Privacy Protection and Technology Diffusion: The case of Electronic Medical Records

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Abstract

Some policymakers argue that consumers need legal protection of their privacy before they adopt interactive technologies. Others argue that privacy regulations impose costs that deter adoption. We contribute to this growing debate by quantifying the effect of state privacy regulation in the diffusion of Electronic Medical Record technology (EMR). EMR allows medical providers to store and exchange patient information using computers rather than paper records. Hospitals may not adopt EMR if patients feel their privacy is not safeguarded by regulation. Alternatively, privacy protection may inhibit adoption if hospitals cannot benefit from exchanging patient information with each other. In the US, state medical privacy laws covering hospitals' ability to disclose patient information vary across time and across states. We explore how this variation affects the network benefits that hospitals receive from adopting EMR. Our results suggest that this inhibition of network benefits reduces hospital adoption by 25 percent. We find similar evidence using variation in state privacy tastes proxied for by signups to the "Do Not Call" list to control for the endogeneity of state laws. We also show that state privacy regulation is associated with a 33 percent reduction in software compatibility between neighboring hospitals.

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1 Introduction

In the growing policy debate surrounding electronic privacy protection, two schools of thought have emerged. The first argues that explicit privacy protection promotes the use of information technology by reassuring potential adopters that their data will be safe. The second holds that such protection inhibits technology diffusion by imposing costs upon the exchange of information. This debate has important economic implications because many new technologies involve information exchange, and economic growth relies on their diffusion. We contribute to the debate by providing empirical evidence quantifying the effect of state privacy protection on the diffusion of Electronic Medical Records (EMR). EMR allows medical providers to store and exchange medical information using computers rather than paper. Although the technology has been available since the 1970s, only 50 percent of hospitals had adopted a basic EMR system by 2005.

This slow diffusion of EMR has attracted attention from both sides of the privacy debate, because widespread adoption of EMR could reduce America's $1.9 trillion annual health care bill by $81 billion through increased efficiency and safety.[1] There is evidence, however, that privacy regulation may be inhibiting the roll-out of EMR. For example, commentators have speculated that costly state-mandated privacy filters partially explain the collapse of the Santa Barbara County Care [Health] Data Exchange (SBCCDE) in 2007.[2] Such worries have prompted the federal government to fund initiatives such as the 3-year $17.3 million "Health Information Security and Privacy Collaboration."

These federal initiatives aim to qualitatively document states', hospitals' and patients' concerns about EMR privacy regulation. By contrast, we aim to quantify empirically how medical privacy regulation affects the diffusion of EMR. In particular, we quantify how a

[1] Hillestad, Bigelow, Bower, Girosi, Meili, Scoville, and Taylor (2005)

[2] "Privacy, funding doubts shutter Calif. RHIO," Government Health IT, March 8, 2007. SBCCDE was formed in 1999 to exchange health information between health providers in Santa Barbara.

hospital's decision to adopt EMR is affected by whether state privacy regulation restricts a hospital's ability to disclose information. First, we document that state privacy regulation inhibits EMR's network benefit. The network benefit of EMR comes from hospitals being able to exchange information with each other about patient histories. This is particularly important for patients with chronic conditions who wish to see a new specialist. It is also important for emergency room patients whose records are stored elsewhere.[3] We use cross-sectional and time-series variation in state privacy laws to document that hospitals in states with privacy regulation are less responsive to adoption by hospitals in their local health service area. Our estimates suggest that privacy laws on average restrict 25 to 40 percent of these positive network effects inherent in the diffusion of Electronic Medical Records. This implies that hospitals in states with privacy laws are roughly 25 percent less likely to adopt.

We confirm this estimate by controlling for the endogeneity of other hospitals' adoption decisions. We use the characteristics of other hospitals in the local area as instrumental variables for the installed base.[4] Our estimates for how the size of the installed base affects hospital adoption decisions vary by whether the state has privacy protection. 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, the installed base has a tiny and insignificant k0.7 percent effect on EMR adoption in states with medical privacy laws.

Next, after controlling for the endogeneity of the installed base, we control for unobserved influences such as patient wealth that could affect both state privacy protection and EMR adoption. To control for this potential endogeneity, we use tastes for privacy as an exogenous shifter for state privacy regulation. We proxy this variation in tastes by using the number of sign-ups for the "Do Not Call" list. Our instrumental variable estimates indicate that state

[3]Brailer (2005)

[4]This is similar to Gowrisankaran and Stavins (2004).

privacy regulation reduces adoption by 29.3%, which is in the same range as previous estimates. We also investigate whether privacy protection not only leads to lower adoption but also to inefficient adoption. We find evidence that state privacy regulation makes hospitals 33 percent less likely to choose software that is easily compatible with neighboring hospitals. If state privacy regulations cause a lack of compatibility between systems, this could hinder the government's goal of having a national health IT network by 2014.

This government goal makes our results particularly timely. It is estimated[5] that a national IT network will cost the US $156 billion in capital investment over 5 years. This large sum makes it crucial that future privacy protection recognizes the tradeoffs between technology diffusion and privacy. [6] Politicians find EMR's unusual combination of "Saving Lives and Saving Money"[7] attractive but there has been little rigorous measurement till now of how privacy regulations affect EMR diffusion.

These results illuminate a broader debate about the potential costs and benefits of privacy protection for all interactive technologies. This debate has grown in importance with the increase in the number of interactive technologies which allow companies and individuals to exchange information online. Our results support earlier work by scholars such Posner (1981) and Varian (1997), which suggests that there are efficiency costs to privacy protection that need to be recognized by policy makers.

