IPE
7/21/08
9:00 am

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

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

July 3, 2008

Abstract

Consumers may want legal protection of their privacy before they adopt interactive technologies. On the other hand, privacy protection may be costly to implement, deterring adoption of IT. This paper quantifies the effect of state privacy regulation on 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 regulation safeguards their privacy. Alternatively, privacy protection may inhibit adoption if hospitals cannot benefit from exchanging patient information to one another. In the US, some states have enacted medical privacy laws that restrict the ability of hospitals to disclose patient information. We find these laws both inhibit the extent to which hospitals choose inter-operable systems, and reduce aggregate Enterprise EMR adoption by 24 percent. We present evidence that suggests that this is due to suppression of network externalities.

Keywords: Technology Diffusion, Privacy Protection, Health-care IT, Network Externalities, Hospitals

JEL Classifications: I1, K2, L5, O3

*Economics Department, University of Virginia, Charlottesville, VA

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

‡We thank HIMSS for providing the data used in this study, our colleagues for their helpful comments and the NET Institute www.NETinst.org for financial support. We also thank multiple discussants and seminar participants for their insights. All errors are our own.

1 Introduction

It is unclear whether electronic privacy protection promotes or discourages information technology diffusion. Privacy protection may promote the use of information technology by reassuring potential adopters that exchange of their data will be safe. Alternatively, privacy protection may inhibit welfare-enhancing technology diffusion by imposing costs on the exchange of information. These privacy trade-offs matter for technologies as diverse as RFID product tracking and the use of "e-wallets" on the internet. In this paper, we study the role of state privacy protection in the diffusion of Electronic Medical Records (EMR). EMR allows medical providers to store and exchange medical information using computers rather than paper.

EMR was pioneered in the 1970s. However, by 2005 only 41 percent of US hospitals had adopted a basic EMR system, even though it has been estimated that widespread adoption could reduce America's $1.9 trillion annual health care bill by $81 billion through increased efficiency and safety.[1] Anecdotal evidence suggests that privacy protection may partially explain this slow diffusion. For example, expensive state-mandated privacy filters may have played a role in the collapse of the Santa Barbara County Care [Health] Data Exchange (SBCCDE) in 2007.[2] Additional confidential interviews with EMR solution providers confirm that concern about conforming to existing state statute play a major role in hospital adoption decisions.[3] In this paper, we provide the first quantitative estimates of the effect of state-level privacy protection on hospital EMR adoption.

We initially explore how the presence of state privacy protection affects the compatibility

[1] This is based on rough calculations by (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.

[3] One IT provider we interviewed described privacy compliance issues as a "terrible" challenge for the roll-out of EMR. Another emphasized that his firm considered unreflective privacy regulation be a crucial impediment to EMR adoption that was being "ignored" by government officials.

of software that hospitals choose. We use cross-sectional and time-series variation in state privacy protection to quantify the *interaction* between the presence of state privacy protection, and a hospital's responsiveness to the size and compatibility of the EMR installed base within the local health service area. We find that in states with privacy protection, hospitals are less likely to choose software that is easily compatible with neighboring hospitals. This suggests that if privacy protection makes the exchange of information more expensive adoption decisions become less likely to reflect the potential network benefits of the technology or network effects.

We then explore the aggregate effect that privacy protection has on hospital EMR adoption decisions. We want to separate the effect of laws that are driven by the local population's taste for privacy, rather than confounding factors (such as education) that are correlated with tastes for both technology and privacy. Therefore we measure the effect of privacy protection that can be explained by state variation in tastes for privacy, using as instruments both the number of sign-ups in a state for the "Do Not Call" list and state-level opposition to national identity cards. Our instrumental variable estimates indicate that state privacy protection (reflecting tastes for privacy) reduces adoption by 24%. We conduct a falsification exercise for software that has no network benefits, and find no statistically significant evidence that state privacy protection affects adoption of such technologies.

