Privacy, Networks Effects and Electronic Medical Record Technology Adoption

Amalia R. Miller* and Catherine E. Tucker†‡

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Abstract

An Electronic Medical Record (EMR) allows medical providers to store and transfer patient information using computers rather than paper records. The ability to transfer existing medical information about a patient to another hospital electronically could be beneficial or detrimental to hospitals. On one hand, the ability to transfer patient records electronically can improve patient safety and reduce the time medical staff spends on paperwork. On the other hand, creating transferable records could make it easier for patients to leave the hospital and seek treatment elsewhere. In both cases, one hospital's EMR adoption decision will rest on the adoption decisions of other hospitals. If hospitals benefit from accessing electronic information about their patients from other hospitals, they will react positively to the adoption of their local competitor. If, on the other hand, hospitals are worried about losing patients to other hospitals, they may be less likely to adopt EMR if their local competitors have already adopted it. We empirically distinguish between these two competing theories by exploiting variation in state privacy laws governing the transfer of patient information. Our results indicate that there are positive network effects in the diffusion of EMR, and that when medical records can be transferred freely, the presence of other hospital adopters encourages adoption.

We present empirical evidence, exploiting both time-series and cross-sectional variation, that the enactment of state privacy laws restricting the transfer of medical information from hospitals inhibits at least 25 percent of the network effects that would have otherwise promoted a hospital's adoption of EMR. We also show that privacy laws affect hospital choices over compatibility of EMR software. The size of the network effects is identified by using characteristics of the other hospitals in the region as instruments for the installed base. We conclude that policymakers face sizable trade-offs between offering strong privacy protection and promoting the network gains from EMR technology.

*Economics Department, University of Virginia, Charlottesville, VA

†MIT Sloan School of Business, MIT, Cambridge, MA.

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1 Introduction

This paper studies how the decision of a hospital to adopt Electronic Medical Records ("EMR") technology is affected by the adoption choices of neighboring hospitals. EMR is an overarching term for the set of hardware and software systems which allow medical providers to store, maintain and transfer medical information using computers rather than paper records. Although the technology has been available as far back as the 1970s, only around 30 percent of hospitals had adopted a comprehensive EMR system by 2004 (Fonkych and Taylor (2005)).

EMR advocates claim that a full transition from paper to electronic record-keeping will improve health outcomes by producing faster and more complete transfer of relevant medical information to health practitioners regarding both patients and appropriate treatments, thereby reducing medical errors. However, it is not clear that all hospitals will warmly embrace the technology. While the ability to access information electronically reduces time spent on procuring paper records by both patients and medical providers, their very portability may make it easier for patients to seek medical treatment elsewhere. Therefore, it is an empirical question whether hospitals are more or less likely to adopt the technology if other neighboring hospitals have also adopted it. In order to isolate the causal effect of how one hospital's ability to transfer patient information to another affects adoption, we exploit variation in state privacy laws that, to a greater or lesser extent, stanch the flow of patient information between hospitals.

The confidentiality of personal health information is an important consumer concern. Some fear that the widespread use of computers to store and transfer patient medical records will increase the risks of medical information being viewed by outsiders or stolen to perpetrate fraud. The weakness of existing federal regulation has led some states to enact laws tightening the privacy rules governing medical information. In this paper, we study the effect of state-level regulations that protect the privacy of individually identifiable medical records when a hospital adopts EMR. Theoretically, tough state laws could encourage positive correlations in adoption because the privacy guards mean that hospitals need not worry about patients leaving them easily. Alternatively, they could discourage positive correlations in adoption if privacy laws mean that hospitals cannot swap patient information.

This paper seeks to inform the debate with empirical evidence on the adoption decisions of a national sample containing detailed information about information technology at over 4,000 U.S. hospitals. We exploit both cross-sectional and time-series variation in state privacy laws to assess the impact of privacy laws on how potential adopters react to the installed base of local hospitals in the local health service area. The empirical evidence consistently points to hospitals reacting positively to the adoption of other hospitals when they are able to transfer information freely. Our estimates using cross-sectional and time-series variation suggest that, as a lower bound, privacy laws on average restrict 25 to 40 percent of positive network effects inherent in the diffusion of Electronic Medical Records.

We employ an additional identification strategy to quantify the total size of these positive network effects, exploiting the characteristics of other hospitals in the local area as instrumental variables. The identifying assumption is that a hospital's decision to adopt EMR does not respond directly to these characteristics, but only indirectly through their effect on the size of the installed local base. The instrumental variable estimates vary by state regulation. In states without hospital privacy laws, the adoption of EMR by one hospital increases the probability of a neighboring hospital's adoption by 5.9 percent. By contrast, network effects in EMR adoption are negligible (0.7 percent, statistically insignificant) in states with medical privacy laws.

Prior studies of technology adoption in healthcare have tended to focus on innovations that increase expenditures, such as magnetic resonance imaging (MRI) equipment. This empirical focus builds on research such as Newhouse (1992) that attribute a large share of recent increases in health spending to technological change. Key variables for explaining technological expenditure have been managed care penetration (see Baker and Phibbs (2002), Spetz and Baker (1999), Hill and Wolfe (1997) and Baker (2001)) and changes to the Medicare program (for example, Acemoglu and Finkelstein (2006)). In general, by reducing the role of price competition among hospitals, greater insurance coverage and less managed care can induce inefficiently high adoption of cost-increasing quality-improving technology. Another branch of the literature has looked explicitly at how technology adoption affects health outcomes, such as Athey and Stern (2002)'s work on the effects of E911 technology adoption. There have also been innovations in using structural techniques to model how market structure and competitive effects directly affect technology adoption (see for example Lenzo (2005), Hamilton and McManus (2005) and Schmidt-Dengler (2006)).

In contrast to this previous literature, we consider a possibly cost-reducing technology, EMR, which is strongly intertwined with hospital interactions with each other. The empirical evidence in this paper suggests that hospitals react positively to other hospitals' adoption when information can flow freely and is not restricted by state privacy laws. One interpretation of this is that there are network effects for this technology. Classically, the coordination problems inherent in network technologies can lead to sub-optimal outcomes (Farrell and Saloner (1985), Katz and Shapiro (1985)). This coordination problem may be particularly welfare-decreasing for EMR adoption outcomes because of the large numbers involved. Hillestad, Bigelow, Bower, Girosi, Meili, Scoville, and Taylor (2005) estimates net potential savings from widespread adoption of EMR systems at more than $81 billion annually, as a result of improved efficiency and safety of care. They argue that prevention and management of chronic disease could eventually double those savings while increasing health and other social benefits. In the face of America's $1.7 trillion annual health care bill, such cost-saving estimates have attracted the interest of policy-makers. U.S. politicians from both parties have argued for the importance of increasing the use of information technology in healthcare. In July 2006, Congress passed a bill to promote the adoption of the computer hardware and software necessary to generate and share digital patient records (Lohr (2006)). There was also much discussion about the necessity of new federal legislation to ensure that patient records remain private. There may be, however, be an unconsidered policy trade-off between strong privacy protections and encouraging the swift diffusion of EMR through network effects.