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. Section 4 uses cross-sectional and time-series variation in privacy regulation to document a lack of evidence of network benefits in states with privacy laws. In Section 5, we use instrumental variables to provide evidence on the relative size of this network benefit. We report results for the

[5] Kaushal, Blumenthal, Poon, Jha, Franz, Middleton, Glaser, Kuperman, Christino, Fernandopulle, Newhouse, and Bates (2005)

[6] As Representative Edward J. Markey has emphasized: "There is going to be much more emphasis placed upon privacy protections [for Health IT] in the next two years than we have seen in the last 12 years."

[7] Former House Speaker Newt Gingrich entitled his book on EMR "Saving Lives and Saving Money."

overall level effect of privacy laws on adoption in Section 6. Last, in Section 7 we explore the compatibility of neighboring hospitals' EMR systems.

2 The Legal and Institutional Context

The extent to which privacy protection inhibits or promote the adoption of new technologies is a contentious issue. There is no doubt, however, that people worry that EMR may compromise their privacy. A Harris Interactive poll in February 2005 found that 70 percent of people surveyed expressed concern about EMR privacy. This is unsurprising given that electronic records are easier than paper files to duplicate and distribute in bulk and that the security of networked computers can be breached remotely. Anecdotal evidence also suggests that privacy concerns about electronic records may be justified. For example, 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.[8] Even if records do not leave the building, privacy is still a concern. This was demonstrated when NewYork-Presbyterian Hospital employees made 1,500 unauthorized attempts to access the patient records of a famous local athlete.[9]

These consumer privacy concerns have led states to enact their own laws to regulate the transfer of health information. However, states have imposed substantially different privacy regulations. These regulations vary in how much they limit 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. So much variation persists that some observers characterize privacy protection in the US as a patchwork of state policies and call for the creation of uniform standards. Our main source for current state privacy regulation is the Pritts, Choy, Emmart, and Hustead (2002) survey of state health privacy statutes,

[8]ConsumerReports.org, 2006

[9]New York Times, Health Hazard: Computers Spilling Your History December 3rd 2006

produced by the Health Privacy Project at Georgetown University. They determine state privacy laws by examining state statutes governing medical privacy. This approach excludes refinements to privacy law stemming from case law or administrative law. We combined data from the 2002 publication with two earlier parallel surveys of state privacy laws (Pritts, Goldman, Hudson, Berenson, and Hadley (1999) and Gostin, Lazzarini, and Flaherty (1996)) to identify historical changes in privacy statutes.

Only some state privacy statutes cover hospitals. Our explanatory variable, HospPrivLaw, indicates whether a hospital is located in a state with a privacy law covering hospitals. Hospitals in these states have explicit statutory requirements to protect the confidentiality of patient medical information, and are restricted in their ability 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. We simply separate states by whether or not Health Privacy Project indicates they have state privacy regulations which cover hospitals; we do not attempt to calibrate the substantial variations in the strength and content of these laws across states. Therefore estimates for HospPrivLaw should be interpreted as an "average effect" of hospitals being covered by a complex array of state law privacy provisions.

This paper uses changes in state privacy regulation across time and states to assess the impact of privacy standards on hospital decisions to adopt EMR. Map 1 shows that by 2002 about half of the states in the US had laws that cover hospital behavior. 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 and numbers of hospitals. 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 also affect adoption, we include them as controls in our robustness checks. Naturally, permanent differences in these characteristics, observed or unobserved, will be absorbed in the state fixed effects.

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 5). During that period, we observe 19 changes in laws: 4 changes to increase privacy protection and 15 to decrease it. Map 2's display of privacy regulations in 1996 shows the difference compared to the 2002 privacy laws in Map 1.

Another significant change between 1996 and 2005 is the introduction of the Federal Privacy Rule in 2003. The rule arose from the requirement in the 1996 HIPAA law that the federal government design and implement rules to address the use and disclosure of individual health information.[10] After Congress failed to pass a rule by 1999, the Department of Health and Human Services proposed this Rule in 1999 and it became law in 2002.[11] Although HIPAA provides a uniform standard of federal privacy protection, actual standards continued to vary from state to state. Federal law focuses on requiring health providers to document how they use health information rather than inhibiting their ability to do so. For example, under HIPAA, consumers can request medical records but a health provider can refuse to provide it as long as they justify why. HIPAA is weakened by its dependence on consumer complaints to initiate actions. This leads to lax enforcement. We control for HIPAA in two ways: first, in our panel estimates, HIPAA's effect on the level of adoption is captured by a series of national-level time dummies; second we repeated our estimation separately for before and after the introduction of HIPAA. Reassuringly, our results did not qualitatively change. However, the most correct interpretation of our estimates is that they measure the

[10] Sections 261 through 264

[11] 45 CFR Part 160 and Part 164

effect of state privacy protection above and beyond existing federal regulation.

3 Health IT Data and Institutional Background

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 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 US 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. This means that HIMSS 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. 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.[12]

We measure EMR adoption by whether a hospital has installed or is installing an "Enterprise EMR" system. Figure 3 displays a screen shot for a typical system. This software is a 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 contracts for future systems. We define a hospital

[12]Results using cross-sectional variation from 2005 including these 537 hospitals are similar.

as an adopter if its EMR status 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.[13]

Though our dependent variable is discrete, we are interested in measuring the underlying costs and benefits of EMR. The benefit, to hospitals of adopting EMR are improved quality of patient care which in turn boosts demand for a hospital, and lower administrative costs. Both increased demand and lower costs should increase profits. Improved patient care may also directly enter into the hospital objective function. As Dafny (2005) and others point out, with over 80 percent of hospitals categorized as non-profit or government owned, it may be more appropriate to think of hospitals as maximizing an objective function that increases separately with patient care quality and with profits. In either case it seems appropriate that the benefits of an EMR system are something that a hospital will trade off against its costs.