The finding that hospitals are less responsive to the compatibility of the installed base suggests that privacy protection reduces network benefits. We go on to calibrate the size of this reduction. The network benefit of EMR comes from hospitals being able to exchange information about patient histories. This is useful for patients with chronic conditions who want to see a new specialist, or emergency room patients whose records are stored elsewhere.[4] Measuring network externalities is difficult because it is hard to conclude that there is a causal link when two neighboring hospitals adopt the same technology. To measure the un-

[4](Brailer 2005)

confounded effect from the health service area installed base, we use variables that affect the pre-existing IT infrastructure and policy of other hospitals in the local area as instruments for the installed base.[5] These instrumental variables proxy for whether other local hospitals' adoption is restricted by a legacy infrastructure and physician resistance. Our estimates for how the size of the installed base affects hospital adoption decisions vary by whether the state has hospital privacy protection. In states without hospital privacy protection, the adoption of EMR by one hospital increases the probability of a neighboring hospital's adoption by 7.06 percent. By contrast, the installed base has a tiny and insignificant effect on EMR adoption in states with hospital privacy protection. We conclude by presenting some suggestive three stage least squares estimates that incorporate the panel data and the full set of instruments. These support our previous findings.

Our findings suggest there are serious trade-offs between consumers' tastes for privacy protection and speedy diffusion of EMR. The results also illuminate the broader debate about the potential costs and benefits of privacy protection for all interactive technologies. In many cases, policy makers have enacted privacy protection without careful quantification of the potential costs in terms of inhibiting technology diffusion. For example, Utah's House of Representatives passed the first-ever RFID privacy bill in 2004, designed to prevent retailers from matching RFID data with consumers' personal information. In the discussion of the bill little attention was paid to how this might hinder the diffusion of RFID. This debate has grown in importance with the increase in the number of interactive technologies which allow companies and individuals to exchange information online, such as e-wallets and online supplier EDI systems. Our results support earlier work by economic scholars such (Posner 1981) and (Varian 1997), which suggests that there are efficiency costs to privacy protection.

Our finding that privacy protection that limits exchange of data can impose costs on technology diffusion, also supports increasing efforts by IS scholars to pinpoint optimal methods

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

of exchanging data while protecting privacy. Studies such as (?), (?) and (?) use cutting-edge statistics to propose methods whereby users can retrieve data from databases while retaining the privacy of the individuals whose data they are accessing. Our findings in particular support the efforts of a fledging literature that studies means of protecting privacy for healthcare data (for example (?)'s study of the optimal level of aggregation for health data exchange.) Given the diffusion costs imposed by the outright bans of data exchange that we study in our paper, such alternative systems and techniques may provide a welfare-enhancing alternative.

This paper is organized as follows. Section 2 discusses the legal context of state variation in privacy protection. Section 3 sets out the data we use in this study. Section 7 uses cross-sectional and time-series variation to explore the effect of privacy laws on the compatibility of neighboring hospitals' EMR systems. Section 4 uses instrumental variables to measure the overall effect of privacy protection on EMR adoption. Section **??** provides evidence on the mechanism for the overall effect, and Section 6 estimates a joint model of privacy laws and EMR adoption. Section 8 concludes.

2 The Legal Context

The extent to which privacy protection inhibits or promotes the adoption of new technologies is a contentious issue. This ambiguity is reflected in reported consumer attitudes. In a Harris Interactive poll conducted in February 2005, 48 percent of consumers felt that the expected benefits outweigh risks to privacy, while 47 percent felt that the privacy risks outweigh the expected benefits. In general, 70 percent of people surveyed expressed concern about EMR privacy.[6] These concerns are unsurprising, because electronic records are easier than paper files to duplicate and distribute in bulk and the security of networked computers

[6]Though it is hard to extrapolate the relative importance of such sentiments, this is similar to the 68 percent of consumers who express concern about the security of credit-card information online.