In addition to offering substantive findings over an important policy question, our paper also contributes to a growing literature on the identification of network effects. One reason that identification of geographic network effects is challenging is the possible presence of unobservable regional differences that could provide an alternative explanation for correlated adoption decisions. Other sources of spurious dependence are common taste shocks and strategic interactions. The previous literature on identifying network effects such as Tucker (2006b) and (Gowrisankaran and Stavins 2004) has focused on finding exogenous shifters of adoption to study the causal effect of one agents adoption on another.[1] By contrast, in this paper we infer network effects from an exogenous shift in the ability of agents within a network to transfer information across a network. To our knowledge this approach of exploiting exogenous variation in the ability to use a network has not been employed before as a means of identifying network effects, despite the fact it is the closest approach to identifying network effects based on actual usage of the network.

This paper is organized as follows: Section 2 discusses the legal context of state variation in privacy laws, while Section 3 sets out the data we use in this study. We report results for cross-sectional and time-series variation in Section 4. We go on to report how to interpret these results further when we take into account the compatibility of neighboring hospitals' systems, in section 4.2. We then use instrumental variables to provide evidence on the relative size of network effects in Section 5, before discussing our conclusions and areas for

[1](Rysman 2004) used exogenous shifters of costs in his study of yellow pages adoption.

future research in Section 6.

2 The Legal Context

A review of the academic literature revealed no other empirical evaluation of the effect of privacy laws on the diffusion of EMR. However, there is plenty of survey-based evidence that privacy is a major concern for patients. A Harris Interactive poll in February 2005 found that 70 percent of those surveyed were concerned about EMR privacy. Electronic records are easier than paper files to duplicate and distribute in bulk. The security of networked computers can be breached on location or remotely. Anecdotal evidence also suggests that privacy concerns about electronic records may be justified. For example, computers that held a disc containing the confidential records of close to 200,000 patients of a medical group in San Jose, California, were posted for sale on Craigslist.org, an online classifieds service.[2]

Statutory health privacy protection varies substantially across the United States in the limits imposed on the disclosure of medical information, the range of covered organizations, the rules for obtaining consent, the exemptions from disclosure rules, and the penalties for violations. Prior to the 2002 enactment of the Health Insurance Portability and Accountability Act (HIPAA) Privacy Law, federal law did not explicitly protect the confidentiality of health information, and statutory protection was determined at the state level.[3] There is anecdotal evidence to suggest that while HIPAA itself did not affect the actual transfer of information, it did encourage a spate of updates of hospital IT systems including EMR, to ensure that hospitals could document their record-keeping in a HIPAA-compliant way.

[2]From ConsumerReports.org.

[3]Expanded electronic record-keeping and use of health information technology led to increased public concern over the privacy of medical information. The 1996 HIPAA law therefore included requirements that the federal government design and implement rules to address the use and disclosure of individual health information (sections 261 through 264). After Congress failed to pass a rule by 1999, the department of Health and Human Services proposed the Privacy Rule, which became law in 2002 (45 CFR Part 160 and Part 164).

Although the Privacy Act provides a uniform standard of federal privacy protection, actual standards continue to vary from state to state. The reason is that the federal law, which provides only a minimum standard, is considered relatively weak, due to its limited scope of covered entities, lax enforcement, and dependency on private consumer complaints to initiate action. In practice, privacy law is often determined by a stricter state statute. So much variation persists that some observers characterize privacy protection in the U.S. as a "patchwork" of state policies and call for creation of uniform standards. These unifotm standards may be established by legislation such as H.R. 4157, which would eliminate state laws that exceed current federal standards. So far, however, there have been no academic studies of the impact of state privacy laws on EMR diffusion.[4]

This paper exploits the legal variation produced by the current "patchwork" of state laws to assess the impact of privacy standards on hospital decisions to adopt EMR.[5] We use legal variation across states and time to measure the association between privacy laws and the regional variation in the installed base.

Our main source for current state privacy regulation is the Pritts, Choy, Emmart, and Hustead (2002) survey of state health privacy statutes, produced by the Health Privacy Project at Georgetown University. Following their categorization, the state legal privacy environment is determined by the statute regarding privacy of medical information. This excludes additional requirements or refinements stemming from case law or administrative law. Data from the 2002 publication were combined with data from two earlier surveys of state privacy laws (Pritts, Goldman, Hudson, Berenson, and Hadley (1999) and Gostin, Lazzarini, and Flaherty (1996)) to identify historical changes in privacy rules and produce

[4]Witnesses in favor of the bill had some illuminating remarks. For example, Alan Mertz, president of the American Clinical Laboratory Association, said that privacy laws such as those in Georgia and Florida, which prevent labs from sending results to anyone other than the physician who ordered the test, are inhibiting EMR technology diffusion.

[5]Other health technology researchers have exploited variation in state laws. For example, Caudill, Ford, and Kaserman (1995) found that certificate-of-need regulation by state health planning organizations had slowed down the diffusion of hemodialysis technology.

a panel database. Due to the limitations described above, protections afforded under the federal Privacy Law are not counted in the estimation. If federal law comes to provide a meaningful standard for all states, estimates for state privacy rules will be attenuated. In our estimation, we pool adoption decisions from before and after the implementation of HIPAA. To ensure that this change in baseline privacy protection did not unduly change our results, we tried omitting observations where there was adoption of EMR prior to HIPAA, and, reassuringly, our results did not change. This is not surprising, given that HIPAA is intended to ensure careful documentation and disclosure about the flow of patient information, rather than explicitly to restrict the flow of patient information as many state privacy laws do.

The aspect of state laws limiting disclosure of medical information that most affects hospital adoption decisions is whether hospitals are included in the organizations covered. Our explanatory variable, HospPrivLaw, is an indicator for the hospital being located in a state with a privacy law that includes hospitals in its coverage. Hospitals in these states have explicit statutory requirements to protect the confidentiality of patient medical information, and are restricted in their rights to disclose such information to outside parties without express prior authorization from the patient. Hospitals in other states are not explicitly covered by state statute governing the privacy of medical information.

As shown in Figure 1, about half of the states in the country include hospitals in their privacy coverage. Coverage is geographically dispersed, and each of the nine census divisions includes at least one state with and one without hospital coverage. For example, Arizona, California, Tennessee, and Vermont have hospital coverage, while Connecticut, Kansas, Michigan, and Pennsylvania do not. States with hospital privacy laws are significantly larger and more populous than other states, but have statistically indistinguishable population densities. States with hospital privacy laws also have significantly higher average incomes and rates of managed care penetration compared to other states. Since these factors may have important independent effects on adoption, we include them as controls in our robustness checks in the estimates presented in Table 2. Naturally, permanent differences in these characteristics, observed or unobserved, will be absorbed in the state fixed effects, when included.

There is not only cross-sectional variation across states in privacy laws but also time-series variation. Our state law panel begins in 1996, covering the great bulk of the relevant period of EMR adoption (see Figure 3). During that period, we observe 19 changes in laws: four changes to increase privacy protection and 15 to decrease it.