These potential costs include the upfront costs of software and hardware installation, training and ongoing maintenance. Healthcare executives also complain about another obstacle to EMR adoption: overcoming resistance from physicians. Physicians may not perceive any personal benefits from EMR, and may instead feel that computerization increases their work time and accountability, while hampering their interactions with patients (Groopman (2007)).[14]

We can decompose the benefit of improved patient care promised by EMR technology into a stand-alone and a network benefit. The stand-alone benefit includes shorter hospital stays prompted by better-coordinated care within the hospital, less nursing time spent on administrative tasks and better use of medications in hospitals. We control for these hospital-

[13] Alternative specifications excluding the 185 observations where adoption is not yet completed have similar results.

[14] For example, Brian Patty, Medical Director for Information Systems at Fairview Ridges Hospital, reports a frequent physician complaint about EMR as being "I am not a robot. This computer is making me into a robot practicing cookbook medicine" (Baldwin (2005)).

specific variations in stand-alone benefits by using controls, such as the number of fully-staffed beds and the number of years open. Table 1 describes the main variables we include in our regressions.

The promise of being able to use EMR to exchange health records with other hospitals may also improve the quality of patient care. In particular, hospitals can provide better care to patients who have chronic conditions and are seeing a new specialist or emergency room situations where a patient is not able to communicate a medical history or allergies.[15] We capture this network benefit by InstalledHSA; the number of other hospitals in the local health service area who have adopted EMR. We use the 815 Health Service Areas as our definition of the local health market area. These were 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).[16]

The number of hospitals in the installed base is only a proxy for the ability to transfer EMR information. Although multiple-hospital adoption of EMR is a necessary condition for electronic information transfer, it is by no means sufficient; there also has to be cooperation and coordination across hospitals. The most formal mechanism for linking patient information is through a local regional health information organization (RHIO). A 2006 eHealth Initiative survey (Covich Bordenick, Marchibroda, and Welebob (2006)) identified over 165 active Health Information Exchange initiatives in the US, of which 45 were being implemented and 26 were fully operational. Over 20 percent of survey respondents reported that they were currently transmitting health information electronically. Given this long process of implementation, it is likely that any installed base measure captures the promise of future health exchange as well as the current ability to do so.

Figures 4 and 5 illustrate the dispersion of EMR adoption over time and across health

[15] Brailer (2005)

[16] 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.

service areas. In our first empirical results, we exploit this variation in adoption over time and across regions.

4 Panel Estimation and Results

4.1 Panel Data

We start by using panel data to explore how changes in privacy regulation over time affect the role that the installed base plays in hospital EMR adoption. We capture this by the interaction between a hospital privacy law and the installed base HospPrivLaw*InstalledHSA.

In the panel data setting, InstalledHSA is a count of the other hospitals who have adopted EMR prior to that year in that Health Service Area. Though we exclude from our observations hospitals who have previously adopted EMR, we include this adoption in InstalledHSA. Conversations with industry specialists reassure us that once adopted, divestiture of an EMR system is rare. We assume that hospitals only consider past adoption and do not use forecasts of future adoption in their decisions. The dependent variable in these panel data regressions is whether a hospital has adopted an Enterprise EMR system. The data for each hospital spans 1999, 2002, and 2005. These years match our data on the status of privacy laws.

Table 2 presents the results of a simple linear probability model. All specifications include a 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 but is not significant. 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 positive correlation with another hospital's adoption.

The InstalledHSA coefficient is a measure of the correlation between one hospital's adoption and adoption by other hospitals in that area. It is tempting to interpret this positive relationship as evidence of network effects: hospitals are more likely to adopt if other hospitals have adopted and make available more medical records for potential patients. However, it is likely that the measured coefficient overstates the extent of network effects. This upwards bias stems from at least three alternative explanations of this positive relationship: (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. Therefore, Installed HSA 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. We revisit the issue below, and provide instrumental variable estimates of the network effects in Section 5.

That said, neither the informational spillovers story nor the medical arms race story predicts the observed negative interaction between privacy laws and other hospitals' adoption. In particular, any additive shock to EMR profitability that is common to all hospitals in a given market but randomly assigned across markets would fail to predict the negative interaction term. Therefore, the observed pattern, which combines a positive InstalledHSA estimate and a negative HospPrivLaw*InstalledHSA estimate, provides stronger evidence for network effects than correlated adoption does alone.

The regressions in Table 2 include three additional covariates that capture 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. MultiHSAHosp is an indicator variable for whether a hospital is part of a chain of hospitals which span multiple networks. Hospitals that are part of a multiple-region hospital chain are less likely to adopt EMR. Industry professionals have told us that this is because multi-region hospitals are more likely to have an old, DOS-based server infrastructure, which is harder to update and interface with EMR.

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, and that therefore the coefficient should not be interpreted as a structural parameter, 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. Though our parameters are not structural and should not be interpreted a causal effect of market structure our results echo research by IO economists such as Lenzo (2005), Hamilton and McManus (2005) and Schmidt-Dengler (2006) who have found competitive structure affects health care technology adoption.

To insure against correlation caused by state-specific trends which cannot be captured by our series of time and state dummies, 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 for the state to account for arbitrary correlation within a state. Consistent with the findings of Baker and Phibbs (2002), Fonkych and Taylor

(2005) and Acemoglu and Finkelstein (2006) 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 influence of the main variables is qualitatively unchanged: HospPrivLaw has a positive and insignificant coefficient, InstalledHSA is positive and highly significant, and HospPrivLaw*InstalledHSA is negative, significant, and about 40% of the size of the InstalledHSA coefficient. The estimates for hospital size, age, and number of hospitals in the local market are not sensitive to the inclusion of additional regressors.

