THE TRILLION DOLLAR CONUNDRUM: COMPLEMENTARITIES AND HEALTH INFORMATION TECHNOLOGY[*]

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Abstract

We examine the heterogeneous relationship between the adoption of electronic medical records (EMR) and hospital operating costs at thousands of US hospitals between 1996 and 2009. Combining data from multiple sources, we first identify a puzzle that has been seen in prior studies: Adoption of EMR is generally associated with a slight increase in costs. We draw on the literature on information technology as a business process innovation to analyze why this average effect arises, and explain why it masks important differences over time, across locations, and across hospitals. We find evidence consistent with this approach, namely, that: (1) EMR adoption is initially associated with a rise in costs; (2) EMR adoption at hospitals in favorable conditions – such as urban locations – leads to a decrease in costs after three years; and (3) Hospitals in unfavorable conditions experience a sharp increase in costs even after six years.

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I. Introduction

As annual U.S. 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 & Medicaid Services). 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. The Congressional Budget Office states: "No aspect of health information technology entails as much uncertainty as the magnitude of its potential benefits" (Congressional Budget Office 2008).[1]

A small sampling of research from the last half dozen years provides a sense of the uncertainty. 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. Other recent studies, cited below, fail to find consistent evidence that EMR savings offset adoption costs. With a lack of consistent research evidence, it remains uncertain whether EMR can fulfill its promise and bring about major reductions in health spending.

This study speaks to this conundrum and reframes the debate. We characterize EMR in terms of the impact new enterprise information technology (IT) has on existing organizations. Specifically, we view EMR as a *business process innovation*, which is a change in the operational practices inside the adopting organization.[2] Just like any other business process innovation, the impact of new EMR depends on complementary assets that reduce the costs associated with "co-invention," which is the process of adapting the business process innovation to unique circumstances and turning the overall change into a net benefit to

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[1] Though EMR is a type of Health Information Technology, the terms are often used interchangeably.

[2] There is a large and established literature on business process innovations in the adoption of large IT platforms. This study builds on the econometric analysis of the adoption of large scale enterprise IT, as found in Bresnahan and Greenstein (1996), Bresnahan, Brynjolfsson, and Hitt (2002), Forman, Goldfarb and Greenstein (2005), and Bloom, Garicano, Sadun, and Van Reenen (2009).

the enterprise. These complementary assets come from several sources. *Local* resources may be available as market services, such as expertise in implementing similar business process innovations. Resources available *internally to the enterprise,* such as expertise with other business processes inside the enterprise, may also help implement the business process innovation and often cannot be purchased from markets in the short run. We argue that prior literature has missed important features of EMR by not using this type of framework to assess its impact and explain why it succeeds in some settings more than others.

We apply this reframing to an empirical examination of the impact of EMR adoption on hospital operating costs during the period 1996 to 2009. The data comes from several sources linking hospital costs to EMR adoption and the potential for complementarities.[3] Our main analysis regresses logged operating costs on EMR adoption, hospital fixed effects, and a large number of controls. We focus on whether the impact of EMR 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 that this is a reasonable assumption; even so, we show robustness to instrumenting for EMR adoption using hospital proximity to EMR vendors and EMR adoption in alliance systems and geographically linked markets. We find the evidence consistent with our reframing of the conundrum, namely, differences in outcomes relate to differences in local conditions. Moreover, the timing of cost savings is also consistent with what we would expect from a business process innovation.

A key assumption in this interpretation is that hospitals are a sufficiently small proportion of local IT expertise and that investments by hospitals have little impact on the overall availability of local complementary assets. Thus, rather than focus on IT adoption by other hospitals, a sector which is a relative

[3] We use data from the American Hospital Association Annual Survey (hospital characteristics), from the Medicare Costs Report (hospital costs), from the Healthcare Information and Management Systems Society Analytics Database (hospital EMR adoption), from the decennial U.S. Census and from U.S. County Business Patterns data (county-level demographics and IT-intensiveness of local industry), and from the Harte Hanks Market Intelligence IT survey (measures of hospital IT capabilities in 1996).

laggard in IT usage, we focus on the role of the IT-intensity of all local industry as a proxy for the availability of local complementary inputs.[4]

Our findings can be summarized as follows: 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 a measure 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 3.4 percent decrease in costs from three years after adoption of basic EMR and a marginally significant 2.2 percent decrease in costs from three years after adoption of advanced EMR. These are significantly better than the up to 4 percent *increase* in costs after adoption by hospitals in other markets.

Figure 1 displays 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 do not fall until 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 also show results suggesting that complementary skills can be found internally in the hospital. For advanced EMR, the initial increase in costs is mitigated substantially if hospitals already have substantial software experience, measured by programmers employed, the intensity of use of clinical software applications, and the intensity of use of business software applications. 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; perhaps they hire or outsource expertise. This suggests

[4] This assumption makes clear that our emphasis on local complements is distinct from an exploration of network externalities through data sharing across hospitals, which Lee, McCullough, and Town (2012) show to be unimportant to hospital productivity.

that, in contrast to complementary assets that depend on a location with favorable agglomeration economies, some complementary assets to business process innovation can be acquired relatively quickly.

These findings have several implications. First, this analysis informs the drivers of EMR's sluggish diffusion. As of 2009, only about 30 percent of America's hospitals have adopted any advanced elements of EMR.[5] This may be 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). In addition, the 2010 Patient Protection and Affordable Care Act promotes EMR adoption. PPACA directs the establishment of quality reporting measures that likely will require providers to adopt EMR in order to comply. PPACA creates a new "shared savings" program for Medicare; participation in this program is predicated on the use of EMR. Finally, PPACA encourages providers to apply to participate in a range of new programs and gives preference to those that have adopted EMR.

Second, our findings may help resolve the ongoing debate between EMR supporters and skeptics. Both sides 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 policy makers so keen to expand adoption? Our results suggest that the debate about EMR should be reframed by drawing on the general literature on business process innovation, where it is very common for successful adoption of enterprise IT to require complementary changes in business processes that often 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 can simultaneously have the potential to generate substantial savings, yet demonstrate mixed results in practice.

[5] Source: Authors' calculations based on data supplied by HIMSS.

Seen through this lens, the debate around the benefits of EMR is just a new manifestation of a similar debate on the benefits of IT investment in manufacturing and services that started a quarter century ago with the Solow 'Productivity Paradox'—"You can see the computer age everywhere but in the productivity statistics" (Solow 1987). That debate eventually faded from view partly because the data began to reject it, as firms achieved productivity benefits, just with a lag. Moreover, the challenges to productivity benefits were due to the costly adaptations and business process innovation 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, or, in other words, had been engaged in the kinds of business process innovations highlighted above.[6] Our paper highlights similar patterns in the benefits to EMR adoption: For the average hospital, the benefits of EMR adoption appear with some delay; however there is significant heterogeneity in the benefits achieved that depend upon the availability of complementary factors such as hospital IT skills and proximity to strong IT locations.

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 organizations, which leads to a reframing of several key hypotheses. Sections V and VI present data and results. Section VII concludes.

II. 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:

- 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.

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

- *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 faxes and paper forms).
- *Computerized Provider Order Entry (CPOE)* is a more sophisticated type of electronic order entry and involves physician entry of orders into the computer network to medical staff and to departments such as pharmacy or radiology. 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. Our data from HIMSS Analytics contain hospital-level adoption data for each of these technologies. Therefore, we are able to explore how different technologies might affect costs in different ways.

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 1 reports hospital adoption rates for the five components of EMR described above. The data is 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, Table 1 lacks several crucial pieces of information. It lacks comparable data on physician adoption of EMR, for example. The conventional wisdom is that physician adoption rates are much lower than hospital adoption rates. 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. Conventional wisdom suggests that many hospitals have experienced a wide range of outcomes, and in some cases this is due to poorly executed installation, poor training, lack of adaptation of the installation to the unique needs of the enterprise, and (as a cause of the other three) lack of ideal conditions for hiring skilled talent.

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 the table. 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). The HITECH Act changes the nature of privacy and security protections and may therefore make it easier for different vendor systems to exchange information in the future.

III. Evidence on the Potential Savings from EMR

Has the adoption of EMR reduced 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 as a business process innovation.

Every EMR study begins from the same place: EMR is expensive. 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 $3000 to $9000. For a typical urban hospital, these figures range from $3-$9 million for adoption and $700,000-$1.35 million for maintenance. In context these costs are quite significant: 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 may 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.[7] Most of the studies they review focus on quality of care.[8] 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. Indeed, only three reported the costs of implementing EMR and two of these studies were more than ten years old.

One of the most widely cited cost studies, Hillestad et al. (2005) (the RAND study cited in our introduction), uses results from prior studies of EMR and medical utilization and extrapolates the potential cost savings net of adoption costs. They identify several dozen potential areas of cost savings, including reduced drug, radiology, and laboratory usage, reduced nursing time, reductions in clerical staff, fewer medical errors, and shorter inpatient lengths of stay. They estimate that if 90 percent of U.S. hospitals were to adopt EMR, total savings in the first year would equal $41.8 billion, rising to $77.4 billion after fifteen 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, in reality, EMR may allow providers to justify ordering additional tests. Sidorov also questions

[7] Chaudry et al state that they study Health Information Technology and they do not indicate if they distinguish between HIT and EMR.
[8] For recent studies of the impact of EMR on patient outcomes, see McCullough, Parente, and Town (2011) and Miller and Tucker (2012).

whether EMR will generate forecasted reductions in medical errors. McCormick et al (2012) document thatphysicians with computerized imaging results tend to order more images, though they do not address the role of omitted variables in driving this result.

Buntin et al. (2011) review 73 studies of the impact of EMR on medical utilization. EMR is associated with a significant reduction in utilization in 51 (70 percent) of these studies. They do not break these down into specific areas of savings, however. Buntin et al. do not identify any studies of EMR and costs. To our knowledge, such studies remain few and far between.

Indeed, we have identified only three focused cost studies.[9] Borzokowski (2009) uses fixed effects regression to examine whether early versions of financial and clinical information technology 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. Second, 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. Finally, Agha (2012) uses variation in hospitals' adoption status over time, analyzing 2.5 million inpatient admissions across 3900 hospitals between the years 1998-2005. Health IT is associated with an initial 1.3 percent increase in billed charges. She finds no evidence of cost savings, even five years after adoption. Additionally, adoption appears to have little impact on the quality of care, measured by patient mortality, medical complication rates, adverse drug events, and readmission rates.

None of the studies frame EMR as a business process innovation. In other words, there is no examination of factors that shape availability of complementary components, such as the characteristics of

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[9] For related work on the implications of HIT for hospital productivity, see Lee, McCullough, and Town (2012).

the local settings or the experience of the hospital with other computing and communications technologies. This may be due to the absence of familiarity with theoretical frameworks 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.

