR adoption (1)	Advanced EMR adoption (2)	Basic EMR adoption (3)	Advanced EMR adoption (4)	Basic EMR adoption (5)	Advanced EMR adoption (6)	Basic EMR adoption (7)	Advanced EMR adoption (8)
Adopt in previous three year period	0.0188 (0.0094)**	0.0386 (0.0112)***	0.0128 (0.0085)	0.0403 (0.0102)***	0.0068 (0.0074)	0.0311 (0.0089)***	0.0042 (0.0106)	0.0514 (0.0132)***
Adopt at least three years earlier	0.0051 (0.0142)	0.0242 (0.0165)	0.0170 (0.0123)	0.0382 (0.0145)***	0.0032 (0.0102)	0.0209 (0.0121)*	0.0066 (0.0155)	0.0714 (0.0194)***
Adopt in previous three yr pd × IT-intensive location	−0.0206 (0.0148)	−0.0229 (0.0165)	−0.0157 (0.0126)	−0.0285 (0.0140)**	−0.0051 (0.0128)	−0.0164 (0.0136)	0.0017 (0.0132)	−0.0375 (0.0155)**
Adopt at least three yrs earlier × IT-intensive location	−0.0435 (0.0019)**	−0.0462 (0.0216)**	−0.0513 (0.0178)***	−0.0597 (0.0189)***	−0.0381 (0.0171)**	−0.0426 (0.0184)**	−0.0230 (0.0189)	−0.0931 (0.0220)***
Controls	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,284	35,733	23,418	34,407	23,418	34,407	23,418	34,407
Number of hospitals	2,247	3,334	2,228	3,306	2,228	3,306	2,228	3,306
R^2	0.51	0.47	0.58	0.56	0.58	0.56	0.58	0.56

Notes: Unit of observation is a hospital-year. Sample includes annual data from 1996 to 2009. Regressions include hospital-specific fixed effects, differenced out at means. Robust standard errors, clustered by hospital, in parentheses. Columns 3–8 include the same set of controls as in Table 3 plus a time trend for IT-intensive location, defined as top quartile in columns 1, 2, 3, and 4, as high all factors in columns 5 and 6, and as MSA in columns 7 and 8.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

where $IT\_INTENSE_i^c$ is a measure of whether the location is IT-intensive.

Table 5 examines three distinct measures of IT-intensity. (i) Columns 1 to 4 use a dummy variable for whether the hospital is in a county that is in the top quartile in terms of IT-using and IT-producing industry.[22] Columns 1 and 2 only control for hospital and year fixed effects while columns 3 and 4 use a full set of controls. Again, the controls do not substantively change the coefficient estimates. (ii) Columns 5 and 6 use a dummy variable for whether the hospital is in a county with high population, income, education and IT-intensive industry (labeled "high all factors" in Forman, Goldfarb, and Greenstein (2012)). (iii) Columns 7 and 8 use a dummy variable for whether the hospital is in an MSA. In this table, we add a control for these location measures interacted with a time trend.

In the previous analysis our identification assumption was that adoption of EMR was uncorrelated with unobservable cost trends that were experienced differentially by adopting hospitals. In this analysis, which is central to our study, our identifying assumption is weaker. We do not need to assume that adopters and non-adopters

[22] We emphasize the discrete measure of IT-intensity to facilitate the interpretation of the coefficients on interaction variables. In the online Appendix, we show that qualitative results are robust to continuous specifications.

experience the same trends in unobservables. Rather, we need to assume that there is no difference in unobservable cost trends around the time of IT adoption in high IT-intensity markets versus low IT-intensity markets; i.e., there is no differential selection on trends in unobservables. Another identification assumption that we require is that hospitals do not relocate to respond to lower EMR adoption costs, and that hospitals cannot easily hire to overcome local IT deficiencies. That is, we assume that an IT-intensive environment requires sufficient local scale, and that hospitals will be a small part of a local IT environment. Our data are consistent with this assumption: for the average county in our data, less than 1 percent of IT workers are employed in hospitals.