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.[7] Even if records do not leave the building, privacy is still a concern. This was demonstrated when New York-Presbyterian Hospital employees made 1,500 unauthorized attempts to access the patient records of a famous local athlete.[8]

These consumer privacy concerns have led certain states to enact their own laws to regulate the transfer of health information. Our main source for current state privacy protection is the (Pritts, Choy, Emmart, and Hustead 2002) survey of state health privacy statutes, produced by the Health Privacy Project at Georgetown University. They determine state privacy protection by examining state statutes governing medical privacy.[9]

Only some state privacy statutes cover hospitals. We use the variable $HospPrivLaw$ to indicate 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 separate states by whether or not the Health Privacy Project indicates they have state privacy protection which covers hospitals.[10] We study the average effects of such laws and do not calibrate the substantial variations in the strength and content of these laws across states.[11] In section **??** in the online appendix, we discuss in detail the nuances of some

[7] ConsumerReports.org, 2006

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

[9] This approach excludes refinements to privacy law stemming from case law or administrative law.

[10] While it is valuable to have an external reporting source to ensure objectivity, we have also performed external verification checks to confirm the accuracy of their reporting.

[11] We have tried comparing adoption in states with laws that we judge to be stronger with those we judge to have weaker protection. Though the results are in the expected direction, they are not significantly different at conventional levels.

sample text from these laws, and the penalties associated with breaking them.

Figure 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. States with hospital privacy protection are significantly larger, have higher incomes, have higher rates of managed care and are more populous than other states, but have statistically indistinguishable population densities and numbers of hospitals. Since these factors may also affect adoption, we include them as controls in our regressions.

In our initial regression specifications we track a panel of adoption decisions. To incorporate a panel of laws, we combined data from the 2002 publication with two earlier parallel surveys of state privacy protection ((Pritts, Goldman, Hudson, Berenson, and Hadley 1999) and (Gostin, Lazzarini, and Flaherty 1996)), to identify historical changes in privacy statutes. Our state law panel begins in 1996, covering the great bulk of the relevant period of EMR adoption (see Figure 4). During that period, we observe 19 changes in laws: 4 changes to increase privacy protection and 15 to decrease it. Figure 2's display of privacy protection in 1996 shows the difference compared to the 2002 privacy protection in Figure 1. These 19 changes in laws allow us to use time-series as well as cross-sectional variation to study the effect of state privacy protection in section 7.

3 Health IT Data

We use technology 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 protection, (Bower 2005) did note that "Conceivably, privacy demands could forestall benefits of networked technology." We matched this with the American Hospital Association survey, and were left with data on the timing of technology adoption decisions of 2,910 hospitals. Details about the matching process and the likely representativeness of these hospitals can be found in the online appendix.

We measure EMR adoption by whether a hospital has installed or is installing an "Enterprise EMR" system.[12] 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.

EMR offers both stand-alone benefits and network benefits. Stand-alone benefits include 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. Network benefits based on the ability to transfer and exchange patient information with other hospitals include providing better care to patients who have chronic conditions and are seeing a new specialist, or are in emergency room situations where they cannot communicate medical history or allergies.[13]

Both these benefits increase the quality of patient care and reduce administrative costs. Higher demand resulting from higher quality and lower costs should increase hospital profits. Furthermore, 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.

Hospitals trade off these benefits against potential costs that include the upfront costs of

[12] Alternative specifications excluding the 185 observations where adoption is not yet complete give similar results.

[13] (Brailer 2005).

software and hardware installation, training, ongoing maintenance and physician resistance ((Groopman 2007)). We control for these hospital-specific variations in stand-alone benefits with variables like the number of fully-staffed beds and the number of years open. Table 1 describes the main variables we include in our regressions. We capture the network benefit by a count[14] of the total number of *other* hospitals in the local health service area who have adopted EMR. In section 7 we separate out the installed base by compatibility. In section **??** when we measure the effect from the aggregate installed base we use a single count measure irrespective of vendor. In all our reported specifications, 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). We also estimated results for 392 "labor market areas" as defined by the 1990 census using commuting data, and obtained similar results.