3 Data

We use data from the 2005 release of the Healthcare Information and Management Systems Society (HIMSS) Dorenfest database. The 2004 release of this data has been used to study the diffusion of EMR technology in three notable RAND studies: Fonkych and Taylor (2005), Hillestad, Bigelow, Bower, Girosi, Meili, Scoville, and Taylor (2005) and Bower (2005). Although these studies did not evaluate the role of privacy laws, Bower (2005) did note that "Conceivably, privacy demands could forestall benefits of networked technology." The HIMSS database covers the majority of U.S. community hospitals, including about 90 percent of non-profit, 90 percent of for-profit, and 50 percent of government-owned (non-federal) hospitals. However, it excludes hospitals that have fewer than 100 beds and are not members of healthcare systems, which under-represents small rural hospitals. Ultimately we have data on 4,010 hospitals. Of these, we have records on 3,988 hospitals' decisions on whether to adopt an enterprise-wide EMR system, and 1,937 hospitals reported that they adopted EMR. Of these, 1,400 hospitals reported the timing of their adoption of EMR. Since we need information about the timing of adoption to exploit time-series variation in state privacy laws, we dropped the 537 observations where no information about timing was provided.[6]

[6]We conducted regressions using cross-sectional variation only, with adoption by 2005 as the dependent variable, including these 537 hospitals. These regressions support the findings of the results presented in

Our EMR adoption variable is an indicator for a hospital that has installed or is installing an "Enterprise EMR" system. This is the basic EMR system which underlies other potential add-ins such as Clinical Decision Support, a Clinical Data Repository and Order Entry. The HIMSS database reports information for actual installations as well as product orders, where a hospital has signed a contract with a vendor to buy a system. We define a hospital as an adopter if its EMR system is "Live and Operational", "Contracted/Not Yet Installed", or "Installation in Process", or if the hospital has an EMR system which it is currently updating.[7]

The installed base is the number of hospitals in the local health service area who have adopted EMR. We use an interaction of the installed base and the presence of a state privacy law to measure the effect that privacy laws have on the effect of the installed base in the diffusion process. As with any study which uses the installed base as an explanatory variable, determining the appropriate measure of local networks is key (Tucker (2006a)). We report results using a Health Service Area market as our definition of the local health market area as defined by Makuc, Haglund, Ingram, Kleinman, and Feldman (1991) and used in subsequent economic studies such as Dranove, Shanley, and Simon (1992) and Schmidt-Dengler (2006). There are 815 health service areas in the US. For robustness, we have also estimated results for 392 "labor market areas" as defined by the 1990 census using commuting data and obtained similar results.

Figures 2 and 3 illustrate the wide dispersion in percentage of adoption over time and across health service areas; similar variation in adoption exists across labor market areas. It appears that there was a spike in adoptions around 2002. We speculate that this coincided with the introduction of HIPAA and the need for hospitals to document more carefully who accessed patient medical records, though IT upgrading in the light of the advent of internet

this paper.

[7]Alternative specifications, in which we exclude the 185 observations where adoption is either in process or just contracted, produce similar results.

and the year 2000 bug are viable alternative explanations.

In addition to the network benefits of being able to transfer medical information between hospitals, there are also stand-alone benefits: shorter hospital stays prompted by better-coordinated care, less nursing time spent on administrative tasks and better use of medications in hospitals. We control for these hospital-specific variations in stand-alone benefits by using controls for the number of fully-staffed beds and the number of years open. Table 1 lists the main variables and gives descriptions.

4 Panel Estimation and Results

We begin by studying the decision to adopt an enterprise-wide EMR system, using the dependent variable $adopt_{it}$, a hospital-year level indicator for adoption and implementation in 1999, 2002, and 2005. We use these time snapshots because this is when we have data on the exact status of privacy laws. Section 4.2 introduces the concept of compatible EMR, and groups vendors into two types: those with an explicit commitment to inter-operability and those without. The basic model is then extended to allow the type of EMR systems adopted by other hospitals to influence the hospital's own adoption decision as well as its choice to acquire a compatible or incompatible system.

The potential gains from EMR adoption stem from improved quality of patient care and lower administrative costs, while the potential costs include the upfront costs of software and hardware installation, training and ongoing maintenance. Quality improvements from EMR may boost patient demand and hence profits. They may also enter into the hospital objective function directly.[8] Each hospital faces an expected net gain from EMR adoption

[8]As Dafny (2005) and others point out, with over 80 percent of hospitals categorized as non-profit or government owned, a hospital model of pure profit maximization may be inappropriate. Rather, economists generally assume that hospitals maximize an objective function that increases separately with patient care quality and with profits.

represented in the basic model by the equation:

$$adopt^*_{it} = f(InstalledHSA_{it}, HospPrivLaw_{it}, HospPrivLaw^*_{it}InstalledHSA_{it}, X_{it}; \theta) + \epsilon_{it}$$

The effect of EMR adoption by other hospitals in the same market on the expected gains from EMR is captured with the variable InstalledHSA, a regional market-level count of the number of hospitals who have adopted EMR by that year in that HSA. Two variables are used to measure the potential effects of privacy laws on hospital adoption. The effect of hospital privacy laws on adoption is captured by HospPrivLaw, an indicator for the presence of an operative state privacy law restricting the rights of hospitals to disclose personal medical information without prior authorization in that year. The interaction with the installed base is measured with HospPrivLaw*InstalledHSA, the product of the first two explanatory variables. Together with the estimate on InstalledHSA, the sign of this interaction term is the focus of the study. A significant and positive sign suggests that there is more correlation in adoption if a state-level hospital privacy law is in effect. A negative and significant sign suggests that there is less correlation in adoption if a state-level hospital privacy law is in effect. A set of regional and hospital characteristics is included as controls in the vector X_{it}, and ϵ_{it} is a stochastic error term.

When the net gain is positive, a hospital will adopt EMR:

$$adopt_{it} = \begin{cases} 1 & \text{if } adopt^*_{it} > 0 \\ 0 & \text{if } adopt^*_{it} \leq 0 \end{cases}$$

Section 4 reports estimates of the parameters in θ under three different functional form specifications. Section 4.2 begins with an extension of the model in which the installed base is divided into compatible and incompatible systems, and goes on to present estimates from a choice model that includes the adoption and compatibility decisions together.

4.1 Determinants of EMR Adoption

The results in Table 2 use a Health Service Area as the definition of the relevant local market. All columns include a full set of state and year dummy variables to capture permanent geographic features and secular adoption trends. The first column presents heteroskedasticity-adjusted robust standard errors. The point estimate for HospPrivLaw is positive 0.021. Although not statistically significant at conventional levels, the estimate is at least consistent with hospital claims that a transition to EMR can reduce within-hospital costs of compliance with privacy laws. The coefficient on InstalledHSA in the first column is positive 0.013 (with standard errors of 0.002) and is significant at 1 percent. The interaction term HospPrivLaw*InstalledHSA is negative and also highly significant. The coefficient is 0.005, which implies a 38.5 percent reduction in the positive effect of another hospital's adoption. These figures provide initial support for the claims of privacy law critics that impeding the flow of healthcare information hampers positive network effects which are otherwise inherent in a shared medical information network.