The first two rows show that costs per admission do not fall in non-IT-intensive counties. In particular, for advanced EMR, costs per admission appear to rise substantially in such locations. The differences between IT-intensive locations and other locations increase after the initial adoption period. Taking the point estimates in columns 3 and 4 of Table 5 at face value, a hospital that installed basic EMR in a favorable location had an average cost reduction of 3.4 percent starting three years after installation, while an installation of advanced EMR in the same location experienced a cost reduction of 2.1 percent. In contrast, a hospital in a poor location would experience an (insignificant) rise in costs of 1.7 percent from three years after adoption of basic EMR and a strongly significant rise of 3.9 percent after adoption of advanced EMR. With average annual operating costs in the tens of millions, these differences are substantial.

The fact that hospitals in favorable locations experienced cost savings after three years, but not initially, might merely be an artifact of depreciation rules, were it not for the absence of any such pattern for hospitals in unfavorable locations. Instead, this suggests the possibility that EMR can generate increasing cost savings over time. In this way, EMR might "bend the cost curve."

Effects by Local IT Workers.—We next explore whether the difference between IT-intensive locations and other locations is driven by workers in the hospital IT sector, or by IT workers of any kind. Specifically, as described above, we use measures of the number of IT programmers (from 1996 and 2002) in hospitals and in all other (non-health) industries in the county:

$$\begin{aligned}(4)\qquad \log(cost_{it}^{c}) = {} & \boldsymbol{\alpha}\mathbf{X}_{it} + \boldsymbol{\beta}t\mathbf{X}_{i} + \boldsymbol{\gamma}t\mathbf{Z}_{i}^{c} + \theta_1 EMR_{it} + \theta_2 EMR_{it-3} \\ & + \omega_1 HIT\_EMPLOYMENT_{i}^{c} \times EMR_{it} \\ & + \omega_2 HIT\_EMPLOYMENT_{i}^{c} \times EMR_{it-3} \\ & + \varphi_1 OTH\_IT\_EMPLOYMENT_{i}^{c} \times EMR_{it} \\ & + \varphi_2 OTH\_IT\_EMPLOYMENT_{i}^{c} \times EMR_{it-3} + \tau_t + \mu_i + \varepsilon_{it}^{c},\end{aligned}$$

Table 6—Location Characteristics: IT Workers and Healthcare IT Workers

Definition of IT-intensive location	Top quartile IT-intensive workers defined in 1996 data		Top quartile IT-intensive workers defined in 2002 data		Top quartile IT-intensive workers defined in 1996 data		Top quartile IT-intensive workers defined in 2002 data	
Technology	Basic EMR adoption (1)	Advanced EMR adoption (2)	Basic EMR adoption (3)	Advanced EMR adoption (4)	Basic EMR adoption (5)	Advanced EMR adoption (6)	Basic EMR adoption (7)	Advanced EMR adoption (8)
Adopt in previous three year period	0.0103	0.0362	0.0105	0.0325	0.0133	0.0389	0.0132	0.0407
	(0.0073)	(0.0084)***	(0.0073)	(0.0085)***	(0.0087)	(0.0104)***	(0.0086)	(0.0104)***
Adopt at least three years earlier	0.0050	0.0279	0.0060	0.0216	0.0173	0.0383	0.0187	0.0407
	(0.0106)	(0.0121)**	(0.0108)	(0.0124)*	(0.0124)	(0.0147)***	(0.0125)	(0.0148)***
Adopt in previous three yr pd × top quartile HIT workers	−0.0370	−0.0290	−0.0315	−0.0380	−0.0295	−0.0313	−0.0224	−0.0219
	(0.0189)*	(0.0200)	(0.0185)*	(0.0181)**	(0.0180)	(0.0173)*	(0.0164)	(0.0162)
Adopt at least three yrs earlier × top quartile HIT workers	−0.0449	−0.0458	−0.0665	−0.0725	−0.0336	−0.0425	−0.0425	−0.0411
	(0.0255)*	(0.0259)*	(0.0257)***	(0.0280)***	(0.0250)	(0.0234)*	(0.0225)*	(0.0220)*
Adopt in previous three yr pd × top quartile non-hospital IT workers	0.0127	−0.0099	0.0097	0.0083				
	(0.0175)	(0.0193)	(0.0179)	(0.0177)				
Adopt at least three yrs earlier × top quartile non-hospital IT workers	−0.0100	−0.0230	0.0102	0.0172				
	(0.0234)	(0.0249)	(0.0245)	(0.0262)				
Adopt in previous three yr pd × IT-intensive location					−0.0025	−0.0110	−0.0052	−0.0199
					(0.0136)	(0.0151)	(0.0130)	(0.0143)
Adopt at least three yrs earlier × IT-intensive location					−0.0359	−0.0364	−0.0331	−0.0437
					(0.0197)*	(0.0210)*	(0.0189)*	(0.0201)**
Observations	22,552	33,133	23,220	34,161	22,552	33,133	23,220	34,161
Number of hospitals	2,114	3,133	2,206	3,278	2,114	3,133	2,206	3,278
R^2	0.59	0.57	0.58	0.56	0.59	0.57	0.58	0.56