IV. Information Technology and Complementarities

Business process innovations alter 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 *business process innovations* in enterprise IT occur on a large scale, they typically involve a range of investments, both in computing hardware and software, and in communications hardware and software. They also involve the retraining of employees, and the redesign of organizational architecture, such as its hierarchy, lines of control, compensation patterns, and oversight norms. In the discussion below, we draw on a wide literature to explain a number of common misunderstandings about business process innovations.[10]

For example, there is a myth that new IT hardware or software yields the vast majority of productivity gains by themselves. In fact, business process innovations are not often readily interchangeable with older products or processes, meaning that the initial investment often does not generate a substantial productivity gain until after complementary investments, adaptations, and organizational changes. Many of these necessary changes are made long after the initial adoption.

This suggests another common misunderstanding, a planning myth. Though the installation of any substantial business process innovation requires planning – i.e., administrative effort by the enterprise in advance of installation – such planning alone rarely ends the administrative tasks required to generate

[10] 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, Garicano, Sadun, and Van Reenen (2009), and Bloom, Sadun, and Van Reenen (2012). Forman and Goldfarb (2005) summarizes the earlier literature.

productivity gains. Administrative effort does not cease after installation, or even necessarily reach a routine set of procedures. Rather, administrative effort continues throughout implementation. Training personnel generates use of new hardware, software, and procedures. New users in new settings then notice unanticipated problems, which generates new insight about unexpected issues. For example, one division may require a maximal set of information on one set of medical issues, while a satellite campus may rarely need to wade through all the screens. Adapting the software to the specific types of users and the specific setting may be required to experience maximal productivity gains.

That relates to a third common misunderstanding, the shrink-wrap myth. Installing business process innovations is not equivalent to installing shrink-wrap software for a PC that works instantly, or merely after training of staff. Instead, prior studies stress the importance of *co-invention*, the post-adoption invention of complementary business processes and adaptations aimed at making adoption useful (Bresnahan and Greenstein 1996). The initial investment in IT is not sufficient for ensuring productivity gains. Those gains depends on whether the employees of the adopting organization–in the case of hospitals, administrative staff, doctors, and nurses–find new uses to take advantage of the new capabilities, and/or invent new processes for many unanticipated problems. Due to co-invention, there is often little immediate payoff to adoption, and a strong potential for lagged payoff, if any arises at all.

Misunderstandings about the necessity for co-invention generate a fourth myth, namely, expectations that the entire cost of investment is incurred as monetary expense. In fact, non-monetary costs comprise a substantial risk from installing a business process innovation. Prior studies emphasize the cost of delays, for example. Delays arise from non-convexities in investment (e.g., all the wiring must be installed before the communications routines can be tested), the technical necessity to invest in one stage of a project only after another is completed (e.g., the client cannot be modified until the servers work as designed), and cognitive limits (e.g., staff does not anticipate idiosyncratic issues until a new process is at their fingertips). Moreover, interruptions to ongoing operations generate large opportunity costs in foregone services that can be substantially mediated with internal resources (e.g., development of middleware by in-house IT staff) for which there may be no market price or, for that matter, no potential for resale. Third-party consulting services, which are often hired on a short-term basis from the local market, can attenuate these costs. The incentives around utilization and investment also can change considerably over time due to changes in the restructuring of the organization's hierarchy and operational practices (Bloom, Garicano, Sadun, and Van Reenen 2009).

Two key implications arise from this discussion. First, enterprises with existing IT facilities should expect lower co-invention costs than establishments without extensive operations, and that should shape costs around the time of adoption. Having more resources elsewhere in the organization means that lower cost resources can be tapped, or loaned between projects of the same organization. Programmers provide experience with IT projects. Prior IT projects may reduce development costs if programmers are able to transfer lessons learned from one project to another.[11] 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.

Second, given that there is considerable heterogeneity across US locations in the availability of complementary factors, such as skilled labor (Forman, Goldfarb, and Greenstein 2005, 2012), third-party software support and service (Arora and Forman 2007), and infrastructure (Greenstein 2005, Greenstein and McDevitt 2011), there should be a visible relationship between investment in health IT and local conditions in a limited metropolitan geographic area. Large cities may have thicker labor markets for complementary services or for specialized skills. Thicker markets lower the (quality-adjusted) price of obtaining IT services such as contract programming and of hiring workers to develop in-house functions. Such locations may also have better availability of complementary information technology infrastructure, such as broadband services. Increases in each of these factors may increase the (net) benefits of adopting complex technologies in some cities and not others, other things being equal. Overall, the presence of thicker labor markets for technical talent, greater input sharing of complex IT processes, and greater

[11] 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 prior related projects can lower the costs of innovation (Cohen and Levinthal 1990).

knowledge spillovers in cities should increase the benefits to adoption of frontier technologies in big cities relative to other locations (Henderson 2003, Forman, Goldfarb, and Greenstein 2008).

In summary, if the productivity impact of EMR follows patterns seen with other business process innovations, then it should come with a lag. Furthermore, 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 the local labor market for skilled labor and third-party software and support.

V. Data

We use a variety of data sources to examine the relationship between EMR adoption and costs. In particular, the data for this study matches 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 U.S. Census and from U.S. County Business Patterns data. We supplement the sources above with information on lagged hospital-level IT capabilities from another private source on IT investment, the Harte Hanks Computer Intelligence Database. Our data are organized as an unbalanced panel, with data available every year from 1996 to 2009. Table 2 provides descriptive statistics.[12]

EMR adoption. Information about EMR adoption comes from the Healthcare Information and Management Systems Society (HIMSS) Analytics data base. 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 5300 healthcare providers nationwide, including well over 3000 community hospitals.[13] Organizations that seek access to HIMSS Analytics data must provide their information on software and hardware use. 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.

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[12] 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, though we document that results are robust to some alternatives.

[13] 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 5000 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.

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.

We aggregate the five EMR applications into two broad categories that we label “basic” and “advanced” EMR. Applications within each of these categories involve similar costs of adoption and require similar types of co-invention 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).

Table 1 shows sharp increases in adoption of all of these technologies over the sample period. By 2009, at least 70 percent of responding hospitals had adopted each of the basic EMR technologies and at least 20 percent had adopted the advanced technologies.

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. Missing data about specific technologies (and to a lesser extent about covariates) mean that our regressions involve 2217 to 3653 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 reveals that hospitals who report basic EMR have similar costs per admit ($9201 versus $9571 for non-reporters) but are substantially smaller, with 31 percent fewer 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.[14]

Hospital costs. Our primary dependent variable is equal to total hospital operating expenses per admission. 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, 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.[15]

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 includes the fully amortized operating costs across the entire hospital. These will include the costs of property, plant, and equipment depreciation, but exclude costs of ancillary services such as parking garages and public cafeterias.[16] Physician salaries are generally excluded from this measure. 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.[17] 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. This will introduce some noise into the measurement of the dependent variable. Table 2 shows that, on average, costs rise considerably over the sample period (from 9.065 to 9.885 in logged values) but there is a great deal of variation across hospitals.

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[14] Additional details are included in Appendix Table A.1.
[15] For further discussion of the latter issue, see Butler (1995).
[16] Depreciation rules are standardized across hospitals. For further details on these rules, see the documentation for the cost report data available at https://www.cms.gov/CostReports/02_HospitalCostReport.asp#TopOfPage.
[17] We obtained annual data on the case mix of Medicare patients for 87% 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 admit 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.

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. Our final data set contains 4231 hospitals, 96 percent of which are observed in all fourteen years of the data (though both cost and EMR adoption information may not be available in all years).

We use information from the AHA data and the Medicare Cost Report to exclude several types of hospitals whose costs might be affected by unobservable and/or idiosyncratic factors unrelated to EMR adoption. In particular, we exclude federal hospitals, as well as hospitals that are not defined as short-term general medical and surgical hospitals. (The hospitals that we exclude are not usually considered to be "community" hospitals). 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 use the AHA data to compute the following covariates[18]:

- 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.
- Hospital Organization: We include indicators of whether the hospital is an independent practice association hospital or a management service organization hospital (as of 1996).[19]
- Hospital ownership: Including indicators of for-profit ownership, non-secular nonprofit ownership, non-profit church ownership, equity model hospital, or foundation hospital (in 1996).
- Other characteristics: Including whether the hospital is a teaching hospital (defined as having a residency program or being a member of the council of teaching hospitals in 1996), number of

[18] 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.
[19] IPAs and MSOs are joint venture arrangements between hospitals and some or all of their medical staffs.

births in 1996, total costs per admit in 1996 (to control for different trends on the base level of the dependent variable), and the number of Medicare and Medicaid discharges in 1996.[20]

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 U.S. 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 U.S. 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 locations to have different cost trends.

To measure the availability of local complementary factors, we use three measures from the Census. 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).[21] Table 2 shows that 43 percent of the hospitals in our data are in counties in the top quartile in IT intensity.

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

[20] We only have discharge information for approximately half the hospitals in our sample. When the information is missing, we assume it does not change over time by setting it at average levels and allowing the hospital fixed effects to absorb differences across hospitals.

[21] These industries are Communications (SIC 48), Business Services (73), Wholesales 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).

“high all factors” counties as those with over 150,000 population that are in the top quartile in income, education, and IT intensity; 23 percent of the hospitals 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.[22] Urban location has been shown to be correlated with lower costs for frontier enterprise IT adoption in a variety of settings (Forman, Goldfarb, and Greenstein 2005, 2008).

IT capabilities. To obtain measures of historical hospital-level IT capabilities, we gather data from the Harte Hanks Market Intelligence Computer Intelligence Technology Database (hereafter CI database). 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 et al. 2012). Interview teams survey establishments throughout the calendar year; our main sample contains the most current information as of December 1996. As has been discussed elsewhere (e.g., Forman, Goldfarb, and Greenstein 2005), this data set represents one of the most comprehensive sources of information on the IT investments of private firms available.

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

[22] Of course, urban location will also have stronger demand for the same factor, making identification of the relationship between IT investment, urban location, and hospital costs difficult and leading us to favor the more direct measures of local IT intensity.

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 document that costs appear to rise on average after adoption. Second, we decompose the rise in costs by years since adoption and show that the rise is largest in the first year of adoption. Third, we examine different margins of complementarity, and show that the results are much stronger for location than for internal IT experience. That result provides suggestive evidence of 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 administrative costs per admit and EMR:

$$(1)\ Log(c_{it}) = \alpha X_{it} + \beta_t X_i + \gamma_t Z_i + \theta EMR_{it} + \tau_t + \mu_i + \varepsilon_{it},$$

Here, τ_t captures average changes to costs over time; μ_i is a hospital-specific fixed effect that gets differenced out in the estimation; 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 have assumed that ε_{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 we allow to 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). 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.[23] We take their 1996 values and interact them with a linear time trend. Third, Z_i are controls for county-

[23] In the Appendix, we show qualitative results are robust to allowing all hospital characteristics to change over time.

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 seem to 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.[24] Put another way, adoption of EMR is uncorrelated with unobservable cost trends that were experienced differentially by adopting hospitals.

Table 3 shows the results of this regression. For columns 1 to 7, the dependent variable is total operating costs per admission, as defined in the AHA data. For column 8 and 9, we use total hospital operating costs (i.e., we do not divide by admissions). Columns 1 to 3 use the specific EMR technologies that together we label "basic EMR"; columns 4 and 8 use the aggregated basic EMR measure (which is equal to one when the hospital has adopted any of the three technologies); column 5 and 6 use the EMR technologies that make up "advanced EMR"; columns 7 and 9 use the aggregated advanced EMR measure.