The regressions in Table 2 include a set of three additional covariates meant to capture important differences across hospitals and local markets. The hospital-level controls are a measure of size (number of staffed beds) and age (years opened). The market control is the number of hospitals in the HSA. Each of the coefficient estimates for the controls is individually significant: larger and older hospitals, and hospitals operating in markets with fewer competitors, are more likely to adopt EMR technology. EMR adoption entails substantial upfront and fixed costs, and produces potential gains that increase in the number of patients, by reducing the per-patient cost of paperwork. Hence, the positive effects of size and of age, which is likely related to prestige, are in the expected direction. While it is certainly possible that the "number of hospitals" measure is capturing some unobservable market characteristics such as regional shifts in taste for technology, the direction of the effect is also consistent with theoretical predictions. Markets with fewer hospitals suffer less from coordination problems; in the extreme case, monopolist hospitals internalize virtually all gains from technology adoption.

The InstalledHSA coefficient is a measure of the correlation between one hospital's adoption and adoption by other hospitals in that area. One interpretation of the positive coefficient is that when other hospitals adopt, this makes adoption more attractive by expanding the set of available medical records from potential patients. As described above, electronic medical records have both internal and external benefits. The positive estimates are certainly consistent with the presence of network externalities. However, they are also consistent with three primary alternative explanations: (1) informational spillovers, through which local hospitals learn from one another about the benefits of EMR technology but do not establish a medical data network, (2) strategic interactions such as a medical arms race, and (3) common regional shocks, observed by hospitals but not by researchers, to the potential profitability of EMR, operating either through demand or production variables.

At this stage, we present the estimate of InstalledHSA as potentially suffering from an upward bias. It is an upper-bound estimate on the size of the pure network effects, making the 38.5% measure for the reduction in network gains caused by privacy laws a lower-bound estimate.[9] That said, it is important to recognize that neither the informational spillovers nor the medical arms race story predicts the observed negative interaction between privacy laws and other hospitals' adoption. While the unobservable factors can theoretically take on many forms, the simple model of an additive shock to EMR profitability that is common to all hospitals in a given market but randomly assigned across markets would also fail to predict the negative interaction term. Also, the hypothesis that hospitals shun EMR adoption because they fear increased patient mobility would predict a negative coefficient on InstalledHSA and a positive one on HospPrivLaw*InstalledHSA. Therefore, the observed pattern, which

[9] We revisit the issue below, and provide instrumental variable estimates of the network effects in Section 5.

combines a positive InstalledHSA estimate and a negative HospPrivLaw*InstalledHSA estimate, provides stronger evidence for the presence of network effects than correlated adoption alone.

As described in Section 2, the laws are not randomly assigned across states, but are in fact correlated with underlying state characteristics which are also correlated with income, population and managed care penetration. Each of these variables can independently affect the profitability of EMR technology to the hospital. In their paper, Fonkych and Taylor (2005) provide a thorough examination of the hospital-level characteristics which are associated with adoption of EMR. They find a negative correlation with Medicare provision, an ambiguous relationship with managed care revenues, and a positive correlation with academic status. The regressions in this section all include a full set of state fixed effects. These capture permanent unobserved state characteristics that may be correlated with privacy laws, and should remove most spurious correlation.

To insure against correlation caused by state-specific trends in these variables, we include additional controls. Unfortunately, the Dorenfest Database only records information for these covariates for a sub-sample of hospitals. Columns 2 and 3 of table 2 report results from estimation on the limited sample (7,387 observations instead of 9,943) with the following additional variables: share of revenue from managed care, revenue share from the major public insurance programs (Medicaid and Medicare), area population and area median income. The second column presents robust standard errors with further control variables, and the third column presents results with robust standard errors clustered at the state level to account for arbitrary correlation within a state. Consistent with the findings of Fonkych and Taylor (2005), the public insurance variables are negative (and statistically significant for Medicare), indicating that hospitals with a greater share of payments from private insurance are more likely to invest in EMR technology. The managed care and teaching variables were not significantly different from zero.

The relationships observed for the main variables of interest are qualitatively unchanged: HospPrivLaw has a positive and insignificant coefficient, InstalledHSA is positive and highly significant, and HospPrivLaw*InstalledHSA is negative and significant, about 40% of the size of the InstalledHSA coefficient. The estimates for hospital size, age, and local market competition are not sensitive to the inclusion of additional regressors.

We interpret HospPrivLaw*InstalledHSA as capturing a causal effect of state privacy laws on hospital's adoption decisions via the adoption decisions of other hospitals. An alternative and non-causal interpretation would require some unobserved underlying conditions that were correlated with both state privacy laws and with the importance of other hospitals' EMR adoption on own adoption. The most compelling of these alternative interpretations we have come across so far is the idea that rural states have lower population densities that reduce the value of transferring information and are simultaneously more likely to enact privacy laws. We rule this out by including a control for population density on the right hand side which proves to be insignificant.

We use a linear probability model for our initial results because the interpretation of interaction terms and fixed effects is simplest in a linear framework. However, since the linear model may only be a weak approximation to some unknown true functional form, we also check our results against the results from alternative non-linear models such as a discrete choice Probit and a survival time Cox Proportional Hazards model.

Table 3 displays results from a Probit model, and Table 4 presents results for a survival time model using a Cox Proportional Hazards specification with time-varying covariates. While the Probit model more closely captures the discrete choice model estimated in Table 2, the survival time model has the advantage of more flexibly fitting the underlying hazard rate and explicitly modeling the fact that an EMR system is usually a sunk and irreversible investment. The regressors are the same as for Table 2. The key findings from the linear probability model are confirmed, and even increase in precision. The positive and significant coefficient on InstalledHSA, together with the negative and significant interaction HospPrivLaw*InstalledHSA, provide additional evidence of network effects that diminish under strict privacy rules. The estimated extent of the dampening caused by privacy rules is similar in the non-linear models: 35 percent in the Probit, and 33 percent in the Hazard model.

4.2 Adoption of Compatible Systems

The data format and software used for storing and transferring health information in an EMR system differs across manufacturers. Sharing information electronically can be cumbersome or impossible if the software is not compatible. EMR systems produced by a single vendor, for example Meditech, are more likely to be compatible with one another than with systems from other vendors. However, some EMR vendors have made more explicit commitments to compatibility than other vendors. The Cerner Corporation, GE Healthcare, IDX, McKesson Provider Technologies, Philips Medical Systems and Siemens Medical Solutions have explicitly made integration statements to IHE.[10] IHE promotes the coordinated use of established standards such as DICOM and HL7 to record information about patient care.

Table 2 suggests that privacy laws are impeding network effects in the diffusion of EMR. If this is the case, this effect should also be borne out in the choice of compatible EMR systems. Hospitals should respond to adoption by others and to privacy laws both in their adoption decisions and in their choice of vendor, producing correlated adoption by vendor type if the flow of information between hospitals is not restricted by state privacy laws. A hospital located in an area with substantial market penetration by a single vendor who is not committed to cross-system compatibility will likely choose that same non-compatible vendor if information transfer between hospitals is important and is not restricted by privacy laws. Alternatively, if the market is penetrated by vendors committed to compatibility, the hospital

[10] As listed by http://www.ihe.net/resources/ihe_integration_statements.cfm in July 2006.

will be more likely to select a system from a vendor who adheres to the shared technical standards, especially if the flow of information is not restricted by privacy laws. Our prediction is that hospital adoption of compatible EMR will respond more to adoption of compatible EMR by others than to adoption of non-compatible EMR. Likewise, hospital adoption of non-compatible EMR will be more responsive to others' adoption of non-compatible EMR. The results in Table 2 and the presence of privacy laws generate another testable prediction. Privacy laws diminish the size of potential network benefits from the transfer of patient information. Therefore, they should diminish the relative importance of installing a compatible EMR system. They would therefore also cause the gap to shrink between the effects of the installed compatible and non-compatible bases. While common unobservable factors can provide an alternative explanation for correlated adoption by vendor type, they do not generate the second prediction regarding differences by privacy statute.