Notes: Unit of observation is a hospital-year. Sample includes annual data from 1996 to 2009. Regressions include hospital-specific fixed effects, differenced out at means. Robust standard errors, clustered by hospital, in parentheses. All regressions include the same set of controls as in Table 3 plus a time trends for location IT intensity characteristics used in the regression.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

where $HIT\_EMPLOYMENT_i^c$ is a dummy indicating if the hospital is in a county where HIT employment is in the top quartile, while $OTH\_IT\_EMPLOYMENT_i^c$ indicates if the hospital is in a top quartile county by non-health IT employment.

This analysis therefore compares whether the correlations between EMR adoption, IT intensity, and costs are more strongly driven by local hospital IT expertise or by IT expertise across other sectors. As noted above, HIT shares many features with other kinds of enterprise IT, so it is possible that labor skills and knowledge will transfer across industries. In Table 6, columns 1 and 2 show the results using the 1996 measures of hospital IT employment and other IT employment and columns 3 and 4 use the 2002 measure. The results suggest that it is local hospital IT employment rather than local IT employment in other sectors that drives the results of the previous subsection. Costs appear to be substantially lower for hospitals located in the top quartile of counties in terms of hospital IT employment. This does not seem to be true of hospitals in the top quartile of counties in non-health IT employment, controlling for hospital IT employment.

Columns 5 through 8 of Table 6, however, suggest that local hospital IT employment may not explain the entire result on IT-intensive locations found in Table 5. In particular, we include both local hospital IT employment and our measure of IT-intensive location in the regression:

$$\begin{aligned}(5)\qquad \log(cost_{it}^{c}) = {} & \boldsymbol{\alpha}\mathbf{X}_{it} + \boldsymbol{\beta}t\mathbf{X}_{i} + \boldsymbol{\gamma}t\mathbf{Z}_{i}^{c} + \theta_1 EMR_{it} + \theta_2 EMR_{it-3} \\ & + \omega_1 HIT\_EMPLOYMENT_i^c \times EMR_{it} \\ & + \omega_2 HIT\_EMPLOYMENT_i^c \times EMR_{it-3} \\ & + \varphi_1 IT\_INTENSE_i^c \times EMR_{it} \\ & + \varphi_2 IT\_INTENSE_i^c \times EMR_{it-3} + \tau_t + \mu_i + \varepsilon_{it}^{c}.\end{aligned}$$

Consistent with columns 1 to 4 of Table 6, we find that local hospital IT employment is strongly correlated with reduced costs. In addition, we find a weakly persistent relationship between IT-intensive locations and reduced costs, even controlling for hospital IT employment. We interpret this to suggest that local expertise in hospital IT is particularly important but it may not explain all of the difference between IT-intensive counties and other counties.