The results suggest that, on average, EMR does not reduce costs. Instead, in many specifications, EMR is associated with a positive and significant increase in costs of about one to two 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 extent to which the increase in costs is driven by initial adoption costs such as co-invention and learning new processes. Specifically, Table 4 splits the *EMR* variable into seven pieces, based on time since adoption:

$$(2)\; Log(c_{it}) = \alpha X_{it} + \beta_t X_i + \gamma_t Z_i + \Sigma_{L=0 \ldots 6} \theta_L EMR_{it+L} + \tau_t + \mu_i + \varepsilon_{it},$$

We therefore identify separate coefficients for the first year observed after adoption and for each of the six subsequent years. For the dummy for the sixth year, we use "adopt at least six years earlier." The hospital fixed effects mean these coefficients should be interpreted relative to the period before adoption.

[24] 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.

Costs often rise significantly immediately after adoption, including 1.9 percent for advanced EMR. After the first period, costs gradually return to the pre-adoption levels. Generally, the costs return to the pre-adoption levels faster for the basic EMR technologies than for advanced EMR. This is consistent with the general literature on IT as a business process innovation: 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.

Table 5 sets up the sparser specifications that are used in the remainder of the paper to facilitate interpretation. In particular, it focuses on the aggregate measures of basic and advanced EMR and it combines individual years into two variables: "adopt in previous three year period" and "adopt at least three years earlier". As expected, the results are similar to Table 4.

Effects by location: The literature on IT as a process innovation has emphasized that efficient use of IT based on 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:

$$(3)\ Log(c_{it}) = \alpha X_{it} + \beta_t X_i + \gamma_t Z_i + \theta_1 EMR_{it} + \theta_2 EMR_{it-3+} \\ + \varphi_1 IT\_INTENSE_i \times EMR_{it} + \varphi_2 IT\_INTENSE_i \times EMR_{it-3+} + \tau_t + \mu_i + \varepsilon_{it},$$

where EMR_{it-3} is a dummy variable for whether the hospital adopted EMR at least three years earlier and $IT\_INTENSE_i$ is a measure of whether the location is IT-intensive.

Table 6 examines three distinct measures of IT-intensity: (i) 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, (ii) a dummy variable for whether the hospitals is in a county with high population, income, education and IT-intensive industry (labeled "high all factors" in Forman, Goldfarb, and Greenstein (2012)), and (iii) a dummy variable for whether the hospital is in an MSA. For these estimates, we add a control for these measures interacted with a time trend.

Recall that 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 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. Although we can think of no obvious economic reason why this assumption would be violated, in later specifications we will instrument for adoption. 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.

The first two rows show that costs per admission do not fall in non-IT intensive counties. In contrast, 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. For basic EMR, after three years, costs fall a statistically significant 3.4 percent in IT-intensive counties while the coefficient is positive but insignificant in all other counties. For advanced EMR, after three years, costs fall a marginally significant (p-value is 0.09) 2.2 percent in IT-intensive counties while costs rise 3.8 percent in other counties.

Taking the point estimates in columns 1 and 2 of Table 6 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 2.2 percent. In contrast, a hospital in poor location would experience an (insignificant) rise in costs of 1.3 percent from three years after adoption of basic EMR and a strongly significant rise of 3.8 percent after adoption of advanced EMR. With average annual operating costs in the tens of millions, these differences are substantial.

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.[25] Table 7 examines the interaction in the following format:

$$(4)\ Log(c_{it}) = \alpha X_{it} + \beta_t X_i + \gamma_t Z_i + \theta_1 EMR_{it} + \theta_2 EMR_{it\text{-}3+} + \varphi_1 HIT\_EXPERIENCE_i \times EMR_{it} + \varphi_2 HIT\_EXPERIENCE_i \times EMR_{it\text{-}3+} + \tau_t + \mu_i + \varepsilon_{it},$$

As measures of hospital IT experience, we examine business software applications, clinical software applications, and programmers employed (all 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 to reduce costs for hospitals that adopt advanced EMR, but only in the first period after adoption. For each of the three measures, a one standard deviation change yields a 2.5 to 3.9 percent decrease in costs per admittance in the initial three years after advanced EMR adoption. Internal expertise therefore seems particularly important for the most advanced applications that might involve a great deal of co-invention 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 Table 6 and 7 is consistent with this study's framing, interpreting EMR as a business process innovation.

Robustness, identification, and plausibility: Next, we explore the degree to which we can claim our main results are causal and general. There are four 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

[25] However, some IT expertise may be firm-specific and learned over time, and so more difficult to contract for. For examples, see Ang, Slaughter, and Ng (2002).

EMR adoption driving changes in costs). Fourth, the large amount of missing data may mean that our sample is not representative.

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. In order to address additional concerns we conduct three types of analyses, examining the timing of the relationship between EMR adoption and cost changes, instrumental variables analysis, and robustness to alternative specifications such as alternative treatments of the missing variables.

In Figure 2, 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 run the equation (2) above, but add variables for 1 year before adoption, 2 years before adoption, 3 years before adoption, and 4 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. The coefficients for these regressions are shown in Appendix Table A.2. The timing of the impact of EMR displayed in Figure 2 suggests that there is not a noticeable 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 Table 8, we apply instruments for EMR adoption to explore concerns about the direction of causality; one possible concern is that hospitals (especially those in IT-intensive locations) anticipating a reduction in costs will buy an EMR system. While the results are, at best, weakly significant, the signs are consistent with the results of the main specifications. We emphasize three instruments that have some power in the first stage (shown in the Appendix) and, under certain assumptions, may not directly impact costs. First, we use geographic variation in hospitals that belong to multi-location hospital systems and use EMR adoption by competing hospitals in other counties within the same systems as an instrument. This instrument is similar to the one used in Forman, Goldfarb, and Greenstein (2008) to examine the impact of internal expertise in IT on advanced internet adoption by US businesses. The identification assumption is that adoption by competing hospitals in other geographic markets will increase the likelihood of EMR adoption by hospitals within the same system but in those other geographic markets. This will decrease the costs of EMR adoption by the focal hospital but should not affect its other costs.

Second, we use the distance from the hospital to the closest EMR vendor as of 1996 (and interact this with a time trend). The identification assumption is that hospitals near EMR vendor offices will have lower costs for learning about EMR systems.

Third, we use information on hospital alliances and use adoption by other hospitals in the same alliance as an instrument for own adoption. The identification assumption is that adoption by other hospitals in the alliance might lead to lower EMR adoption costs or better information about EMR but will not be coincident with trends in costs for other operating procedures. Given that we think the third instrument requires the strongest assumptions, we show results for all three and for just the first two. In the Appendix, we show results for each instrument separately.

Because the instruments are at the hospital level rather than the hospital-year level, we focus on one covariate for EMR adoption: whether the hospital adopted EMR at least three years earlier. There is variation in the power of the instruments in the first stage, though they are generally weak with first stage F-statistics ranging from 2.00 to 23.23. The competing hospitals instrument is the most powerful; it works best for basic adoption but also for advanced adoption. The distance to nearest vendor instrument is quite weak. The hospital alliance instrument has some power for advanced adoption but little for basic adoption. For the second stage, Hausman tests show that the coefficient values are not significantly different from the main results, though this is driven more by high standard errors than similar coefficient values. The p-values of the overidentification tests range from 0.28 to 0.75.

Column 1 of Table 8 shows that the coefficients on the main effect of basic EMR adoption turn negative when we instrument for adoption. The main effect is positive (but not significant) for advanced EMR adoption in column 2. Perhaps more importantly, columns 3 and 4 show that the signs of the results on the difference between IT-intensive counties and other counties hold, and the results are weakly significant for basic EMR. Columns 5 through 8 provide nearly identical qualitative results with just two instruments. While not conclusive, we view the instrumental variables analysis as suggestive that our result on the difference between IT intensive locations and other locations is unlikely to be driven by anticipated changes in costs leading to more adoption.

In the Appendix we address other concerns regarding specification. We show that results are robust to dropping all controls, to adding controls for time-varying hospital characteristics and the Medicare case mix index, and to changing the dependent variable to labor costs per admit, direct costs per admit, or total costs per admit weighted by the Medicare case mix index. 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.

VI. Conclusion

Drawing on a variety of data sources on IT, EMR, local demographics, and hospital characteristics, this study shows that the impact of EMR adoption is consistent with the view of EMR as a business process innovation. 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 2.2 percent decrease in costs after adopting advanced EMR. In contrast, hospitals in other locations experience an increase in costs, even after several years.

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 a different experience. While we believe it is likely that the general principles of business process innovation would apply broadly, our evidence is specific to hospitals. 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 both more effective and easier to implement. Third, a key assumption is that hospitals represent only a small fraction of local IT expertise and employment. If this assumption fails, then our explanation based on complementarities related to co-invention costs is hard to justify.

This study also leaves open questions such as why hospitals adopt if their costs do not fall. It might be due to misconceptions, expected benefits that we do not measure, or something else. We have tried to address the endogeneity of this adoption through various techniques, but we cannot completely rule out the possibility that adopting 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. 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.

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Table 1: Types of EMR and Hospital Adoption Rates

EMR	Description	% of Hospitals Adopting 1996	% of Hospitals Adopting 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

Table 2: Summary statistics

Variable	Mean	Std. Dev.	Min	Max	# obs.
EMR MEASURES (2009 VALUES)					
CDR	0.809	0.393	0	1	2856
CDSS	0.752	0.432	0	1	2587
Order entry	0.851	0.357	0	1	3046
Basic EMR adoption (CDR, CDSS, or order entry)	0.870	0.336	0	1	2149
CPOE	0.242	0.428	0	1	3527
Physician documentation	0.227	0.420	0	1	3479
Advanced EMR adoption (CPOE or Physician doc’n)	0.306	0.461	0	1	3198
COST MEASURES (2009 VALUES)					
Log total costs	17.987	1.326	14.015	21.950	4231
Log total costs per admit	9.885	0.511	5.902	15.977	4231
Log labor costs	8.933	0.540	5.293	14.897	4231
Log direct costs	9.840	0.512	5.902	15.946	4231
HOSPITAL-LEVEL CONTROLS (2009 VALUES)					
Log inpatient days	9.833	1.405	1.792	13.194	4196
Log outpatient visits	11.113	1.408	0.000	15.124	4202
FIXED HOSPITAL-LEVEL CONTROLS (1996 DATA)					
Log total costs per admit	9.065	0.388	7.232	11.928	4016
Log total hospital beds	4.807	0.904	1.792	7.233	4016
Independent practice association hospital	0.250	0.433	0	1	4016
Management service organization hospital	0.200	0.400	0	1	4016
Equity model hospital	0.079	0.270	0	1	4016
Foundation hospital	0.156	0.363	0	1	4016
Log admissions	8.214	1.188	2.773	10.931	4016
Births (000s)	0.810	1.119	0.000	13.614	4016
For-profit ownership	0.146	0.353	0	1	4016
Non-secular nonprofit ownership	0.483	0.500	0	1	4016
Non-profit church ownership	0.124	0.330	0	1	4016
Number of discharges Medicare (000s)	3.554	1.899	1.001	17.876	4016
Number of discharges Medicaid (000s)	2.798	1.228	1.001	21.184	4016
Residency or Member of Council Teaching Hospitals	0.189	0.392	0	1	4016
LOCATION-LEVEL CONTROLS					
Log population in 2000 census	11.840	1.781	7.643	16.069	4016
% Black in 2000 census	0.113	0.144	0.000	0.843	4016
% age 65+ in 2000 census	0.136	0.038	0.028	0.347	4016
% age 25-64 in 2000 census	0.853	0.046	0.455	1.047	4016
% university education in 2000 census	0.137	0.059	0.037	0.402	4016
Log median household income in 2000 census	10.552	0.243	9.697	11.303	4016
OTHER VARIABLES USED					
Top quartile county IT-intensive industry	0.424	0.494	0	1	4231
Top county in IT-intensity, education, income, and pop.	0.234	0.423	0	1	4231
County is in an MSA	0.544	0.498	0	1	4231
Number of programmers in 1996	1.238	6.284	0	101	1469
Number of business applications in 1996	4.204	3.736	0	36	1461
Number of clinical applications in 1996	2.019	2.117	0	14	1461