First, Table 5 considers the adoption of compatible EMR systems. The coefficient on installed base of compatible systems, InstalledCompHSA, is positive 0.020 (and significant at 1% across specifications). The coefficient on InstalledNonCompHSA, the installed base of non-compatible systems, is negative 0.009 (significant at 5% or lower). When a state privacy law is in place, the effect of the compatible installed base on adoption is reduced. The interaction terms HospPrivLaw*InstalledCompHSA and HospPrivLaw*InstalledNonCompHSA are -0.009 and 0.008. In states with privacy laws, the installed base of non-compatible systems has no effect on adoption of compatible EMR.

The pattern is repeated for the adoption of non-compatible EMR systems in Table 6. Adoption of non-compatible systems by other area hospitals has a positive 0.019 (standard error of 0.004) effect, in contrast with the negative 0.005 (standard error of 0.002) effect produced by the adoption of compatible systems. State-level privacy laws narrow the gap, by increasing the effect of InstalledCompHSA by 0.004 and reducing the effect of InstalledNonCompHSA by 0.011. The coefficients of interest in the table are all significantly different from zero at the 5% level, with the exception of HospPrivLaw*InstalledCompHSA.

Correlated adoption for non-compatible EMR is most reasonable for purchases from the same vendor, since non-compatible systems are not necessarily inter-operable across vendors. To verify that this is indeed the force driving the results in Table 6, we repeat estimation focusing on the decision to invest in EMR from a single large vendor who has sometimes been described as having a closed loop proprietary system, Meditech. Results are shown in Table 7. The coefficient on InstalledNonCompHSA now increases to a highly statistically significant 0.021, and decreases in the presence of a privacy law (HospPrivLaw*InstalledNonCompHSA is -0.014, significant at 1%). There is a negative correlation with adoption of EMR from compatible vendors of -0.003, an effect that does not vary with privacy law.

The market control NumHospitalsHSA decreases adoption of both compatible and non-compatible EMR, while hospital size NofStaffedBeds increases adoption. The YearsOpened coefficient shows that older hospitals are more likely to have non-compatible and Meditech EMR systems (possibly older systems). The effect of age is reversed and no longer significant for adoption of compatible EMR.

The results in this section consider differences in the types of EMR software purchased by hospitals. Taken together, they provide additional support for the importance of network effects in adoption decisions, and the role of privacy laws in reducing those effects.

5 Instrumental Variable Estimates of Network Effects

As discussed in Section 4, the coefficient on InstalledHSA in Tables 2 to 4 should not be interpreted as a causal network effect. There are many reasons that a hospital's adoption of EMR could be correlated with the adoption of other local hospitals. For example, neighboring hospitals may share a taste for technology; there may be informational spill-overs between hospitals about EMR technology; or there may be a particularly adept software vendor working in that region.[11] We are interested, however, in estimating a causal network effect where we can trace the effect of one hospital's adoption on the adoption decisions of neighboring hospitals.

In this section, we use instrumental variables to identify a causal network effect for our installed base measure. We follow the work of Gowrisankaran and Stavins (2004) on identifying network effects in banking payments technology, and use the characteristics of other hospitals in the networks as instruments for the installed base measure InstalledHSA. To satisfy the exclusion restriction, the characteristics must have no direct impact on the EMR adoption decisions of other area hospitals. We use three instruments. The first is the average number of beds for other hospitals in the HSA. The second is the average number of years that the other hospitals in the HSA have been open. Last, we use the number of hospitals in that HSA that are owned by a parent company that owns hospitals in multiple HSA. We take the presence of a multi-region hospital as exogenous to any of the confounding factors discussed above. The disadvantage of these instruments is that they do not vary across time in a manner that would allow us to also identify time effects and state effects in a two-stage least squares.

The model is first estimated on the sample of hospitals in states with hospital privacy laws, using an IV-Probit model to address the endogeneity of InstalledHSA. These results are presented in Table 8, alongside the results of the basic Probit on the same hospital sample. As anticipated, the basic Probit estimate of InstalledHSA is found to be biased upward, as it greatly exceeds the IV estimate (0.041 versus 0.007). The latter causal estimate of the network effect is not only smaller, but is statistically insignificant. For states without hospital privacy coverage, the IV estimate for InstalledHSA remains large and statistically significant at the 10% level, though it is again substantially smaller than its Probit counterpart (0.088

[11]EMR software manufacturers are national in scope. However, there could be regional variation in the skill of their sales reps.

versus 0.059). Together, these results show that network effects do indeed promote EMR diffusion, but that the gains are virtually eliminated by state privacy laws.

In addition to these main effects on a hospital's own adoption, the IV-Probit tables present evidence that the instrumental variables are significant predictors of adoption at the HSA level, satisfying a necessary condition for their validity. The estimates regarding hospital age and size are consistent with earlier estimates. In contrast to Gowrisankaran and Stavins (2004)'s work, where multi-region banks were more likely to adopt, hospitals in our study that are part of a multiple-region hospital chain are actually less likely to adopt EMR. Conversations with industry professionals make us believe that this occurs for two reasons. First, multi-region hospitals are more likely individually to have an old, DOS-based server infrastructure which is harder to update and interface with EMR. Second, it is often the case that each of the hospitals in a multi-hospital chain has its own separate IT system, which makes it difficult and expensive for health managers to institute technology updates such as EMR that require system-wide compatibility.

6 Conclusion

In this paper, we study the impact of state health privacy laws on the diffusion of Electronic Medical Records. An Electronic Medical Record (EMR) allows medical providers to store, maintain and transfer patient information using computers rather than paper records. Electronic medical records could lead to positive or negative net network benefits for hospitals. The positive network benefit for a potential adopter is derived from the ability to transfer patient information between hospitals. There could, however, be a negative network effect if electronic records make it easier for patients to switch hospitals. Therefore, one hospital's EMR adoption decision may rest on the adoption decisions of other hospitals, but the direction of this effect is ambiguous. Concerns for privacy have led some states to enact laws governing the transfer of medical information. We exploit this artificial hindrance to the transfer of information to distinguish between these two competing network theories. We find that state privacy laws reduce the likelihood of correlated adoption in states where they are enacted. We interpret this to imply that there are positive network effects in the diffusion of EMR.

We present cross-sectional and panel evidence that the enactment of state privacy laws restricting the transfer of medical information from hospitals inhibits over 25 percent of the network effects which would have otherwise promoted a hospital's adoption of EMR. Further evidence from estimation using instrumental variables suggests that in states which have no privacy laws, one hospital's adoption increases the propensity of another hospital to adopt by 16 percent. In states with privacy laws, network effects are negligible. We also present evidence which suggests that there is a similar effect on vendor's choices over potential software incompatibility: A reduction of 33 percent of the network gains. We conclude that policymakers face sizable tradeoffs between offering strong privacy protection and promoting the network gains from EMR technology.