Effects by Hospital IT Experience.—Internal expertise also can mitigate the costs of adoption of a new process innovation. Importantly, unlike local factors, a hospital may be able to overcome some of these issues by hiring outside expertise. Table 7 examines the interaction in the following format:

$$\begin{aligned}(6)\quad \log(cost_{it}^{c}) = {} & \boldsymbol{\alpha}\mathbf{X}_{it} + \boldsymbol{\beta}t\mathbf{X}_{i} + \boldsymbol{\gamma}t\mathbf{Z}_{i}^{c} + \theta_1 EMR_{it} + \theta_2 EMR_{it-3} \\ & + \omega_1 HIT\_EXPERIENCE_i \times EMR_{it} \\ & + \omega_2 HIT\_EXPERIENCE_i \times EMR_{it-3} + \tau_t + \mu_i + \varepsilon_{it}^{c}.\end{aligned}$$

As measures of hospital IT experience, we examine business software applications, clinical software applications, and programmers employed (all measured in 1996, at the beginning of the sample). These can be seen as measures of whether the hospital had prior experience in managing software. Given that the sample is reduced by more than half when we merge in the CI database that contains experience information, the additional insight imposes a significant cost on the analysis.

Still, Table 7 suggests a striking contrast to the effects of local IT-intensity. Internal expertise appears to have little impact on the relationship between basic EMR and costs. It does appear related to reduced costs for hospitals that adopt

Table 7—Interactions with Internal Experience with Healthcare IT

Definition of internal HIT experience	Number of business applications used in 1996		Number of clinical applications used in 1996		Number of programmers employed in 1996	
Technology	Basic EMR adoption (1)	Advanced EMR adoption (2)	Basic EMR adoption (3)	Advanced EMR adoption (4)	Basic EMR adoption (5)	Advanced EMR adoption (6)
Adopt in previous three year period	0.0065	0.0480	0.0036	0.0533	0.006[illegible]	0.0320
	(0.0120)	(0.0129)***	(0.0120)	(0.0134)***	(0.008[illegible]	(0.0090[illegible]***
Adopt at least three years earlier	−0.0076	0.0296	−0.0032	0.0256	−0.0048[illegible]	0.0173
	(0.0181)	(0.0208)	(0.0163)	(0.0193)	(0.0115[illegible]	(0.0138[illegible]
Adopt in previous three year period × HIT experience	0.00004	−0.0040	0.0016	−0.0103	0.0001	−0.0011
	(0.0018)	(0.0017)**	(0.0036)	(0.0035)***	(0.000[illegible])	(0.0009[illegible]
Adopt at least three years earlier × HIT experience	0.0013	−0.0023	0.0007	−0.0029	0.001[illegible]	0.000[illegible]
	(0.0028)	(0.0029)	(0.0051)	(0.0050)	(0.001[illegible]	(0.001[illegible])
Observations	10,262	14,557	10,262	14,557	10,290	14,653
Number of hospitals	827	1,183	827	1,183	829	1,190
R^2	0.67	0.62	0.67	0.62	0.67	0.62

Notes: Dependent variable is costs per admission. Unit of observation is a hospital-year. Sample includes annual data from 1996 to 2009. Regressions include hospital-specific fixed effects, differenced out at means. Robust standard errors, clustered by hospital, in parentheses. All regressions include the same set of controls as in Table 3 plus a time trend for HIT experience.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

advanced EMR, but only in the first period after adoption. For the three measures, a one standard deviation change yields a 2.5 to 3.9 percent decrease in costs per admission in the initial three years after advanced EMR adoption. Internal expertise therefore seems most important for advanced applications that might involve a great deal of coinvention to be successfully employed but any cost disadvantages from a lack of expertise are quickly overcome. We speculate that this might be because it is not difficult for the hospital to hire the expertise from outside. Broadly, the main message of Tables 5, 6, and 7 is consistent with this study's framing, using the results of prior literature on enterprise IT to understand EMR adoption.