Table 3: Main effects by technology

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Log total costs per admit	**Log total costs per admit**	**Log total costs per admit**	**Log total costs per admit**	**Log total costs per admit**	**Log total costs per admit**	**Log total costs per admit**	**Log total costs**	**Log total costs**
Technology	**CDR**	**CDSS**	**Order entry**	**Basic EMR adoption**	**CPOE**	**Physician documentation**	**Advanced EMR adoption**	**Basic EMR adoption**	**Advanced EMR adoption**
Adopted EMR	0.0123	0.0114	0.0018	0.0045	0.0103	0.0248	0.0195	0.0195	0.0387
	(0.0055)**	(0.0059)*	(0.0053)	(0.0064)	(0.0068)	(0.0075)***	(0.0070)***	(0.0062)***	(0.0070)***
Observations	31175	27849	33388	23418	38167	37519	34407	23418	34407
# of hospitals	2964	2679	3161	2228	3653	3597	3306	2228	3306
R-squared	0.58	0.57	0.58	0.58	0.56	0.56	0.56	0.74	0.71
CONTROLS									
Log inpatient days	-0.5061	-0.4917	-0.5331	-0.4476	-0.5564	-0.6086	-0.6094	-0.2584	-0.1279
	(0.1476)***	(0.1688)***	(0.1736)***	(0.1873)**	(0.1433)***	(0.1380)***	(0.1433)***	(0.0974)***	(0.0762)*
Log outpatient visits	-0.0493	-0.0386	-0.0561	-0.0605	-0.0545	-0.0572	-0.0581	-0.0975	-0.0613
	(0.0960)	(0.0977)	(0.0987)	(0.1190)	(0.0878)	(0.0878)	(0.0903)	(0.0542)*	(0.0467)
Log inpatient days x	0.0280	0.0257	0.0317	0.0298	0.0276	0.0309	0.0299	0.0264	0.0205
Log inpatient days	(0.0079)***	(0.0080)***	(0.0073)***	(0.0086)***	(0.0071)***	(0.0067)***	(0.0070)***	(0.0052)***	(0.0038)***
Log outpatient visits x	0.0123	0.0102	0.0150	0.0171	0.0105	0.0112	0.0104	0.0088	0.0088
Log outpatient visits	(0.0059)**	(0.0054)*	(0.0056)***	(0.0067)**	(0.0050)**	(0.0050)**	(0.0050)**	(0.0019)***	(0.0013)***
Log inpatient days x	-0.0211	-0.0180	-0.0267	-0.0306	-0.0173	-0.0181	-0.0165	-0.0020	-0.0048
Log outpatient visits	(0.0129)	(0.0127)	(0.0120)**	(0.0143)**	(0.0115)	(0.0115)	(0.0118)	(0.0060)	(0.0047)
Log total costs per admit	-0.0234	-0.0221	-0.0221	-0.0202	-0.0228	-0.0229	-0.0230	-0.0118	-0.0141
in 1996 x year	(0.0026)***	(0.0029)***	(0.0024)***	(0.0030)***	(0.0022)***	(0.0023)***	(0.0024)***	(0.0027)***	(0.0022)***
Log total hospital beds x	-0.0077	-0.0082	-0.0090	-0.0083	-0.0092	-0.0091	-0.0098	-0.0016	-0.0029
year	(0.0020)***	(0.0021)***	(0.0019)***	(0.0024)***	(0.0018)***	(0.0019)***	(0.0020)***	(0.0020)	(0.0016)*
Independent practice	-0.0003	-0.0005	-0.0000	-0.0009	0.0008	-0.0001	0.0001	-0.0016	-0.0012
assn. hospital x year	(0.0013)	(0.0014)	(0.0013)	(0.0015)	(0.0012)	(0.0012)	(0.0013)	(0.0015)	(0.0013)
Mngmt service org.	-0.0017	-0.0017	-0.0024	-0.0021	-0.0033	-0.0024	-0.0028	-0.0026	-0.0024
hospital x year	(0.0013)	(0.0014)	(0.0012)**	(0.0015)	(0.0012)***	(0.0012)*	(0.0013)**	(0.0017)	(0.0014)*
Equity model hospital x	-0.0027	-0.0022	-0.0041	-0.0025	-0.0024	-0.0025	-0.0016	0.0016	0.0002
year	(0.0027)	(0.0028)	(0.0027)	(0.0032)	(0.0024)	(0.0025)	(0.0025)	(0.0034)	(0.0027)
Foundation hospital x	0.0017	0.0023	0.0018	0.0022	0.0017	0.0014	0.0015	-0.0016	-0.0008
year	(0.0016)	(0.0017)	(0.0016)	(0.0019)	(0.0015)	(0.0015)	(0.0016)	(0.0022)	(0.0019)
Log admissions x year	0.0011	0.0021	0.0034	0.0027	0.0035	0.0033	0.0040	-0.0045	-0.0028
	(0.0020)	(0.0020)	(0.0019)*	(0.0022)	(0.0018)*	(0.0019)*	(0.0020)**	(0.0019)**	(0.0016)*

Births (000s) x year	0.0016	0.0021	0.0014	0.0018	0.0017	0.0016	0.0018	0.0013	0.0014
	(0.0007)**	(0.0007)***	(0.0006)**	(0.0008)**	(0.0006)***	(0.0006)***	(0.0007)***	(0.0007)*	(0.0006)**
For-profit ownership x	-0.0101	-0.0102	-0.0105	-0.0105	-0.0096	-0.0096	-0.0097	-0.0079	-0.0056
year	(0.0021)***	(0.0021)***	(0.0019)***	(0.0022)***	(0.0018)***	(0.0019)***	(0.0019)***	(0.0024)***	(0.0019)***
Non-secular nonprofit	0.0004	-0.0000	-0.0004	0.0005	-0.0004	0.0000	-0.0004	0.0022	0.0014
ownership x year	(0.0015)	(0.0015)	(0.0014)	(0.0016)	(0.0013)	(0.0013)	(0.0014)	(0.0016)	(0.0014)
Non-profit church	-0.0009	-0.0007	-0.0013	-0.0007	-0.0008	-0.0005	-0.0002	-0.0004	-0.0012
ownership x year	(0.0018)	(0.0020)	(0.0017)	(0.0021)	(0.0017)	(0.0017)	(0.0018)	(0.0022)	(0.0019)
Number of discharges	0.0003	0.0003	0.0002	0.0001	0.0002	0.0003	0.0002	0.0005	0.0004
Medicare (000s) x year	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Number of discharges	0.0004	0.0003	0.0003	0.0002	0.0004	0.0006	0.0005	-0.0007	-0.0005
Medicaid (000s) x year	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)*	(0.0004)
Residency/Mmbr Council	0.0036	0.0032	0.0039	0.0031	0.0028	0.0026	0.0028	0.0019	0.0012
Teaching Hosps x year	(0.0015)**	(0.0016)**	(0.0014)***	(0.0018)*	(0.0014)**	(0.0014)*	(0.0015)*	(0.0019)	(0.0016)
Year 1997	0.2244	0.1872	0.2002	0.1744	0.2103	0.2217	0.2127	0.0690	0.0920
	(0.0414)***	(0.0421)***	(0.0389)***	(0.0449)***	(0.0370)***	(0.0381)***	(0.0398)***	(0.0461)	(0.0390)**
Year 1998	0.4411	0.3730	0.3891	0.3399	0.4115	0.4324	0.4155	0.1164	0.1574
	(0.0821)***	(0.0840)***	(0.0770)***	(0.0893)***	(0.0736)***	(0.0755)***	(0.0790)***	(0.0917)	(0.0771)**
Year 1999	0.6618	0.5606	0.5843	0.5077	0.6222	0.6522	0.6295	0.1728	0.2359
	(0.1227)***	(0.1257)***	(0.1150)***	(0.1336)***	(0.1099)***	(0.1129)***	(0.1181)***	(0.1366)	(0.1151)**
Year 2000	0.8973	0.7641	0.7903	0.6987	0.8397	0.8827	0.8525	0.2578	0.3378
	(0.1633)***	(0.1674)***	(0.1532)***	(0.1778)***	(0.1465)***	(0.1505)***	(0.1575)***	(0.1820)	(0.1533)**
Year 2001	1.1234	0.9622	0.9869	0.8770	1.0528	1.1018	1.0656	0.3313	0.4252
	(0.2043)***	(0.2094)***	(0.1915)***	(0.2224)***	(0.1831)***	(0.1882)***	(0.1969)***	(0.2274)	(0.1915)**
Year 2002	1.3838	1.1876	1.2240	1.0860	1.2987	1.3614	1.3172	0.4202	0.5396
	(0.2448)***	(0.2509)***	(0.2295)***	(0.2665)***	(0.2195)***	(0.2256)***	(0.2360)***	(0.2727)	(0.2297)**
Year 2003	1.6243	1.3972	1.4375	1.2787	1.5223	1.5947	1.5428	0.4992	0.6341
	(0.2855)***	(0.2927)***	(0.2678)***	(0.3109)***	(0.2561)***	(0.2632)***	(0.2754)***	(0.3181)	(0.2679)**
Year 2004	1.8421	1.5819	1.6271	1.4423	1.7264	1.8067	1.7488	0.5501	0.7080
	(0.3264)***	(0.3345)***	(0.3059)***	(0.3553)***	(0.2927)***	(0.3008)***	(0.3147)***	(0.3636)	(0.3062)**
Year 2005	2.0953	1.8078	1.8492	1.6494	1.9646	2.0578	1.9914	0.6339	0.8105
	(0.3671)***	(0.3763)***	(0.3441)***	(0.3997)***	(0.3292)***	(0.3383)***	(0.3539)***	(0.4092)	(0.3445)**
Year 2006	2.3531	2.0338	2.0802	1.8581	2.2093	2.3127	2.2389	0.7091	0.9042
	(0.4079)***	(0.4182)***	(0.3823)***	(0.4441)***	(0.3657)***	(0.3759)***	(0.3933)***	(0.4545)	(0.3828)**
Year 2007	2.6015	2.2542	2.3023	2.0581	2.4429	2.5551	2.4736	0.7775	0.9870
	(0.4489)***	(0.4604)***	(0.4207)***	(0.4888)***	(0.4025)***	(0.4137)***	(0.4327)***	(0.5000)	(0.4211)**
Year 2008	2.8390	2.4531	2.5108	2.2439	2.6635	2.7864	2.6971	0.8364	1.0649
	(0.4895)***	(0.5021)***	(0.4589)***	(0.5330)***	(0.4390)***	(0.4513)***	(0.4720)***	(0.5455)	(0.4594)**
Year 2009	3.0933	2.6777	2.7375	2.4494	2.9075	3.0419	2.9475	0.8960	1.1451