We interpret HospPrivLaw*InstalledHSA as capturing the extent to which state privacy laws reduce a hospital's benefits from an installed base of other hospitals to exchange health information with. 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 a hospital's own adoption. The most compelling alternative interpretation we have come across is that rural states have lower population densities, reducing the value of transferring information. A more rural and consequently more conservative state is 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, and by noting that density is uncorrelated with privacy regulation.

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 (Ai and Norton (2003)). 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 advantages of more flexibly fitting the underlying hazard rate and of 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.[17]

In addition to offering substantive evidence about the role of privacy in the diffusion of technology, these findings also contribute to a growing literature on the identification of network effects. Our estimates suggest that hospitals react positively to other hospitals' adoption when information can flow freely and is not restricted by state privacy laws. We interpret this positive correlation as evidence of network effects. Classically, economists such as Farrell and Saloner (1985) and Katz and Shapiro (1985) have worried than network effects can lead to suboptimal outcomes due to coordination failure. Here, we show that inhibiting network effects through restricting medical information flow can reduce a hospital's likelihood of adoption. One reason that identification of geographic network effects is challenging is that there may be unobservable regional differences in tastes and institutions across networks which could also explain correlated adoption decisions. The previous literature on identifying network effects, such as Tucker (2006) and (Gowrisankaran and Stavins 2004), has focused on finding exogenous shifters of adoption to study the causal effect of one agent's adoption

[17]As discussed by Ai and Norton (2003) the interpretation of interaction terms in non-linear models is problematic. To confirm our findings we also estimated the interaction in the Probit model using the formula in Ai and Norton (2003). The interaction term was negative and significant at the 10 percent level.

on another.[18] 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 used before as a means of identifying network effects, despite being the closest approach to identifying network effects based on actual usage of the network.

5 Endogeneity of the Installed Base

Section 4 emphasized that the coefficient on InstalledHSA in Tables 2 to 4 should not be interpreted as a causal network effect. There are many alternative 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 for a national firm in that region. 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 Gowrisankaran and Stavins (2004), who identify network effects in banking payments technology and use the characteristics of other hospitals in the networks as instruments for the installed base measure InstalledHSA. For the estimates to be valid, the exclusion restriction must hold that the characteristics of neighboring hospitals must have no direct impact on the EMR adoption decisions. 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 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

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

HSAs. We take whether a neighboring hospital has branches across HSAs as exogenous to the confounding factors discussed above. The disadvantage of these instruments is that they do not vary across time in a way that would allow us to identify time effects and state effects.

We first obtain estimates for hospitals in states without hospital privacy laws, using a GMM probit with instrumental variables model to address the endogeneity of InstalledHSA. These results are presented in Table 5, alongside the results of the basic Probit on the same hospital sample. The first stage regressions presented in 5 suggests that the instrumental variables are significant predictors of adoption at the HSA level, satisfying a necessary condition for their validity. The first stage estimates regarding hospital age, and multi-region and size are consistent with earlier estimates.

As anticipated, the basic Probit estimate of InstalledHSA is biased upward, as the IV estimate is substantially smaller (0.088 versus 0.059), but still large and statistically significant at the 10% level. This implies that network benefits are present across hospitals in a local area for EMR adoption, but it does not isolate information transfer as the source of these network effects. Turning to states with hospital privacy coverage, we again find evidence of upward bias in the basic Probit. The IV estimate of InstalledHSA is reduced from 0.041 to a negligible and statistical insignificant 0.007 (standard error of 0.008). Together, these results show that network effects do indeed promote EMR diffusion, but that the gains are virtually eliminated by state privacy laws. Furthermore, the constant terms are more negative and significant in privacy law states, indicating that privacy laws are associated with lower overall adoption rates, conditional on observable factors. Given that network externalities can lead to multiple equilibria, the coefficient estimate for InstalledHSA should be interpreted as an equilibrium, rather than a structural effect, as in (Gowrisankaran and Stavins (2004)).

6 Effect of State Privacy Laws on Adoption

In our initial results we focused on the interaction between the InstalledHSA and HospPrivLaw because taken independently these variables were likely to be endogenous. The previous section addressed the endogeneity of the installed base. In this section we address the endogeneity of state privacy laws. The concern is that these laws could be correlated with unobserved state characteristics that may also be correlated with the profitability of EMR technology to the hospital. For example, the enactment of privacy laws could be positively correlated with the underlying sophistication, lobbying force and associated financial resources of patients. And these unobserved influences on the legislative process could also affect technology adoption.

To deal with this endogeneity we use a GMM probit model with instrumental variables. An ideal instrument would be something which shifted state privacy laws but was not correlated to unobservable influences of a hospital's technology adoption decision. We use as an exogenous shifter tastes for privacy as proxied for by the proportion of people in state signed up for the national "Do Not Call" registry.[19] Individuals who sign up for the national "Do Not Call" registry do not want tele-marketers to contact them at home, and may have stronger tastes for privacy. Varian, Wallenberg, and Woroch (2005) describes the data summary statistics about this data. It seems likely that variation in signups to the do not call list are unrelated to hospital demand or returns to technology investment in healthcare, and should have no independent effect on EMR adoption.