Robustness, Identification, and Plausibility.—Next, we explore the degree to which we can claim our main results in Table 5 are causal and general. There are three potential types of concerns. First, there might be an omitted variable correlated with EMR adoption and with costs. Second, and related to this, it is possible that unobservable changes in cost drivers are associated with EMR adoption differentially in high and low IT intensity markets. Third, it is possible that anticipated changes in costs drive EMR adoption (rather than EMR adoption driving changes in costs).

In anticipation of these concerns, we included in our previous analyses hospital and time fixed effects as well as a very large set of covariates as controls. Comparing the results with only hospital and year fixed effects to the results with additional controls (columns 1 and 2 versus columns 3 and 4 of Tables 4 and 5) shows that the many controls do not change the estimates by much, thereby suggesting that the impact of unobservables would have to be large relative to the impact of the

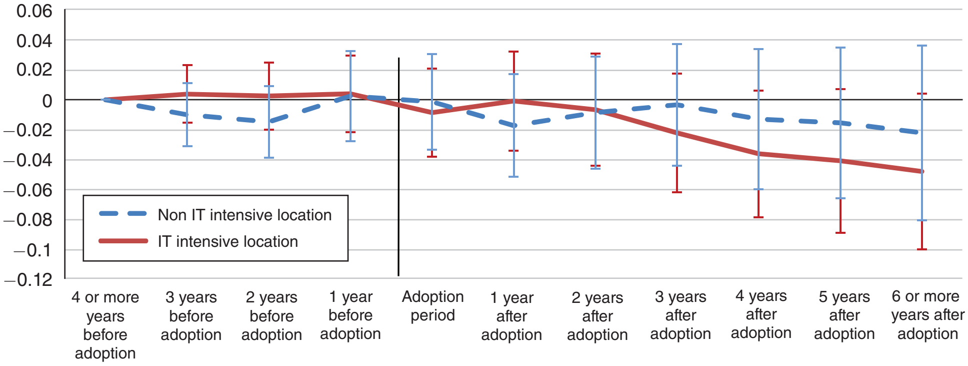

Figure 2A. Coefficients by Years from Basic EMR Adoption

Notes: Error bars show 95 percent confidence intervals. Full set of coefficients shown in the online Appendix.

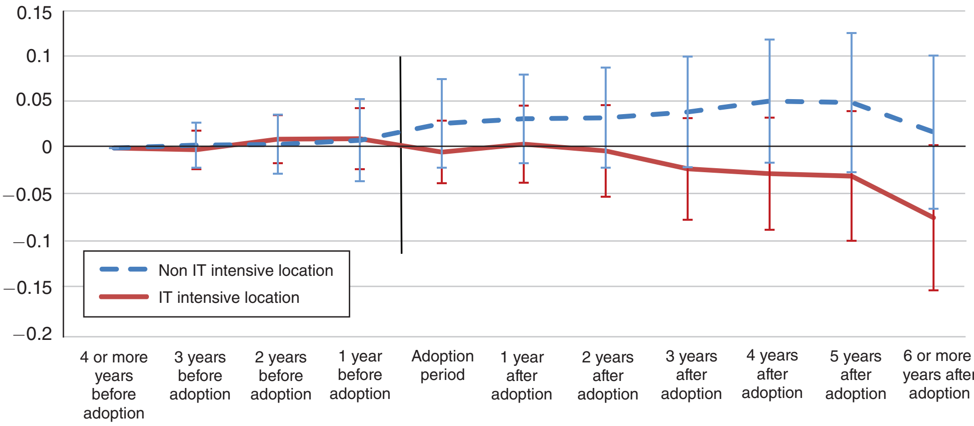

Figure 2B. Coefficients by Years from Advanced EMR Adoption

Notes: Error bars show 95 percent confidence intervals. Full set of coefficients shown in the online Appendix.

observables (Altonji, Elder, and Taber 2005). Still, in order to address additional concerns we analyze a number of alternative specifications.