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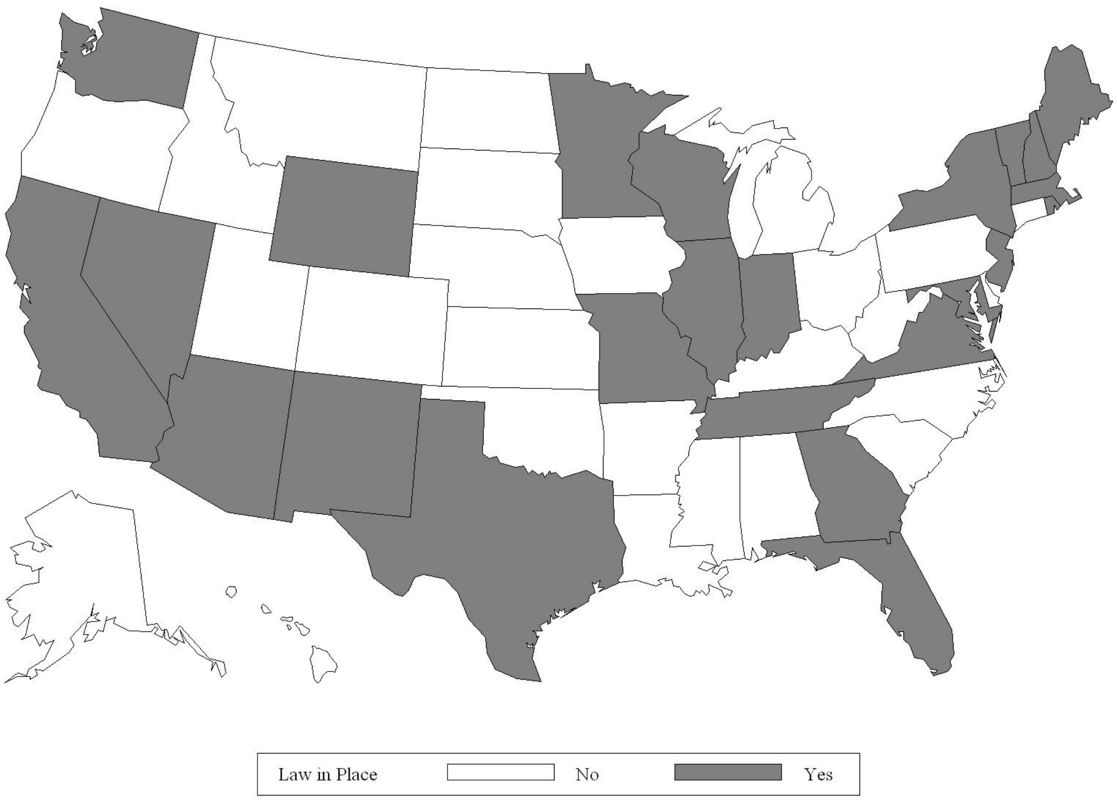