	(0.5301)***	(0.5439)***	(0.4971)***	(0.5775)***	(0.4755)***	(0.4888)***	(0.5113)***	(0.5912)	(0.4979)**
Log population in 2000	-0.0008	-0.0015	-0.0010	-0.0013	-0.0012	-0.0014	-0.0014	0.0000	-0.0005
census x year	(0.0006)	(0.0006)**	(0.0005)*	(0.0007)*	(0.0005)**	(0.0005)***	(0.0006)**	(0.0007)	(0.0005)
% Black in 2000 census	-0.0202	-0.0207	-0.0215	-0.0198	-0.0197	-0.0183	-0.0180	-0.0142	-0.0129
x year	(0.0042)***	(0.0043)***	(0.0040)***	(0.0046)***	(0.0038)***	(0.0039)***	(0.0041)***	(0.0049)***	(0.0042)***
% age 65+ in 2000	-0.0460	-0.0306	-0.0355	-0.0333	-0.0409	-0.0436	-0.0344	-0.0221	-0.0286
census x year	(0.0172)***	(0.0178)*	(0.0163)**	(0.0188)*	(0.0157)***	(0.0161)***	(0.0166)**	(0.0207)	(0.0182)
% age 25-64 in 2000	-0.0216	-0.0384	-0.0212	-0.0311	-0.0189	-0.0163	-0.0181	-0.0462	-0.0472
census x year	(0.0133)	(0.0133)***	(0.0127)*	(0.0137)**	(0.0126)	(0.0132)	(0.0139)	(0.0144)***	(0.0129)***
% university education	0.0379	0.0290	0.0301	0.0267	0.0413	0.0470	0.0498	0.0278	0.0429
in 2000 census x year	(0.0133)***	(0.0142)**	(0.0126)**	(0.0154)*	(0.0120)***	(0.0125)***	(0.0131)***	(0.0150)*	(0.0128)***
Log median hh income in	0.0082	0.0117	0.0088	0.0107	0.0080	0.0071	0.0076	0.0175	0.0174
2000 census x year	(0.0041)**	(0.0042)***	(0.0038)**	(0.0045)**	(0.0037)**	(0.0038)*	(0.0040)*	(0.0044)***	(0.0038)***

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. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 4: Main effects by technology, by years since adoption

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Log total costs per admit	**Log total costs per admit**	**Log total costs per admit**	**Log total costs per admit**	**Log total costs per admit**	**Log total costs per admit**	**Log total costs per admit**	**Log total costs**	**Log total costs**
Technology	**CDR**	**CDSS**	**Order entry**	**Basic EMR adoption**	**CPOE**	**Physician documentation**	**Advanced EMR adoption**	**Basic EMR adoption**	**Advanced EMR adoption**
Adopt this year	0.0121	0.0072	-0.0041	0.0023	0.0114	0.0228	0.0189	0.0148	0.0331
	(0.0058)**	(0.0063)	(0.0057)	(0.0067)	(0.0068)*	(0.0085)***	(0.0074)**	(0.0062)**	(0.0065)***
Adopt 1 year earlier	0.0132	0.0073	0.0023	-0.0002	0.0123	0.0270	0.0260	0.0185	0.0444
	(0.0065)**	(0.0070)	(0.0061)	(0.0075)	(0.0075)	(0.0087)***	(0.0078)***	(0.0072)***	(0.0073)***
Adopt 2 years earlier	0.0125	0.0133	0.0037	0.0037	0.0106	0.0338	0.0235	0.0199	0.0418
	(0.0072)*	(0.0076)*	(0.0069)	(0.0083)	(0.0087)	(0.0089)***	(0.0087)***	(0.0075)***	(0.0079)***
Adopt 3 years earlier	0.0087	0.0159	-0.0039	-0.0012	0.0146	0.0275	0.0160	0.0184	0.0400
	(0.0081)	(0.0083)*	(0.0076)	(0.0091)	(0.0099)	(0.0105)***	(0.0100)	(0.0087)**	(0.0095)***
Adopt 4 years earlier	0.0004	0.0048	-0.0090	-0.0142	0.0075	0.0280	0.0147	0.0078	0.0383
	(0.0091)	(0.0093)	(0.0084)	(0.0102)	(0.0121)	(0.0108)***	(0.0112)	(0.0098)	(0.0104)***
Adopt 5 years earlier	-0.0016	0.0078	-0.0141	-0.0164	0.0004	0.0244	0.0148	0.0018	0.0432
	(0.0105)	(0.0105)	(0.0098)	(0.0115)	(0.0130)	(0.0135)*	(0.0135)	(0.0111)	(0.0129)***
Adopt at least 6 years earlier	0.0028	0.0007	-0.0158	-0.0192	-0.0056	-0.0197	-0.0232	0.0050	0.0145
	(0.0122)	(0.0123)	(0.0112)	(0.0132)	(0.0165)	(0.0144)	(0.0145)	(0.0133)	(0.0151)
Observations	31175	27849	33388	23418	38167	37519	34407	23418	34407
# of hospitals	2964	2679	3161	2228	3653	3597	3306	2228	3306
R-squared	0.58	0.57	0.58	0.58	0.56	0.56	0.56	0.74	0.71

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. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 5: Main effects by technology, by years since adoption

	(1)	(2)	(3)	(4)
	Log total costs per admit	**Log total costs per admit**	**Log total costs**	**Log total costs**
Technology	**Basic EMR adoption**	**Advanced EMR adoption**	**Basic EMR adoption**	**Advanced EMR adoption**
Adopt in previous 3 year period	0.0053	0.0253	0.0195	0.0410
	(0.0063)	(0.0069)***	(0.0061)***	(0.0066)***
Adopt at least 3 years earlier	-0.0077	0.0065	0.0115	0.0340
	(0.0089)	(0.0097)	(0.0087)	(0.0099)***
Observations	23418	34407	23418	34407
# of hospitals	2228	3306	2228	3306
R-squared	0.58	0.56	0.74	0.71

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. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 6: Interactions with IT-intensive location

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log total costs per admit						Log total costs	
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**		**Top quartile county IT-intensive industries**	
Technology	**Basic EMR adoption**	**Advanced EMR adoption**	**Basic EMR adoption**	**Advanced EMR adoption**	**Basic EMR adoption**	**Advanced EMR adoption**	**Basic EMR adoption**	**Advanced EMR adoption**
Adopt in previous 3 year period	0.0128	0.0403	0.0068	0.0311	0.0042	0.0514	0.0306	0.0517
	(0.0085)	(0.0102)***	(0.0074)	(0.0089)***	(0.0106)	(0.0132)***	(0.0086)***	(0.0102)***
Adopt at least 3 years earlier	0.0170	0.0382	0.0032	0.0209	0.0066	0.0714	0.0393	0.0561
	(0.0123)	(0.0145)***	(0.0102)	(0.0121)*	(0.0155)	(0.0194)***	(0.0119)***	(0.0140)***
Adopt in previous 3 yr pd x IT-intensive location	-0.0157	-0.0285	-0.0051	-0.0164	0.0017	-0.0375	-0.0232	-0.0202
	(0.0126)	(0.0140)**	(0.0128)	(0.0136)	(0.0132)	(0.0155)**	(0.0120)*	(0.0131)
Adopt at least 3 yrs earlier x IT-intensive location	-0.0513	-0.0597	-0.0381	-0.0426	-0.0230	-0.0931	-0.0578	-0.0415
	(0.0178)***	(0.0189)***	(0.0171)**	(0.0184)**	(0.0189)	(0.0220)***	(0.0171)***	(0.0193)**
Observations	23418	34407	23418	34407	23418	34407	23418	34407
# of hospitals	2228	3306	2228	3306	2228	3306	2228	3306
R-squared	0.58	0.56	0.58	0.56	0.58	0.56	0.74	0.71

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 IT-intensive location, defined as top quartile in columns 1,2,7, and 8, as high all factors in columns 3and 4, and as MSA in columns 5 and 6. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 7: Interactions with internal HIT experience

	(1)	(2)	(3)	(4)	(5)	(6)
Definition of internal HIT experience	**Number of business applications in 1996**		**Number of clinical applications in 1996**		**Number of programmers employed in 1996**	
Technology	**Basic EMR adoption**	**Advanced EMR adoption**	**Basic EMR adoption**	**Advanced EMR adoption**	**Basic EMR adoption**	**Advanced EMR adoption**
Adopt in previous 3 year period	0.0065	0.0480	0.0036	0.0533	0.0070	0.0317
	(0.0120)	(0.0129)***	(0.0120)	(0.0134)***	(0.0080)	(0.0088)***
Adopt at least 3 years earlier	-0.0076	0.0296	-0.0032	0.0256	-0.0040	0.0171
	(0.0181)	(0.0208)	(0.0163)	(0.0193)	(0.0115)	(0.0138)
Adopt in previous 3 yr pd x HIT experience	0.00004	-0.0040	0.0016	-0.0103	0.0001	-0.0013
	(0.0018)	(0.0017)**	(0.0036)	(0.0035)***	(0.0006)	(0.0006)**
Adopt at least 3 yrs earlier x HIT experience	0.0013	-0.0023	0.0007	-0.0029	0.0010	0.0007
	(0.0028)	(0.0029)	(0.0051)	(0.0050)	(0.0008)	(0.0013)
Observations	10262	14557	10262	14557	10290	14653
# of hospitals	827	1183	827	1183	829	1190
R-squared	0.67	0.62	0.67	0.62	0.67	0.62

Dependent variable is costs per admit. 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 10%; ** significant at 5%; *** significant at 1%

Table 8: Instrumental variables results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Three instruments				Two instruments			
Technology	**Basic EMR adoption**	**Advanced EMR adoption**	**Basic EMR adoption**	**Advanced EMR adoption**	**Basic EMR adoption**	**Advanced EMR adoption**	**Basic EMR adoption**	**Advanced EMR adoption**
Adopted EMR at least 3 years earlier	-0.0595	0.1648	0.1804	0.4133	-0.0652	0.5014	0.1813	0.9304
	(0.1069)	(0.1625)	(0.1386)	(0.2277)*	(0.1073)	(0.4985)	(0.1424)	(0.6882)
Adopted EMR at least 3 years earlier x IT-intensive county			-0.3799	-0.2827			-0.3867	-0.6318
			(0.2142)*	(0.2315)			(0.2177)*	(0.5814)
Observations	23407	34385	23407	34385	23407	34385	23407	34385
# of hospitals	2217	3284	2217	3284	2217	3284	2217	3284
Overidentification test (p-value)	0.51	0.38	0.65	0.56	0.28	0.41	0.31	0.75
Hausman test (p-value)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
R-squared	0.58	0.54	0.55	0.52	0.58	0.45	0.55	0.38

Dependent variable is total operating costs per admit. 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 time trends for IT-intensive location (in columns 3,4, 7, and 8). First stage results shown in Appendix Table A.8. Three instruments are log distance to nearest vendor in 1996 multiplied by a time trend, percent of hospitals in alliance adopting EMR technology, and EMR adoption by competitors in other markets where hospital operates. The alliance instrument does not appear in the two instruments results. Overidentification test uses Hansen J statistic.