In Figures 2A and 2B, we examine the timing of the relationship between EMR adoption and changes in costs. Specifically, we focus on eventual adopters and exploit variation across hospitals in year of adoption. We replace the measures of adoption with dummies for three years before adoption, two years before adoption, one year before adoption, the year of adoption, one year after adoption, two years after adoption, three years after adoption, four years after adoption, five years after adoption, and six or more years after adoption. The base period is four or more years before adoption. Figures 2A and 2B demonstrate distinct effects for IT-intensive and non-IT-intensive locations, defined by the top quartile of counties in terms of IT-intensive industry. Figure 2A examines basic EMR adoption and Figure 2B examines advanced EMR adoption. Prior to adoption, the costs follow similar patterns. During and after the initial adoption, however, the costs in non-IT-intensive locations rise while the costs in IT-intensive locations fall substantially. While Figure 2B shows a particularly sharp drop in the coefficient for six or more years after adoption, we interpret this cautiously because it may be driven by unobserved differences between early adopters and others. The coefficients for these regressions are shown in the online Appendix. The timing of the impact of EMR displayed in Figures 2A and 2B suggests that there is not a noticeable trend in an omitted variable driving the estimates. Similarly, there is no evidence of differential time trends between IT-intensive and non-IT-intensive locations prior to EMR adoption.

In the online Appendix, we address other concerns regarding specification. We show that qualitative results are robust to using continuous measures of IT-intensive location, to adding controls for time-varying hospital characteristics and the Medicare case mix index, to adding hospital-specific time trends, and to switching the dependent variable to labor costs, non-physician labor costs, or direct costs.[23] We also show that the results are robust to including only those hospitals observed in all years (a balanced panel), to including only hospitals in the top quartile or the bottom quartile of the 1996 cost distribution, and to dropping locations in which hospital IT workers make up a substantial fraction of IT employment. We also document strong similarity between the coefficients on the controls for our main sample and for a sample that excludes hospitals that never adopt, suggesting that the control group of hospitals has a similar cost function to the treatment group.

Furthermore, and importantly, we do not see other significant systematic changes in hospital activity associated with EMR adoption and its interaction with IT-intensive locations when we change the dependent variable to the number of beds, a (noisy) measure of physician compensation per admission, the number of admissions, or the share of discharges from Medicare. Thus, consistent with our core identifying assumption, we do not see substantial other changes at the hospitals.

VI. Conclusion

Drawing on a variety of data sources on IT, EMR, local demographics, and hospital characteristics, this study demonstrates the value of viewing EMR adoption through the lens of the prior literature on IT use in enterprises. While EMR adoption appears to be associated with an increase in costs on average, there is important heterogeneity over time, across technologies, across locations, and across hospitals. Both basic and advanced EMR adoption are initially associated with a rise in costs, and this initial increase in costs is mitigated in hospitals with some internal information technology expertise. After three years, hospitals in IT-intensive locations experience a significant 3.4 percent decrease in costs after adopting basic EMR, and a marginally significant 2.1 percent decrease in costs after adopting advanced EMR. These benefits are greatest in locations with a large number of HIT workers, though the benefits of IT-intensive locations likely extend beyond local expertise in hospital IT. In contrast, hospitals in other locations experience an increase in costs, even after several years.

[23] Direct costs are equal to total operating expenses excluding capital depreciation expense.

Our results also have implications for policy discussions. Policies such as the HITECH Act go a long way towards encouraging EMR adoption. EMR is likely to become more effective when market forces align in the same direction—e.g., as workers gain experience, as hospitals pass lessons on to independent IT consulting firms, and as labor markets for hospital IT adjust and become thicker at a local level. Broadly, the results suggest a positive externality from EMR adoption. This implies that hospitals in areas blessed with "IT richness" already enjoy the equivalent of a public good, and subsidies to hospitals in those areas are unlikely to yield much in the way of additional public goods at the local level. However, subsidies to these areas might accelerate earlier adoption among those who are inclined to already adopt. While the main beneficiaries would appear to be those who collect the subsidy, other beneficiaries are those who gain from the lessons learned, such as software vendors and consultants, and their clients. This could then indirectly benefit hospitals in other locations.