Table 6 reports results from GMM Probit estimates of hospital EMR adoption, treating privacy laws as endogenous.[20] Since the instrument is time-invariant and collected from 2002, we use a cross-sectional sample of all EMR adoption in 2002. The first stage of the GMM

[19]We thank Hal Varian for this idea. We thank Fredrik Wallenberg for giving us the data,

[20]Since the estimation of binary endogenous regressor can be problematic in a discrete choice model we also tried a linear probability model specification. The results were qualitatively similar. We also estimated a regression where we put our instrument directly into the regression and obtained similar results.

regressions shows that, reassuringly, the proportion of sign-ups to the do not call list was a strong and significant predictor of state privacy laws. The level effect of the HospPrivLaw goes from positive (0.066) to negative (-1.100*) and significant at the 10% level. A calculation of the marginal effects suggest that a state privacy law reduces a hospitals propensity to adopt EMR by 29%. [21]

7 Adoption of Compatible Systems

These previous results document that state privacy regulations affect current levels of EMR adoption. However, state privacy regulation could have a longer lasting impact if hospitals who could potentially exchange information adopt non-compatible systems. When hospitals buy EMR systems from different vendors, these systems may be incompatible if they use different data formats. Therefore, sharing information electronically becomes cumbersome and costly if two hospitals' EMR software is not inter-operable.

Choices over inter-operability may be affected by state privacy laws. In this paper we focus on whether a hospital located in an area where many other hospitals have chosen inter-operable systems is more likely to also choose an inter-operable system if there are no privacy laws. The underlying idea is that 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. Correspondingly, privacy laws may imply that hospitals will be less deterred from choosing a non-compatible system even if other nearby hospitals have compatible systems. While common unobservable factors can provide an alternative explanation for correlated adoption by vendor type, they cannot explain differences by privacy statute.

[21] We tried specifications which instrument for InstalledHSA and HospPrivLaw*InstalledHSA as well using a pairwise interactions between the instruments in table 5 and the proportion of people signed up to the do not call list. The results for InstalledHSA and HospPrivLaw*InstalledHSA were qualitatively similar to previous results but not significant at conventional levels.

The HIMSS database tells us the vendor a hospital purchased their EMR system from, but does not supply information about the compatibility of that software. We gathered this information from the IHE project, which promotes the coordinated use of established standards such as DICOM and HL7 to record information about patient care. It listed seven vendors who had made explicit integration statements. They were Cerner Corporation, GE Healthcare, IDX, McKesson Provider Technologies, Philips Medical Systems and Siemens Medical Solutions.[22] We categorized hospital technology purchases into compatible and non-compatible systems.

We estimated three separate specifications: The decision to adopt compatible technology; the decision to adopt incompatible technology; and the decision to adopt one largely closed loop proprietary system.[23] First, Table 7 presents estimates for 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). When a state privacy law is in place, the effect of the compatible installed base on adoption is reduced. The coefficient on InstalledNonCompHSA, the installed base of non-compatible systems, is negative 0.009 (significant at 5% or lower). This suggests that when hospitals can exchange information freely they are less likely to choose a compatible system when other hospitals have installed incompatible systems. However, this effect is almost entirely canceled out in states which do have privacy laws as the interaction terms HospPrivLaw*InstalledNonCompHSA is -0.009.

This pattern is repeated for the adoption of non-compatible EMR systems in Table 8. The coefficients of interest in the table are all significantly different from zero at the 5% level, with the exception of HospPrivLaw*InstalledCompHSA. Adoption of non-compatible systems by other area hospitals has a positive 0.019 (standard error of 0.004) effect. When a state has a privacy law this effect is reduced by 0.011. An installed base of compatible

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

[23] We present estimates for each of these specifications separately. We have also estimated a nested model which produces similar results.

systems, however deters adoption of a non-compatible systems, but again in states with privacy laws the point estimates suggest that this deterrence effect is canceled out.

Correlated between adoption decisions for non-compatible EMR is most reasonable for purchases from the same vendor, since non-compatible systems are not necessarily inter-operable across vendors. We check that this is the process underlying Table 8 by focusing on the decision to invest in EMR from a single large vendor named Meditech that has been described as having a closed-loop proprietary system. Results are shown in Table 9. The coefficient on InstalledNonCompHSA now increases to a highly statistically significant 0.021, and decreases if there is privacy regulation (HospPrivLaw*InstalledNonCompHSA is -0.014, significant at 1%). This suggests that privacy laws reduce choices for compatibility in this instance by over two thirds. There is a negative correlation with adoption of EMR from compatible vendors of -0.003, an effect that does not vary with privacy law.

This suggests that the privacy regime drives the types of EMR systems that hospitals purchase. Therefore, current state privacy regulations both deters hospitals from adopting an EMR system and also deters hospitals from choosing inter-operable systems. This could have costly implications in the future for regional health data exchanges.

8 Conclusion

In this paper, we present evidence from panel data 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 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 6 percent. In states with privacy laws, network effects are negligible. Variation in tastes for privacy across states as measured by sign-ups to the "Do Not Call" list is a potential source of variation state privacy laws. We use this to measure how state privacy statutes affects adoption decisions. We find confirmation that privacy regulation over hospital medical disclosure is inhibiting adoption by 25 percent. Our estimates also suggest that there is a 33 percent reduction in software compatibility in states with privacy regulations. This suggests there could be a longer term impact from state privacy regulation when it comes to future integration efforts.

Our evidence suggests that though there may be many reasons for states to restrict medical providers' ability to disclose information, there are potential losses in terms of the speed and compatibility of EMR adoption choices. It should be emphasized that our research explores the effect on adoption of the subset of state privacy statutes which govern in the disclosure of information by hospitals. There are plenty of other state privacy regulations relevant to the establishment of a national health information network which we do not address. The other aspects are: patient access to and ownership of information, such as requirements to give records to patients upon request, government power to compel collection and disclosure for contagious diseases, access for people in civil litigation (malpractice suits) and for government law enforcement agencies for civil or criminal procedures, quality review and insurance access, and data use for research. We leave this, and further work on the effect of state privacy laws on the adoption decisions of ambulatory facilities, laboratories and physicians, to future research.