We employ both panel and cross-sectional data in our empirical specifications. In the cross-sectional data, the dependent variable is simply whether or not the hospital has adopted EMR by 2005. In our panel data, the dependent variable is whether or not the hospital has adopted EMR by that year. In this panel data, reflecting when we have data on changes to state statutes, we group the technology adoption data into three time periods, ending in 1999, 2002, and 2005. In our regressions we exclude from our observations hospitals who have previously adopted EMR, though we include this adoption in the installed base. Adoption decisions before 1996 are not studied in the panel framework, but are included in the installed base measures. Conversations with industry specialists reassure us that once adopted, divestiture of an EMR system is rare. This is supported by the fact that only 2.4 percent of EMR systems were replaced. We assume that hospitals only consider past

[14]In addition to a simple count we have also tried percentage adoption and weighting this count measure by the number of beds, with similar results.

adoption and do not use forecasts of future adoption in their decisions.

An installed base of hospitals is only a necessary, but is not a sufficient, condition for the transfer of health information. There also has to be a mechanism for cooperation and coordination across hospitals, such as 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. This slow implementation may explain why in 2005, only 38 percent of hospitals reported that they shared electronic patient data with other hospitals, which is lower than the 41 percent adoption rate of EMR.[15] Given this long implementation period, it is likely that any installed base measure captures the promise of future health exchange as well as the current ability to do so.

4 Privacy Protection and Propensity to Adopt Compatible Systems

When hospitals buy EMR systems from different vendors, the systems may be incompatible if they use different data formats. Therefore, sharing information electronically becomes cumbersome and expensive if two hospitals' EMR software is not inter-operable.

We study 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 is no privacy protection. The underlying idea is that privacy protection diminishes the size of potential network benefits from the transfer of patient information. Therefore, privacy protection should diminish the relative importance of installing an EMR system that is inter-operable with other hospitals. Correspondingly, privacy protection may imply that hospitals will be less deterred from choosing a system that is not easily inter-operable even if

[15] Continued Progress: Hospital Use of Information Technology, American Hospital Association, 2007.

other nearby hospitals have easily compatible systems. While common unobservable factors can provide an alternative explanation for correlated adoption by vendor type, they cannot explain differences in responsiveness to different kinds of installed base by the status of state privacy protection.

The HIMSS database tells us the vendor from which a hospital purchased their EMR system. It does not supply information about the compatibility of that software. We gathered that 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.[16] We categorized hospital technology purchases into open-loop and closed-loop systems by whether they had purchased software from one of these vendors committed to integration or from another vendor that had made no such commitment.

We use a multinomial logit model for our panel data to analyze four competing decisions: the decision to not adopt EMR at all; the decision to adopt "open-loop" EMR enterprise system; the decision to adopt a "closed-loop" EMR enterprise system from a small firm that has no commitment to inter-operability; and the decision to adopt one largely closed-loop proprietary EMR enterprise system that, while inter-operable across adopters of its own system, is expensive to integrate with other systems. In our multinomial specification we include fixed effects for both state and year. These control for permanent differences in propensity to adopt by state or by year.

The first column of Table **??** presents multinomial logit estimates for the adoption of open-loop EMR systems. The coefficient on installed base of open-loop systems, InstalledOpenLoopHSA, is positive 0.26 (and significant at 1% across specifications). When a state privacy law is in place, the effect of the inter-operable installed base (the number of hos-

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

pitals who had bought software from vendors committed to inter-operable standards) on adoption is reduced by 32%, a value that is statistically and economically significant. The coefficients on InstalledClosedLoopHSA and InstalledMeditechHSA, which together comprise the installed base of non inter-operable systems, are negative and statistically insignificant. This suggests that when hospitals can exchange information freely, their EMR adoption decisions are highly correlated by vendor. However, this relationship is substantially reduced in states with privacy protection, as indicated by the significant negative interaction HospPrivLaw*InstalledOpenLoopHSA.