* significant at 10%; ** significant at 5%; *** significant at 1%

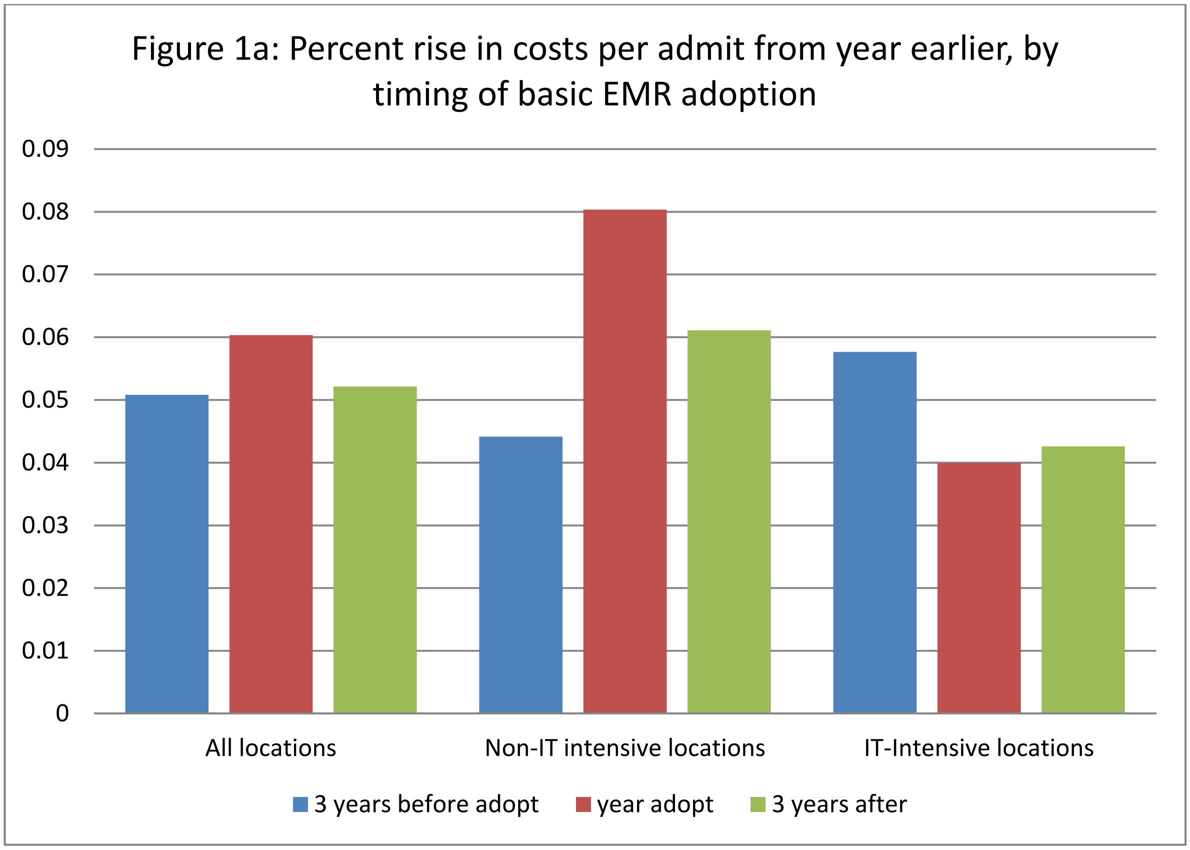


Figure 1a: Percent rise in costs per admit from year earlier, by timing of basic EMR adoption
0.09
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0
All locations
Non-IT intensive locations
IT-Intensive locations
3 years before adopt
year adopt
3 years after

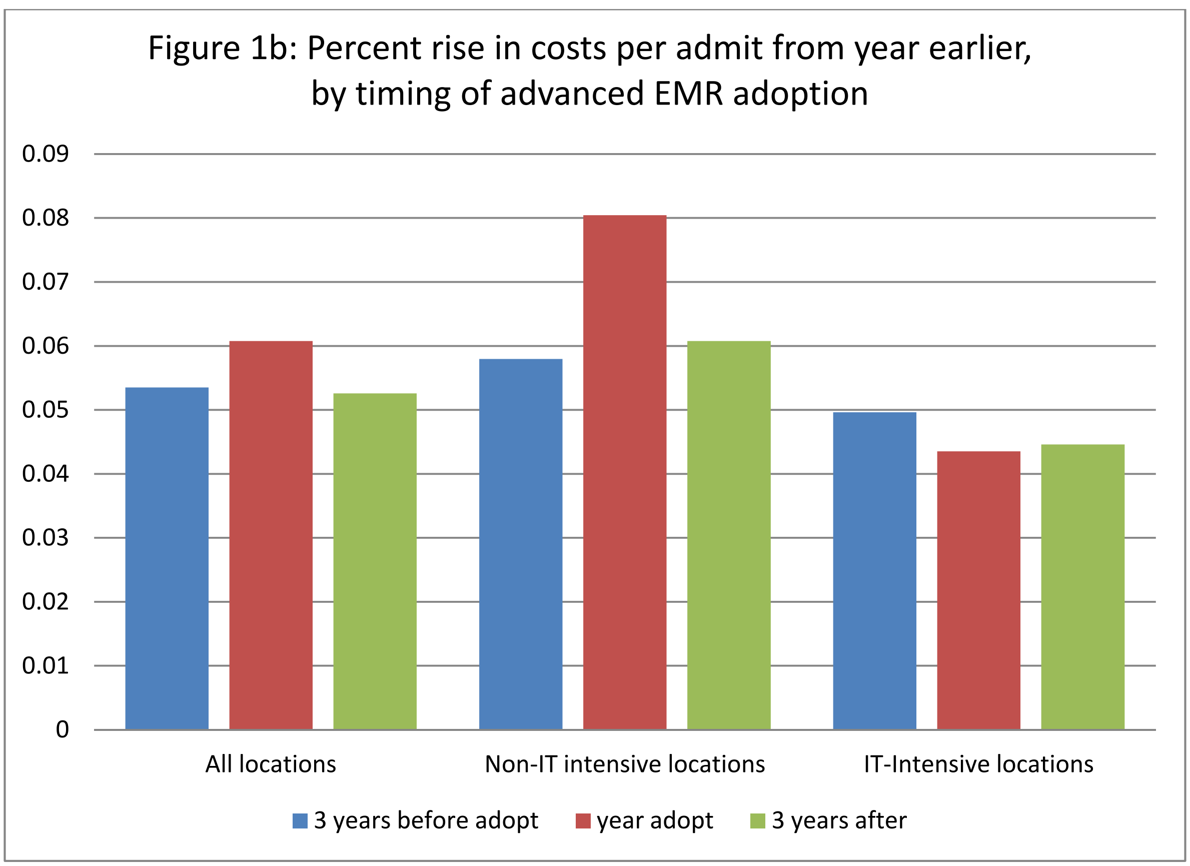
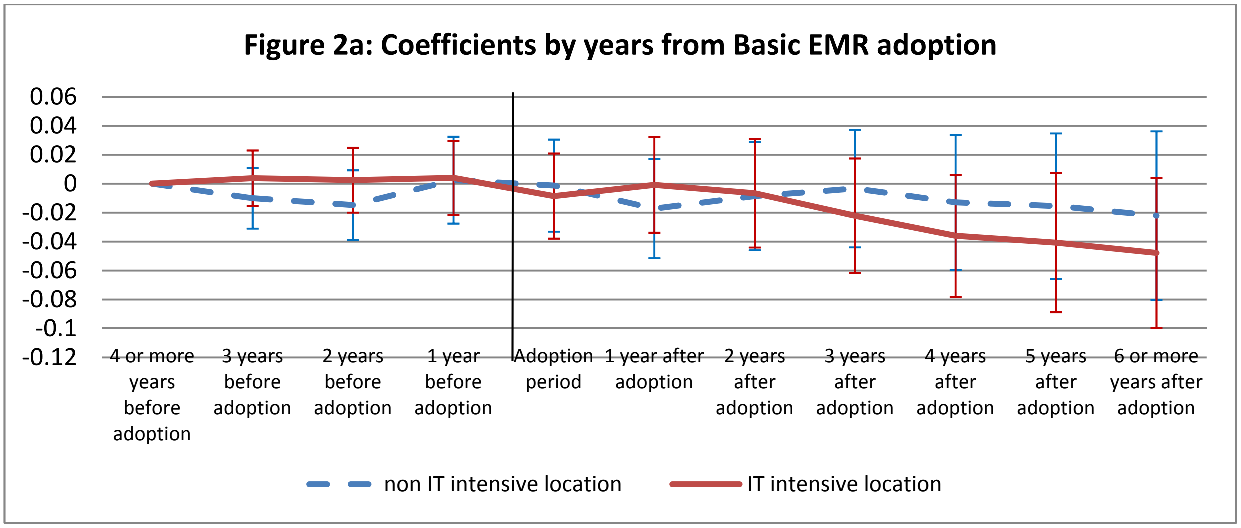
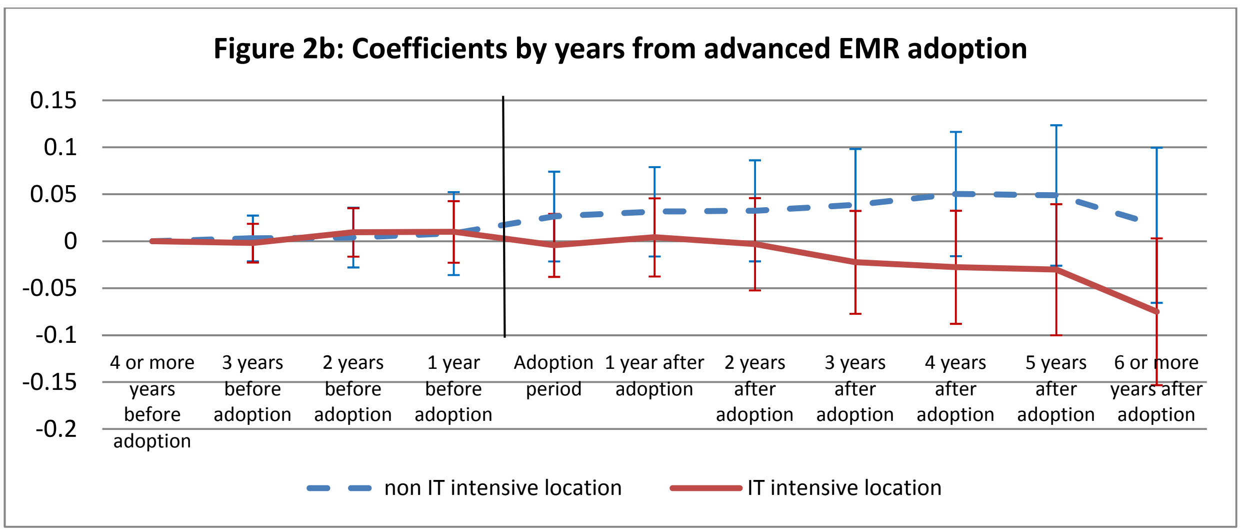