Figure 1: Map of States with Hospital Privacy Laws

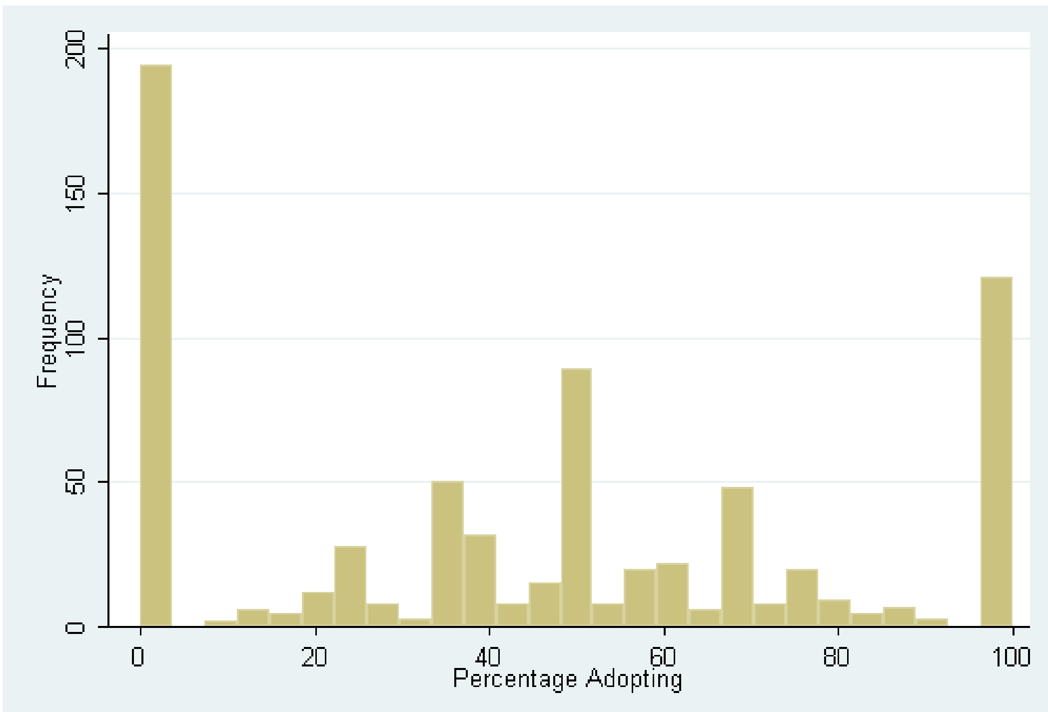

Figure 2: Histogram showing distribution of adoption in 2005 by HSA

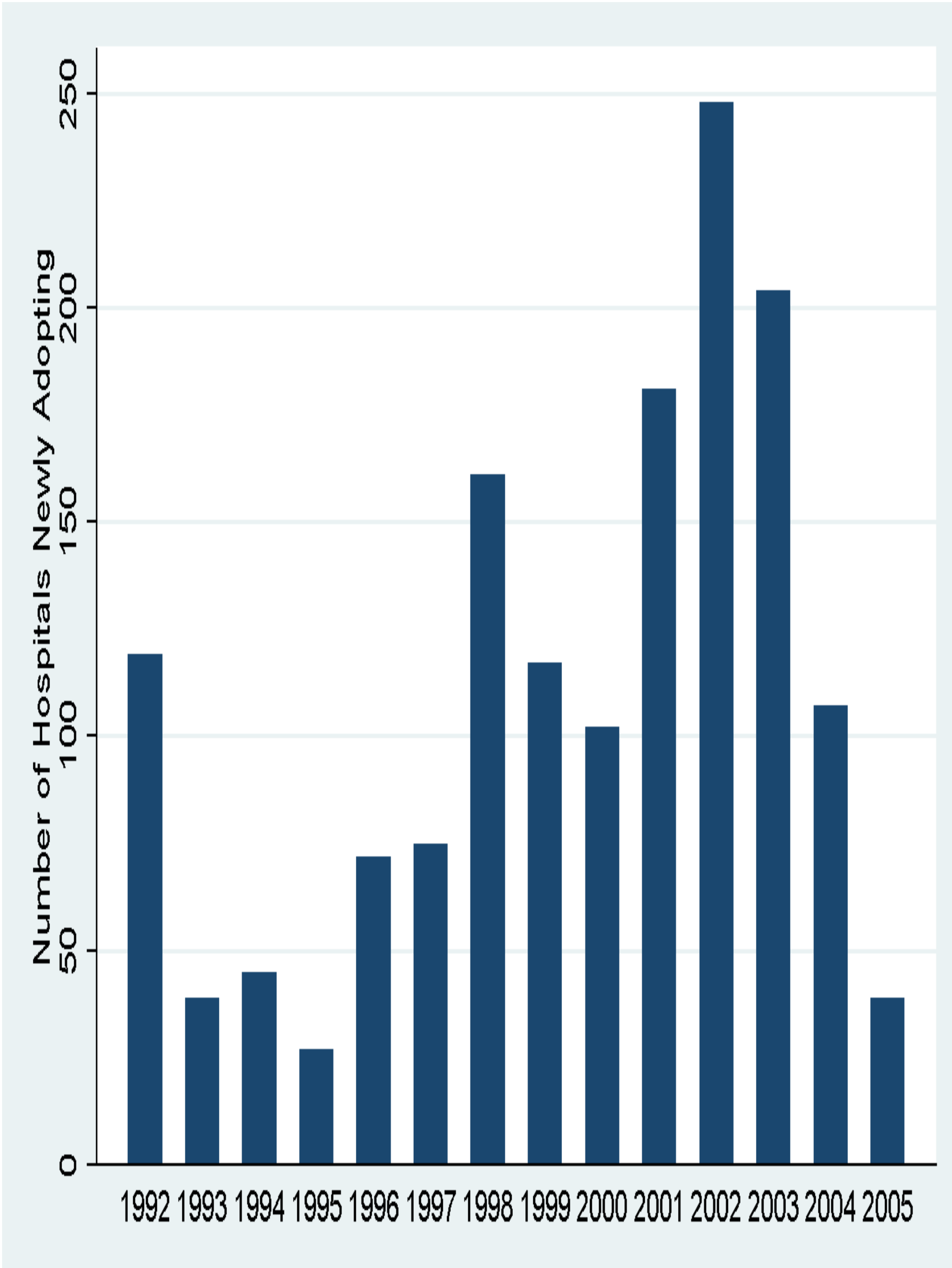

Figure 3: New Adoptions of EMR by Year

Observations are censored before 1992. Adoption in 1992 means before or during 1992.

Table 1: Summary of Variables

Description	Variable	Mean	Std. Dev.	N
Adopted Enterprise EMR by 2005	adopt	0.534	0.499	3996
Hospital Privacy Law enacted in State in 2005	HospPrivLaw	0.581	0.493	3996
Number of hospitals in HSA who have adopted EMR	InstalledHSA	8.67	13.68	3996
Number of hospitals in HSA	NumberofHospitals	16.84	24.57	3996
Number of staffed beds	NofStaffedBeds	181.791	166.414	3996
Years open	YearsOpened	29.701	34.011	3988
Percent of revenue from Managed care	Revmanagedcare	24.894	18.746	3030
Percent of revenue from Medicare	Revmedicare	37.572	13.107	3081
Percent of revenue from Medicaid	Revmedicaid	12.306	10.44	3030

Table 2: The effect of state privacy laws on hospital EMR adoption 1999-2005

	Robust	**Robust**	**Cluster State**
HospPrivLaw	0.021	0.021	0.021
	(0.015)	(0.018)	(0.029)
InstalledHSA	0.013***	0.015***	0.015***
	(0.002)	(0.003)	(0.003)
HospPrivLaw*InstalledHSA	-0.005**	-0.006**	-0.006*
	(0.002)	(0.003)	(0.003)
NofStaffedBeds	0.000**	0.000*	0.000**
	(0.000)	(0.000)	(0.000)
NumHospitalsHSA	-0.002***	-0.004***	-0.004***
	(0.000)	(0.001)	(0.001)
MultiHSAHosp	-0.021**	-0.031***	-0.031
	(0.009)	(0.011)	(0.022)
YearsOpened	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
Academic	0.022	0.030	0.030
	(0.017)	(0.020)	(0.023)
PopulationHSA		0.000***	0.000***
		(0.000)	(0.000)
IncomeMedianHSA		0.000	0.000
		(0.001)	(0.001)
RevMedicare		-0.002***	-0.002***
		(0.000)	(0.001)
RevMedicaid		-0.001	-0.001
		(0.001)	(0.001)
RevManagedCare		-0.001**	-0.001
		(0.000)	(0.001)
Year Dummies	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes
Observations	9943	7387	7387

Dependent Variable: Whether Hosp. has installed Enterprise EMR by that year
Linear Probability Model Estimates
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 3: The effect of state privacy laws on hospital EMR adoption 1999-2005

	Robust	**Robust**	**Cluster State**
HospPrivLaw	0.096	0.092	0.092
	(0.067)	(0.077)	(0.125)
InstalledHSA	0.055***	0.060***	0.060***
	(0.008)	(0.010)	(0.013)
HospPrivLaw*InstalledHSA	-0.018**	-0.021**	-0.021**
	(0.008)	(0.009)	(0.011)
NofStaffedBeds	0.000**	0.000**	0.000**
	(0.000)	(0.000)	(0.000)
NumHospitalsHSA	-0.011***	-0.018***	-0.018***
	(0.002)	(0.003)	(0.004)
MultiHSAHosp	-0.112***	-0.151***	-0.151
	(0.037)	(0.046)	(0.094)
YearsOpened	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)
Academic	0.075	0.108	0.108
	(0.064)	(0.073)	(0.089)
PopulationHSA		0.000***	0.000***
		(0.000)	(0.000)
IncomeMedianHSA		-0.001	-0.001
		(0.003)	(0.003)
RevMedicare		-0.008***	-0.008***
		(0.002)	(0.002)
RevMedicaid		-0.003	-0.003
		(0.002)	(0.004)
RevManagedCare		-0.003**	-0.003
		(0.001)	(0.002)
Year Dummies	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes
Observations	9943	7387	7387

Dependent Variable: Whether Hosp. has installed Enterprise EMR by that year
Probit Estimates
* p<0.10, ** p<0.05, *** p<0.01

Table 4: The effect of state privacy laws on hospital EMR adoption 1999-2005

	Standard	**Robust**	**Cluster HSA**
HospPrivLaw	0.133	0.131	0.131
	(0.101)	(0.114)	(0.189)
InstalledHSA	0.079***	0.085***	0.085***
	(0.012)	(0.013)	(0.017)
HospPrivLaw*InstalledHSA	-0.021**	-0.028**	-0.028**
	(0.010)	(0.012)	(0.013)
NofStaffedBeds	0.000***	0.000*	0.000**
	(0.000)	(0.000)	(0.000)
NumHospitalsHSA	-0.019***	-0.027***	-0.027***
	(0.003)	(0.004)	(0.005)
MultiHSAHosp	-0.146***	-0.213***	-0.213
	(0.055)	(0.068)	(0.140)
YearsOpened	0.004***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)
Academic	0.110	0.127	0.127
	(0.087)	(0.097)	(0.115)
PopulationHSA		0.000***	0.000***
		(0.000)	(0.000)
IncomeMedianHSA		-0.001	-0.001
		(0.004)	(0.004)
RevMedicare		-0.012***	-0.012***
		(0.003)	(0.003)
RevMedicaid		-0.004	-0.004
		(0.003)	(0.006)
RevManagedCare		-0.004**	-0.004
		(0.002)	(0.004)
Year Dummies	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes
Observations	9803	7325	7325