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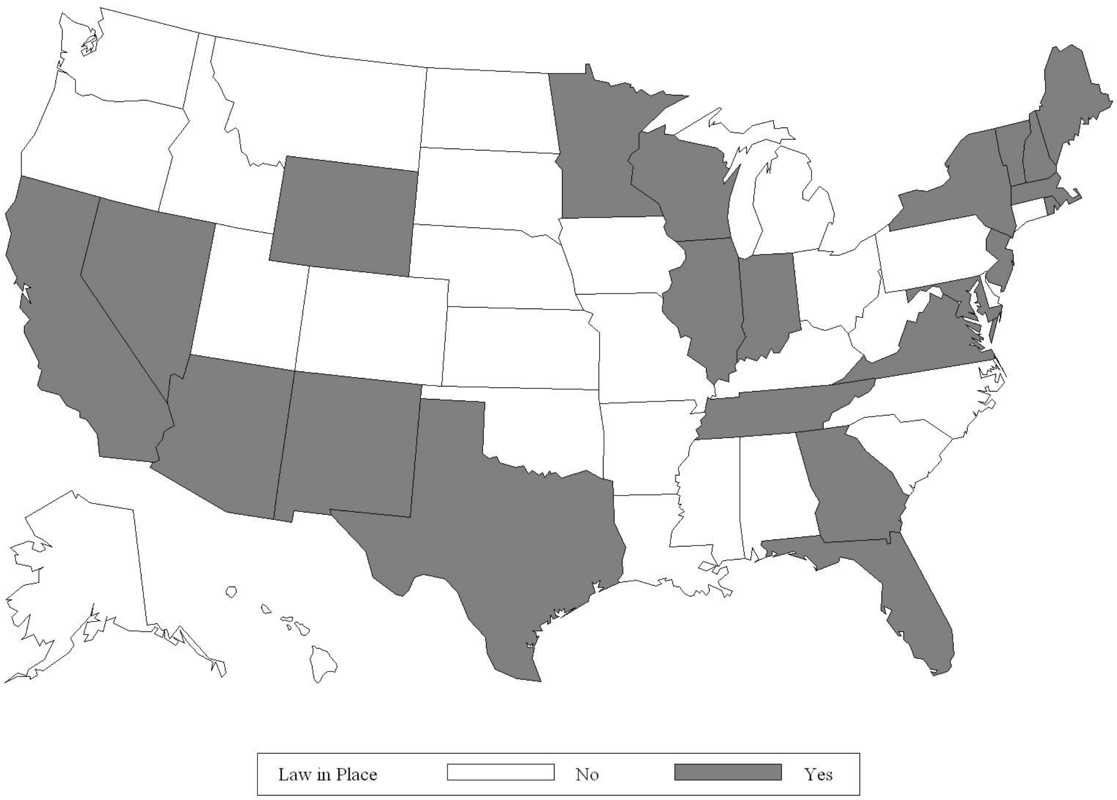