A second implication is quite different: the targeting of adoption subsidies, such as those in the HITECH act, could be extended to IT-poor locations where markets are not encouraging adoption. These hospitals may be reluctant to adopt EMR due to the high costs and lack of local complementary assets. Because many of these assets, such as independent IT consulting firms with EMR experience, may be thought of as public goods, the availability of these assets will increase once some hospitals adopt EMR and all hospitals will benefit. As a result, if subsidies have a sufficiently large impact on adoption, they may generate a greater incentive for all hospitals in IT-poor communities to adopt and a greater ability for those hospitals to succeed. This is particularly likely for relatively large IT-poor communities.

A third policy implication highlights the importance of the unimpeded flow of information. Prior research has examined the flow of information between competing hospitals, and how this objective can conflict with the protection of privacy and the proprietary concerns of hospitals (e.g., Miller and Tucker 2009). Our perspective also stresses the importance to society of sharing lessons on effective implementation across hospitals that otherwise do not compete, and between hospitals and third-party providers. Such sharing also can come into conflict with privacy protection and the tendency of many hospitals to treat their processes and investments as trade secrets. If policy can alleviate these concerns, the effectiveness of EMR might increase.

As with any empirical work, our analysis has a number of limitations. First, we observe only a subset of the medical providers in the United States. Doctors' offices, outpatient clinics, nursing homes, and other medical practices may have had different experiences. While we believe it is likely that the general principles of the prior literature on IT would apply broadly, our evidence is specific to hospitals. Relatedly, if hospital adoption of EMR impacts costs for either patients or medical practices outside of hospitals, then our estimates will miss some of the impact, whether positive or negative. Second, we focus on a particular set of EMR technologies over a particular time period. It is possible that the technologies that have arisen since 2009 may be more effective and easier to implement. Third, our EMR adoption data contains binary indicators of adoption rather than measures of intensity of use. If the variance in use of EMR across hospitals differs from that of adoption, then our results will mismeasure some of the impact of EMR. Fourth, if the cost savings in IT-intensive areas lead to higher unmeasured costs, such as patient effort, then our estimates will overstate the effect. Fifth, a key assumption is that hospitals represent a small fraction of local IT expertise and employment. If this is not the case, then our explanation based on complementarities related to coinvention costs is hard to justify. Sixth, while we have tried to address the endogeneity of adoption through various techniques, we cannot completely rule out the possibility that hospitals in IT-intensive locations adopt because they expect their costs to fall for some reason other than the complementarities of the local IT environment.

This study also leaves open questions such as why hospitals adopt if their costs do not fall. Potential reasons for this pattern could include the pursuit of a societal ideal in spite of the cost, misconceptions about EMR's costs and benefits, expected benefits that we do not measure, the difference between ex ante aspirations and ex post experience, or something else. Relatedly, though the evidence in the literature is mixed on whether hospitals accrue benefits, such as improved clinical outcomes or reduced errors, it is possible that hospitals outside IT-intensive locations experience a sharp increase in benefits such as clinical outcomes and reduced errors. In that case our findings on reduced costs only tell part of the story.

Despite these limitations, we believe our results help inform the discussion on the "trillion dollar conundrum," providing the (perhaps missing) link between healthcare IT and healthcare costs. Indeed, our results can be restated as a possible resolution to the trillion dollar conundrum: EMR may succeed when the necessary complements are present and the complementary components are in place. Until then, the results of EMR implementation, at best, can be only mixed. While EMR's past mixed performance is no guarantee of a future result, the past experience also is no guarantee of future failure. Over time, complementary IT skills are expected to become more widely available, and the various components more widely deployed. If so, more hospitals will enjoy the benefits of EMR and it may yet fulfill its promise.

AQ3

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