Dependent Variable: Whether Hosp. has installed Enterprise EMR by that year
Cox Proportional Hazard Model Estimates
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 5: The effect of state privacy laws on hospital adoption of compatible EMR systems 1999-2005

	Standard	**Robust**	**Cluster HSA**
HospPrivLaw	-0.003	-0.003	-0.005
	(0.011)	(0.011)	(0.012)
InstalledCompHSA	0.020***	0.020***	0.020***
	(0.002)	(0.003)	(0.005)
HospPrivLaw*InstalledCompHSA	-0.008***	-0.008**	-0.008
	(0.003)	(0.004)	(0.005)
InstalledNonCompHSA	-0.009**	-0.009**	-0.008*
	(0.004)	(0.004)	(0.004)
HospPrivLaw*InstalledNonCompHSA	0.008**	0.008**	0.007*
	(0.004)	(0.004)	(0.005)
NofStaffedBeds	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
NumHospitalsHSA	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
YearsOpened	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
MultiHSAHosp	0.002	0.002	0.002
	(0.006)	(0.006)	(0.008)
Academic	0.025**	0.025*	0.022
	(0.011)	(0.014)	(0.015)
Year Dummies	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes
Observations	9943	9943	9833

Dependent Variable: Whether Hosp. has installed Compatible Enterprise EMR by that year

Linear Probability Model Estimates

* p<0.10, ** p<0.05, *** p<0.01

Table 6: The effect of state privacy laws on hospital adoption of non-compatible EMR systems 1999-2005

	Standard	**Robust**	**Cluster HSA**
HospPrivLaw	0.022*	0.022**	0.024*
	(0.012)	(0.011)	(0.013)
InstalledCompHSA	-0.005**	-0.005**	-0.005**
	(0.002)	(0.002)	(0.003)
HospPrivLaw*InstalledCompHSA	0.004	0.004	0.004
	(0.003)	(0.003)	(0.003)
InstalledNonCompHSA	0.019***	0.019***	0.019***
	(0.004)	(0.004)	(0.004)
HospPrivLaw*InstalledNonCompHSA	-0.011***	-0.011***	-0.011***
	(0.004)	(0.004)	(0.004)
NofStaffedBeds	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
NumHospitalsHSA	-0.001***	-0.001***	-0.001**
	(0.000)	(0.000)	(0.001)
YearsOpened	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
MultiHSAHosp	-0.023***	-0.023***	-0.023***
	(0.006)	(0.006)	(0.007)
Academic	-0.004	-0.004	-0.003
	(0.012)	(0.012)	(0.012)
Year Dummies	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes
Observations	9943	9943	9833

Dependent Variable: Whether Hosp. has installed Non-Compatible Enterprise EMR by that year
Linear Probability Model Estimates
* p<0.10, ** p<0.05, *** p<0.01

Table 7: The effect of state privacy laws on hospital adoption of Meditech EMR systems 1999-2005

	Standard	**Robust**	**Cluster HSA**
HospPrivLaw	0.013	0.013	0.014
	(0.008)	(0.008)	(0.010)
InstalledCompHSA	-0.003*	-0.003**	-0.003*
	(0.002)	(0.001)	(0.002)
HospPrivLaw*InstalledCompHSA	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.002)
InstalledNonCompHSA	0.021***	0.021***	0.021***
	(0.003)	(0.004)	(0.004)
HospPrivLaw*InstallednonCompHSA	-0.014***	-0.014***	-0.014***
	(0.004)	(0.005)	(0.005)
NumHospitalsHSA	-0.000**	-0.000**	-0.000
	(0.000)	(0.000)	(0.000)
NofStaffedBeds	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
YearsOpened	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
MultiHSAHosp	-0.020***	-0.020***	-0.020***
	(0.004)	(0.004)	(0.005)
Academic	-0.026***	-0.026***	-0.026***
	(0.008)	(0.008)	(0.007)
Year Dummies	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes
Observations	9943	9943	9833

Dependent Variable: Whether Hosp. has installed Non-Compatible Meditech Enterprise EMR by that year
Linear Probability Model Estimates
* p<0.10, ** p<0.05, *** p<0.01

Table 8: Identifying the size of network effects for an HSA region by using instruments for the installed base in states with and without privacy laws

	No Privacy Law		Privacy Law	
	Probit	**IV Probit**	**Probit**	**IV Probit**
InstalledHSA	0.088***	0.059*	0.041***	0.007
	(0.012)	(0.031)	(0.005)	(0.008)
NofStaffedBeds	0.001***	0.001***	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
NumHospitalsHSA	-0.025***	-0.019***	-0.011***	-0.004**
	(0.004)	(0.007)	(0.002)	(0.002)
YearsOpened	0.002*	0.002*	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
MultiHSAHosp	-0.124*	-0.121*	-0.190***	-0.190***
	(0.065)	(0.065)	(0.055)	(0.054)
Academic	-0.041	-0.039	0.199**	0.237***
	(0.118)	(0.118)	(0.088)	(0.088)
RevManagedCare	-0.005***	-0.005***	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)
RevMedicare	-0.009***	-0.009***	-0.007***	-0.006***
	(0.003)	(0.003)	(0.002)	(0.002)
RevMedicaid	-0.002	-0.002	-0.003	-0.003
	(0.003)	(0.003)	(0.003)	(0.003)
IncomeMedianState	-0.017*	-0.018*	0.005	0.009
	(0.010)	(0.010)	(0.007)	(0.007)
Populationstate	0.000	0.0001	-0.000	-0.0001
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.197	-0.188	-0.739***	-0.823***
	(0.273)	(0.274)	(0.245)	(0.243)
		First Stage GMM regressions		
OtherHospMultiHSA		-0.055***		-0.406***
		(0.018)		(0.011)
OtherBedsHSA		-0.001***		-0.001***
		(0.000)		(0.000)
OtherHospAgesHSA		-0.003***		-0.008***
		(0.000)		(0.000)
NofStaffedBeds		-0.000		-0.000
		(0.000)		(0.000)
NumHospitalsHSA		0.447***		0.791***
		(0.012)		(0.012)
YearsOpened		-0.001		0.003*
		(0.001)		(0.002)
MultiHSAHosp		0.049		0.539***
		(0.094)		(0.133)
Academic		-0.054		1.342***
		(0.170)		(0.224)
RevManagedCare		0.002		-0.000
		(0.003)		(0.004)
RevMedicare		0.010***		0.006
		(0.004)		(0.005)
RevMedicaid		0.003		0.008
		(0.005)		(0.006)
IncomeMedianState		0.007		0.066***
		(0.014)		(0.019)
Populationstate		0.001***		0.000
		(0.000)		(0.000)
Observations	3119	3119	4268	4268

Dependent Variable: Whether Hosp. has installed Enterprise EMR
Probit Estimates
Instruments are number of multiregion hospitals, age of other hospitals, number of beds in other hospitals in local area
* p<0.10, ** p<0.05, *** p<0.01