Figure 1: Map of States with Hospital Privacy Laws: 2002

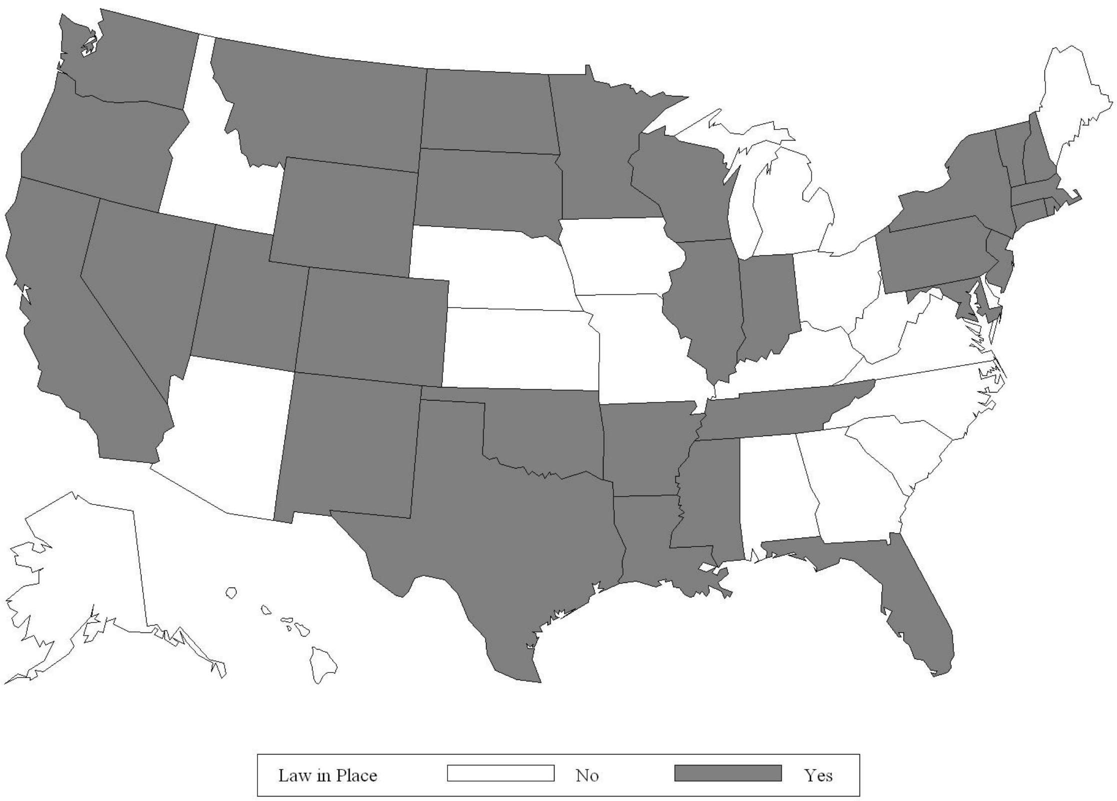

Figure 2: Map of States with Hospital Privacy Laws: 1996

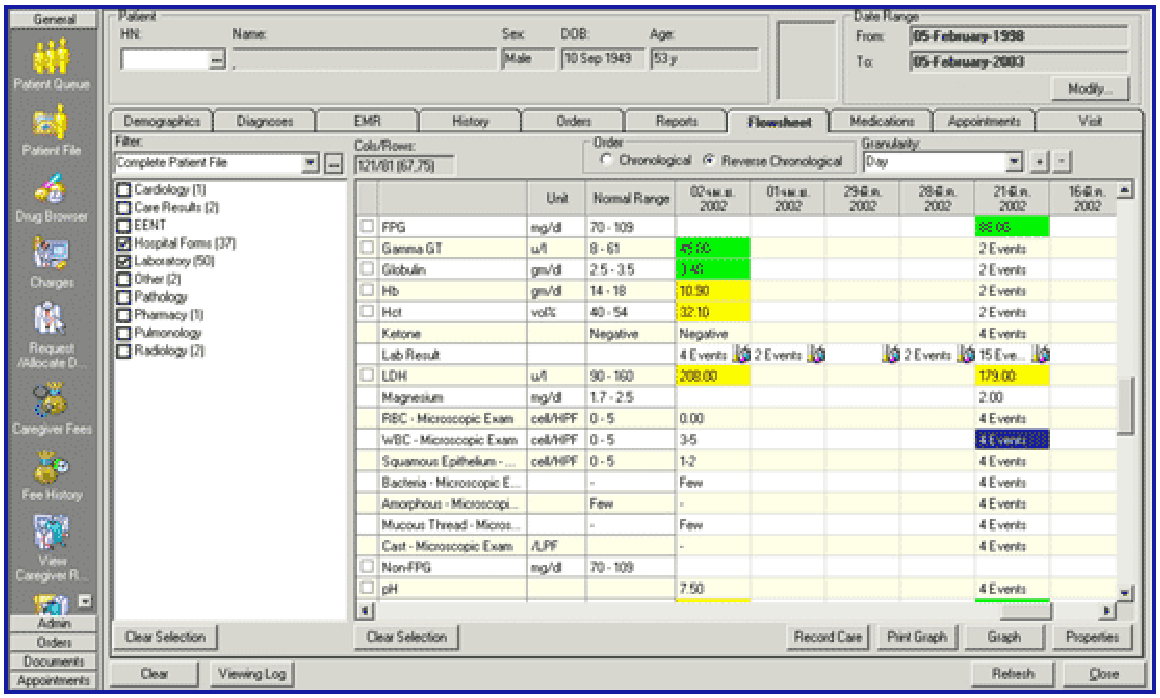

Figure 3: Screen Capture

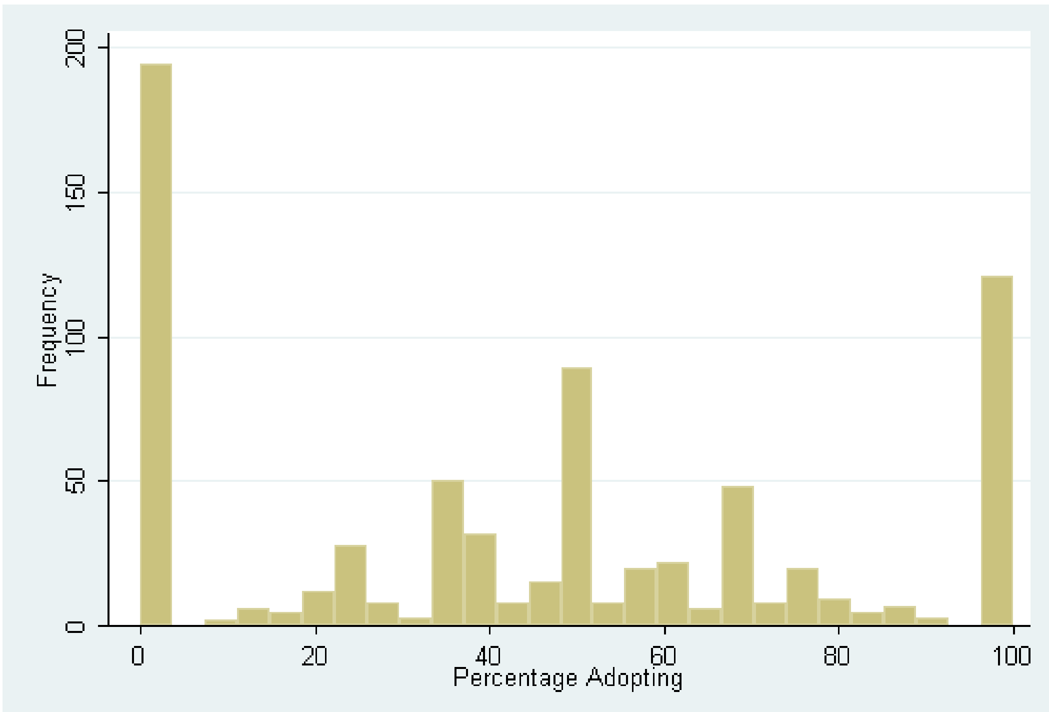

Figure 4: Histogram showing distribution of adoption in 2005 by HSA

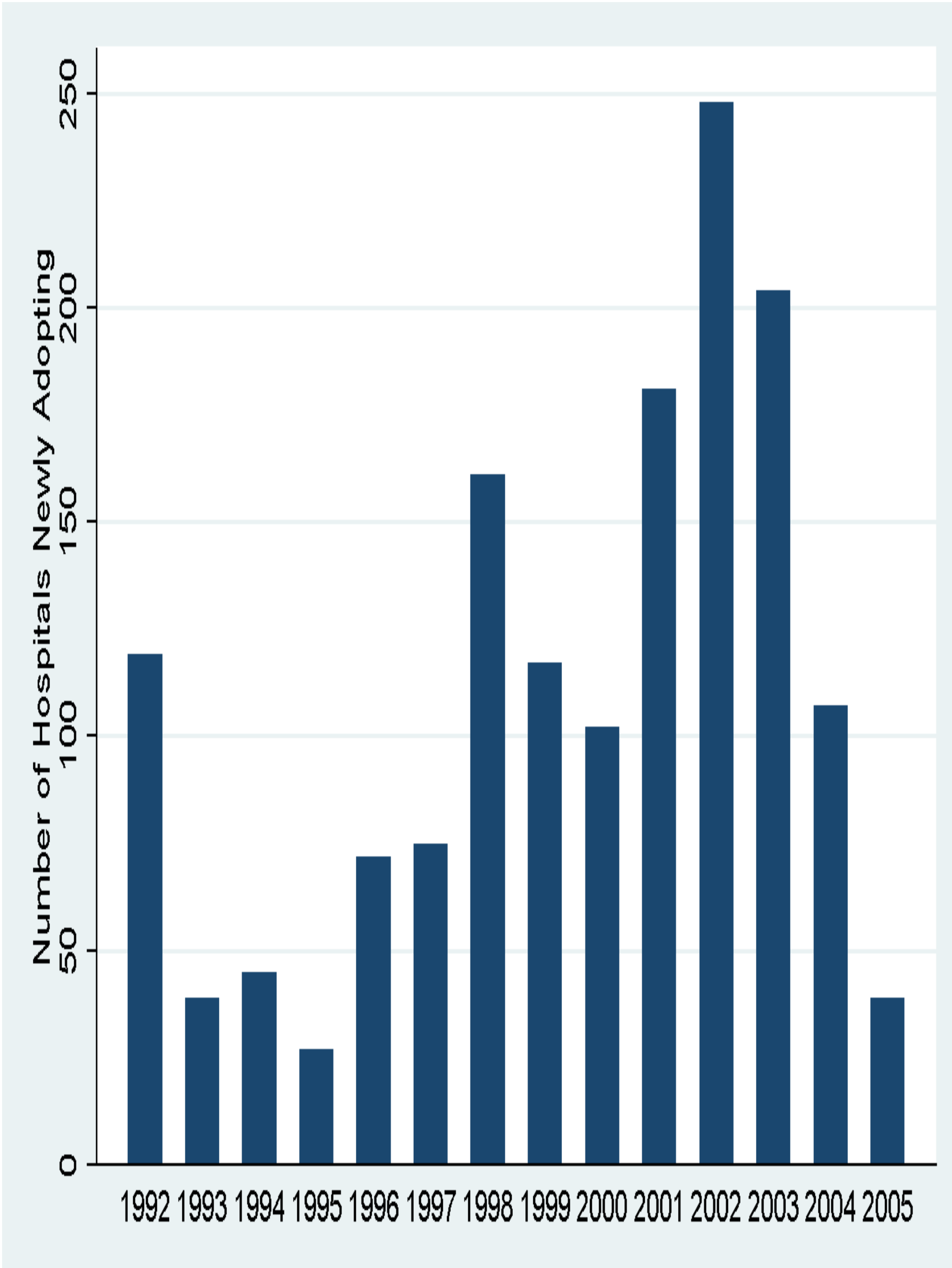

Figure 5: New Adoptions of EMR by Year

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: Linear Probability Model

	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: Probit Specification

	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: Cox-Proportional Hazards Model Specification

	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: 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

Table 6: Instrumental variables estimates for the effect of hospital privacy laws on hospital adoption

	Regression	**IV Regression**
HospPrivLaw	0.066	-1.100*
	(0.059)	(0.611)
NofStaffedBeds	0.000**	0.000***
	(0.000)	(0.000)
NumHospitalsHSA	-0.004	0.004
	(0.003)	(0.005)
YearsOpened	0.003***	0.002
	(0.001)	(0.001)
MultiHSAHosp	-0.186***	-0.163**
	(0.063)	(0.066)
PopulationHSA	0.000	0.000
	(0.000)	(0.000)
Constant	-1.212**	-0.495
	(0.073)	(0.498)
	First Stage GMM regressions for Privacy Law	
ProportionDNC		0.218***
		(0.067)
NofStaffedBeds		0.000**
		(0.000)
NumHospitalsHSA		0.006***
		(0.001)
YearsOpened		-0.000
		(0.000)
MultiHSAHosp		-0.002
		(0.018)
PopulationHSA		-0.000***
		(0.000)
Constant		0.326***
		(0.041)
Observations	3357	3357

Dependent Variable: Whether Hosp. has installed Enterprise EMR in 2002

Probit GMM Estimation.

Instrument for Privacy Law is the proportion of people in states signed up for do not call list

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

Table 7: 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 8: 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 9: 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)
InstalledMeditechHSA	0.021***	0.021***	0.021***
	(0.003)	(0.004)	(0.004)
HospPrivLaw*InstalledMeditechHSA	-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