Figure 1b: Percent rise in costs per admit from year earlier, by timing of advanced EMR adoption
0.09
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0
All locations
Non-IT intensive locations
IT-Intensive locations
3 years before adopt
year adopt
3 years after





Error bars show 95% confidence intervals. Full set of coefficients in Appendix Table A.2

Appendix Table A.1: Comparing Hospitals With and Without IT Data

Variable	Reports Basic EMR Adoption	Does Not Report Basic EMR Adoption
Total costs per admit	9201.1	9571.8
Total hospital beds	222.4	154.3
Residency or Member of Council Teaching Hospitals	0.250	0.154
MSA dummy	0.675	0.532
Total admissions	8664.8	5438.7
Independent practice association hospital	0.265	0.242
Management service organization hospital	0.222	0.187
Equity model hospital	0.076	0.081
Foundation hospital	0.158	0.156
For profit hospital	0.143	0.147

Table compares mean 1996 values for each of the variables for hospitals who do and do not report whether they have adopted advanced EMR.

Appendix Table A.2: Leads and lags to get timing of impact

	(1)	(2)	(3)	(4)	(5)	(6)
Technology	**Basic EMR adoption**			**Advanced EMR adoption**		
Sample	**All firms**	**Bottom 3 quartiles IT-intensive counties**	**Top quartile IT-intensive counties**	**All firms**	**Bottom 3 quartiles IT-intensive counties**	**Top quartile IT-intensive counties**
Will adopt in 3 years	-0.0034	-0.0100	0.0038	0.0016	0.0031	-0.0019
	(0.0072)	(0.0105)	(0.0096)	(0.0081)	(0.0122)	(0.0103)
Will adopt in 2 years	-0.0055	-0.0147	0.0025	0.0093	0.0040	0.0095
	(0.0083)	(0.0120)	(0.0112)	(0.0104)	(0.0159)	(0.0129)
Will adopt in 1 year	-0.0011	-0.0025	0.0040	0.0088	0.0083	0.0100
	(0.0099)	(0.0150)	(0.0128)	(0.0136)	(0.0221)	(0.0164)
Adopt this year	-0.0060	-0.0013	-0.0085	0.0134	0.0264	-0.0043
	(0.0111)	(0.0159)	(0.0147)	(0.0145)	(0.0239)	(0.0168)
Adopt 1 year earlier	-0.0101	-0.0172	-0.0008	0.0209	0.0315	0.0042
	(0.0120)	(0.0171)	(0.0165)	(0.0159)	(0.0238)	(0.0208)
Adopt 2 years earlier	-0.0080	-0.0085	-0.0066	0.0182	0.0325	-0.0031
	(0.0133)	(0.0187)	(0.0187)	(0.0183)	(0.0269)	(0.0246)
Adopt 3 years earlier	-0.0137	-0.0033	-0.0221	0.0114	0.0388	-0.0224
	(0.0144)	(0.0203)	(0.0198)	(0.0203)	(0.0298)	(0.0274)
Adopt 4 years earlier	-0.0271	-0.0129	-0.0360	0.0135	0.0504	-0.0276
	(0.0160)*	(0.0233)	(0.0211)*	(0.0225)	(0.0331)	(0.0301)
Adopt 5 years earlier	-0.0311	-0.0154	-0.0407	0.0113	0.0489	-0.0302
	(0.0175)*	(0.0251)	(0.0240)*	(0.0258)	(0.0374)	(0.0349)
Adopt at least 6 years earlier	-0.0393	-0.0220	-0.0478	-0.0278	0.0171	-0.0750
	(0.0198)**	(0.0291)	(0.0259)*	(0.0283)	(0.0413)	(0.0391)*
Observations	21086	11002	10084	11178	5375	5803
# of hospitals	1934	1052	882	1009	501	508
R-squared	0.62	0.65	0.60	0.64	0.67	0.62

Dependent variable is total operating costs per admit. Unit of observation is a hospital-year. Sample includes annual data from 1996 to 2009. Sample restricted to those that eventually adopt. 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. * significant at 10%; ** significant at 5%; *** significant at 1%

Appendix Table A.3: Other specifications of controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	No controls				Add controls for current levels of hospital characteristics			
Technology	**Basic EMR adoption**	**Advanced EMR adoption**	**Basic EMR adoption**	**Advanced EMR adoption**	**Basic EMR adoption**	**Advanced EMR adoption**	**Basic EMR adoption**	**Advanced EMR adoption**
Adopt in previous 3 year period	0.2597	0.3060	0.2805	0.3323	0.0151	0.0327	0.0263	0.0445
	(0.0068)***	(0.0083)***	(0.0084)***	(0.0112)***	(0.0056)***	(0.0060)***	(0.0079)***	(0.0092)***
Adopt at least 3 years earlier	0.5075	0.5026	0.5515	0.5580	0.0074	0.0244	0.0346	0.0490
	(0.0072)***	(0.0096)***	(0.0097)***	(0.0153)***	(0.0080)	(0.0089)***	(0.0111)***	(0.0129)***
Adopt in previous 3 year period x IT-intensive county			-0.2809	-0.3127			-0.0235	-0.0223
			(0.0142)***	(0.0166)***			(0.0111)**	(0.0120)*
Adopt at least 3 years earlier x IT-intensive county			-0.5862	-0.5622			-0.0566	-0.0462
			(0.0175)***	(0.0208)***			(0.0158)***	(0.0173)***
Observations	24284	35733	24284	35733	23361	34262	23361	34262
# of hospitals	2247	3334	2247	3334	2228	3306	2228	3306
R-squared	0.27	0.10	0.36	0.25	0.73	0.71	0.73	0.71

Dependent variable is total operating costs per admit. 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, 4, 7, and 8 include time trends for IT-intensive location. Columns 5-8 include the same set of controls as in Table 3 plus 5-8 include the current values by year for all hospital-level controls from Table 3. * significant at 10%; ** significant at 5%; *** significant at 1%

Appendix Table A.4: Labor costs and direct costs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable		**Total labor costs per admit**				**Total direct costs per admit**		
Technology	**Basic EMR adoption**	**Advanced EMR adoption**	**Basic EMR adoption**	**Advanced EMR adoption**	**Basic EMR adoption**	**Advanced EMR adoption**	**Basic EMR adoption**	**Advanced EMR adoption**
Adopt in previous 3 year period	-0.0029	0.0261	0.0052	0.0365	0.0063	0.0255	0.0121	0.0380
	(0.0063)	(0.0072)***	(0.0085)	(0.0105)***	(0.0063)	(0.0070)***	(0.0085)	(0.0103)***
Adopt at least 3 years earlier	-0.0152	0.0150	0.0121	0.0454	-0.0082	0.0037	0.0154	0.0322
	(0.0092)*	(0.0100)	(0.0128)	(0.0149)***	(0.0089)	(0.0097)	(0.0123)	(0.0146)**
Adopt in previous 3 year period x IT-intensive county			-0.0171	-0.0196			-0.0123	-0.0238
			(0.0127)	(0.0145)			(0.0126)	(0.0141)*
Adopt at least 3 years earlier x IT-intensive county			-0.0566	-0.0572			-0.0488	-0.0536
			(0.0186)***	(0.0194)***			(0.0178)***	(0.0190)***
Observations	23416	34405	23416	34405	23418	34407	23418	34407
# of hospitals	2228	3306	2228	3306	2228	3306	2228	3306
R-squared	0.53	0.50	0.53	0.50	0.56	0.54	0.56	0.54

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 time trends for IT-intensive location (columns 3, 4,7, 8). * significant at 10%; ** significant at 5%; *** significant at 1%

Appendix Table A.5: Include adjustments for difficulty of the Medicare case mix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Add Medicare case mix index as control				Weight dependent variable by the Medicare case mix index			
Technology	**Basic EMR adoption**	**Advanced EMR adoption**	**Basic EMR adoption**	**Advanced EMR adoption**	**Basic EMR adoption**	**Advanced EMR adoption**	**Basic EMR adoption**	**Advanced EMR adoption**
Adopt in previous 3 year period	0.0045	0.0269	0.0125	0.0371	0.0034	0.0248	0.0090	0.0286
	(0.0063)	(0.0068)***	(0.0087)	(0.0108)***	(0.0064)	(0.0069)***	(0.0088)	(0.0109)***
Adopt at least 3 years earlier	-0.0070	0.0137	0.0208	0.0410	-0.0055	0.0151	0.0195	0.0383
	(0.0090)	(0.0097)	(0.0125)*	(0.0149)***	(0.0091)	(0.0097)	(0.0127)	(0.0145)***
Adopt in previous 3 year period x IT-intensive county			-0.0163	-0.0188			-0.0117	-0.0070
			(0.0124)	(0.0137)			(0.0125)	(0.0139)
Adopt at least 3 years earlier x IT-intensive county			-0.0562	-0.0503			-0.0507	-0.0427
			(0.0177)***	(0.0190)***			(0.0178)***	(0.0190)**
Medicare case mix index	0.2013	0.1899	0.1977	0.1871				
	(0.0303)***	(0.0309)***	(0.0304)***	(0.0309)***				
Observations	20214	29545	20214	29545	20214	29545	20214	29545
# of hospitals	1642	2403	1642	2403	1642	2403	1642	2403
R-squared	0.62	0.60	0.62	0.60	0.62	0.60	0.62	0.60

In columns 1-4, dependent variable is total operating costs per admit. In columns 5-8, dependent variable is total operating costs per admit, weighted by the Medicare case mix index. Note that the Medicare case mix is a weak proxy for the total case mix. Unit of observation is a hospital-year. Sample includes annual data from 1996 to 2009, subject to having data on the Medicare case mix (eliminating approximately 13% of the sample). 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 time trends for IT-intensive location (columns 3, 4, 7, 8). * significant at 10%; ** significant at 5%; *** significant at 1%

Appendix Table A.6: Comparison of coefficients when only eventual adopters included in the estimation

	(1)	(2)	(3)	(4)
Technology	**Basic EMR adoption**		**Advanced EMR adoption**	
	All data	**Only adopters**	**All data**	**Only adopters**
Adopt in previous 3 year period	0.0128	0.0106	0.0403	0.0338
	(0.0085)	(0.0087)	(0.0102)***	(0.0118)***
Adopt at least 3 years earlier	0.0170	0.0125	0.0382	0.0363
	(0.0123)	(0.0125)	(0.0145)***	(0.0173)**
Adopt in previous 3 year period x IT-intensive county	-0.0157	-0.0141	-0.0285	-0.0304
	(0.0126)	(0.0123)	(0.0140)**	(0.0161)*
Adopt at least 3 years earlier x IT-intensive county	-0.0513	-0.0474	-0.0597	-0.0617
	(0.0178)***	(0.0173)***	(0.0189)***	(0.0228)***
Observations	23418	21086	34407	11178
# of hospitals	2228	1934	3306	1009
R-squared	0.58	0.62	0.56	0.64
CONTROLS				
IT-intensive county x year	0.0000	-0.0006	-0.0013	0.0016
	(0.0019)	(0.0020)	(0.0014)	(0.0027)
Log inpatient days	-0.4578	-0.4134	-0.6154	-0.6742
	(0.1870)**	(0.2109)*	(0.1426)***	(0.2969)**
Log outpatient visits	-0.0600	-0.2506	-0.0590	-0.0770
	(0.1191)	(0.1525)	(0.0902)	(0.2072)
Log inpatient days x Log inpatient days	0.0304	0.0367	0.0301	0.0331
	(0.0086)***	(0.0094)***	(0.0069)***	(0.0151)**
Log outpatient visits x Log outpatient visits	0.0170	0.0329	0.0103	0.0130
	(0.0067)**	(0.0101)***	(0.0050)**	(0.0098)
Log inpatient days x Log outpatient visits	-0.0306	-0.0463	-0.0163	-0.0191
	(0.0143)**	(0.0146)***	(0.0118)	(0.0196)
Log total costs per admit in 1996 x year	-0.0202	-0.0202	-0.0231	-0.0285
	(0.0030)***	(0.0028)***	(0.0024)***	(0.0047)***
Log total hospital beds x year	-0.0081	-0.0069	-0.0098	-0.0056
	(0.0023)***	(0.0024)***	(0.0020)***	(0.0038)
Independent practice assn. hospital x year	-0.0009	-0.0010	0.0001	-0.0011
	(0.0015)	(0.0015)	(0.0013)	(0.0020)
Mngmt service org. hospital x year	-0.0022	-0.0020	-0.0030	-0.0010
	(0.0015)	(0.0015)	(0.0013)**	(0.0020)
Equity model hospital x year	-0.0025	-0.0002	-0.0017	-0.0036

	(0.0032)	(0.0031)	(0.0025)	(0.0043)
Foundation hospital x year	0.0019	0.0022	0.0014	-0.0005
	(0.0019)	(0.0020)	(0.0016)	(0.0027)
Log admissions x year	0.0023	-0.0005	0.0039	0.0008
	(0.0022)	(0.0024)	(0.0020)**	(0.0040)
Births (000s) x year	0.0019	0.0024	0.0018	0.0017
	(0.0008)**	(0.0008)***	(0.0007)***	(0.0009)*
For-profit ownership x year	-0.0101	-0.0092	-0.0097	-0.0210
	(0.0022)***	(0.0022)***	(0.0019)***	(0.0037)***
Non-secular nonprofit ownership x year	0.0006	0.0006	-0.0004	-0.0007
	(0.0016)	(0.0016)	(0.0014)	(0.0023)
Non-profit church ownership x year	-0.0003	0.0001	0.0000	-0.0036
	(0.0021)	(0.0021)	(0.0018)	(0.0027)
Number of discharges Medicare (000s) x year	0.0001	0.0001	0.0002	0.0000
	(0.0004)	(0.0004)	(0.0003)	(0.0005)
Number of discharges Medicaid (000s) x year	0.0002	0.0000	0.0005	0.0001
	(0.0005)	(0.0005)	(0.0004)	(0.0006)
Residency/Mmbr Council Teaching Hosps x year	0.0036	0.0039	0.0032	0.0056
	(0.0018)**	(0.0018)**	(0.0015)**	(0.0025)**
Log population in 2000 census x year	-0.0009	-0.0007	-0.0011	-0.0017
	(0.0007)	(0.0007)	(0.0006)*	(0.0009)*
% Black in 2000 census x year	-0.0192	-0.0160	-0.0173	-0.0211
	(0.0046)***	(0.0049)***	(0.0041)***	(0.0075)***
% age 65+ in 2000 census x year	-0.0301	-0.0261	-0.0319	-0.0383
	(0.0189)	(0.0194)	(0.0167)*	(0.0248)
% age 25-64 in 2000 census x year	-0.0306	-0.0246	-0.0163	0.0177
	(0.0135)**	(0.0132)*	(0.0138)	(0.0230)
% university education in 2000 census x year	0.0343	0.0488	0.0565	0.0685
	(0.0157)**	(0.0156)***	(0.0134)***	(0.0216)***
Log median hh income in 2000 census x year	0.0109	0.0076	0.0075	-0.0033
	(0.0045)**	(0.0045)*	(0.0040)*	(0.0067)

Dependent variable is total operating costs per admit. 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. The controls are the same as those listed in Table 3. * significant at 10%; ** significant at 5%; *** significant at 1%

Appendix Table A.7: Baseline specification to help interpretation of instrumental variable results

	(1)	(2)	(3)	(4)
Technology	**Basic EMR adoption**	**Advanced EMR adoption**	**Basic EMR adoption**	**Advanced EMR adoption**
Adopted EMR at least 3 years earlier	-0.0127	-0.0091	0.0052	0.0134
	(0.0060)**	(0.0080)	(0.0082)	(0.0118)
Adopted EMR at least 3 years earlier x IT-intensive county			-0.0366	-0.0425
			(0.0118)***	(0.0156)***
Observations	23418	34407	23418	34407
# of hospitals	2228	3306	2228	3306
R-squared	0.58	0.56	0.58	0.56

Dependent variable is total operating costs per admit. 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 time trends for IT-intensive location (columns 3,4). * significant at 10%; ** significant at 5%; *** significant at 1%

Appendix Table A.8: First stage of Table 8 instrumental variables results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(3a)	(4a)	(7a)	(8a)
	First stage for EMR adoption								First stage for EMR adoption x IT-intensive county			
	All three instruments				Two instruments				All three instruments		Two instruments	
Technology	**Basic EMR adoption**	**Advanced EMR adoption**	**Basic EMR adoption**	**Advanced EMR adoption**	**Basic EMR adoption**	**Advanced EMR adoption**	**Basic EMR adoption**	**Advanced EMR adoption**	**Basic EMR adoption**	**Advanced EMR adoption**	**Basic EMR adoption**	**Advanced EMR adoption**
EMR adoption by competitors in other markets	0.1959	0.0942	0.1776	0.0551	0.1981	0.0875	0.1802	0.0499	0.00086	-0.0052	0.00004	-0.0047
	(0.0314)***	(0.0472)**	(0.0436)***	(0.0507)	(0.0313)***	(0.0474)*	(0.0435)***	(0.0510)	(0.0066)	(0.0120)	(0.0066)	(0.0125)
EMR adoption by competitors in other markets x IT-intensive county			0.0350	0.0898			0.0339	0.0857	0.2024	0.1411	0.2057	0.1298
			(0.0603)	(0.0963)			(0.0603)	(0.0970)	(0.0428)***	(0.0820)*	(0.0427)***	(0.0827)
Distance to nearest EMR vendor	-0.0014	0.0005	-0.0036	0.0023	-0.0014	0.0004	0.0036	0.0022	0.0004	0.0008	0.0003	0.0010
	(0.0006)**	(0.0005)	(0.0013)***	(0.0010)**	(0.0006)**	(0.0005)	(0.0013)***	(0.0010)**	(0.0002)	(0.0002)***	(0.0002)	(0.0002)***
Distance to nearest EMR vendor x IT-intensive county			-0.0027	-0.0023			-0.0028	-0.0023	-0.00027	-0.0012	-0.0003	-0.0015
			(0.0014)*	(0.0011)**			(0.0014)*	(0.0011)**	(0.00068)	(0.0006)**	(0.0007)	(0.0006)***
Percent in alliance adopting	-0.0303	0.1746	-0.0311	0.1089					0.008309	-0.0530		
	(0.0299)	(0.0350)***	(0.0400)	(0.0437)*					(0.0106)	(0.0125)***		
Percent in alliance adopting x IT-intensive county			0.0047	0.1469					-0.0409	0.3311		
			(0.0575)	(0.0671)*					(0.0421)	(0.0518)***		
Partial R-squared	0.006	0.005	0.007	0.006	0.006	0.001	0.006	0.002	0.006	0.012	0.006	0.002
F-statistic	15.78	9.85	8.63	6.22	23.23	2.00	12.67	2.17	4.49	11.60	6.41	6.83

Dependent variable is total operating costs per admit. 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 time trends for IT-intensive location (columns 3a, 4a, 7a, 8a). * significant at 10%; ** significant at 5%; *** significant at 1%

Appendix Table A.9: Second stage for running the instruments separately (just-identified models)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Percent competitors adopt in related markets				Distance to nearest vendor				Percent members of alliance adopt			
Technology	**Basic EMR adoption**	**Advanced EMR adoption**	**Basic EMR adoption**	**Advanced EMR adoption**	**Basic EMR adoption**	**Advanced EMR adoption**	**Basic EMR adoption**	**Advanced EMR adoption**	**Basic EMR adoption**	**Advanced EMR adoption**	**Basic EMR adoption**	**Advanced EMR adoption**
Adopted EMR at least 3 years earlier	-0.1037	0.3007	0.0327	0.6984	0.1897	1.2022	0.5236	0.9436	0.1198	0.1016	0.2348	0.1739
	(0.1169)	(0.5196)	(0.1735)	(1.0850)	(0.2629)	(1.5925)	(0.3123)*	(0.7253)	(0.5019)	(0.1808)	(0.4803)	(0.2583)
Adopted EMR at least 3 years earlier x IT-intensive county			-0.2382	-0.6982			-0.9678	-0.2605			-0.2769	-0.1239
			(0.2364)	(1.2692)			(0.8224)	(1.0469)			(0.6898)	(0.2378)
Observations	23407	34385	23407	34385	23407	34385	23407	34385	23407	34385	23407	34385
# of hospitals	2217	3284	2217	3284	2217	3284	2217	3284	2217	3284	2217	3284
Hausman test (p-value)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
R-squared	0.57	0.52	0.57	0.47	0.54	0.29	0.38	0.29	0.56	0.55	0.56	0.55
1st stage F-stat	40.51	3.44	20.20	1.76	6.06	0.73	4.88	2.60	2.45	24.11	1.33	13.58
1st stage interaction F	N/A	N/A	11.82	1.33	N/A	N/A	1.12	12.90	N/A	N/A	1.19	27.72

Dependent variable is total operating costs per admit. 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 time trends for IT-intensive location (columns 3,4,7,8,11,12). * significant at 10%; ** significant at 5%; *** significant at 1%