This pattern is echoed in the adoption of smaller non-inter-operable EMR systems in the second column of Table **??**, that is, the decision of hospitals to purchase a EMR system from a small vendor that had no commitment to inter-operability. Hospitals with these systems may need to incur substantial costs to exchange information electronically with other hospitals, and seem to be less responsive to other's adoption. The coefficients of interest in the column are generally insignificant, with the exceptions of a large increase in inter-operable adoption in states with privacy protection (0.735, significant at 1%), and a positive correlation with the installed open-loop base. Although it may be less expensive to communicate with systems from outside vendors who are committed to compatibility, the second term does suggest the potential presence of common unobservable factors that influence all hospitals in an HSA, making installed base potentially endogenous. This motivates our instrumental variables analysis of installed base effects in Section **??**. The lack of credible instruments for vendor choice prevents us from employing a similar strategy for the compatibility decision.

The last column of Table **??** examines the decision to invest in EMR from a single large vendor named Meditech that has been described as having a closed-loop proprietary system. Hospitals' decisions to purchase an EMR system from Meditech is highly correlated within HSAs, as seen by the 0.487 coefficient on InstalledMeditechHSA. However, in states where the exchange of information between hospitals is restricted, and the benefits from common systems are lower, the effect of the installed Meditech base is reduced by a full 67% (significant at 1%).

These results imply that the privacy regime influences the types of EMR systems that hospitals purchase and how responsive their technology adoption decision is to other hospitals' adoption decisions. The results are consistent with privacy protection reducing the network benefits from medical information exchange, but are not conclusive due to the potential endogeneity of the installed base, and of the laws themselves. We turn to instrumental variables in Sections 4 to 6 to quantify the legal adoption effects. In those sections, we restrict our attention on the decision to adopt Enterprise EMR and ignore the choice of vendor.

The regressions in Table **??** include numerous co-variates that capture differences across hospitals and local markets. 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 (Total Outpatients, Staffed Beds) and of age, which is likely related to prestige, are in the expected direction.

The consistently negative coefficient on NumbHospitalsHSA shows that hospitals operating in markets with fewer competitors are more likely to adopt EMR technology. While it is certainly possible that the 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 that competitive structure affects health care technology adoption.

MultiHSAHosp is an indicator variable for whether a hospital is part of a chain of hospitals that spans multiple networks. Hospitals that are part of a multi-region hospital chain are less likely to adopt EMR. Multi-region hospitals are more likely to have an old, DOS-based server infrastructure, which is harder to update and interface with EMR.

Our main variables of interest in these regressions are the series of interaction terms between different kinds of installed bases and the presence of a privacy law. As pointed out by (Ai and Norton 2003), care is needed when evaluating the significance of such terms in non-linear models. To check the robustness of our results, we have also run each of these specifications using a linear probability model and obtained similarly significant results.

5 Effect of State Privacy Protection on Adoption

We explore the aggregate effect of state privacy protection on adoption of Enterprise EMR. As with studying the effect of any legal regulation, there is a concern that the effect of laws is not causally linked to that state's taste for privacy, but instead reflects state characteristics (such as wealth or education level) that are otherwise correlated with adoption decisions. The endogeneity concern is that these laws could be correlated with unobserved state characteristics that may also themselves be correlated with the profitability of EMR technology to the hospital. For example, the enactment of privacy protection could be positively correlated with the underlying sophistication, lobbying force and associated financial resources of patients. Then, these unobserved influences on the legislative process could also in turn affect technology adoption.

An ideal instrument would be something that reflects tastes for state privacy protection but was not correlated with 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 enrolled in the national "Do Not Call" registry.[17] Individuals who sign up

[17]We thank Hal Varian and Fredrik Wallenberg for giving us the data.

for the national "Do Not Call" registry do not want tele-marketers to contact them at home, and may therefore have stronger tastes for privacy extending beyond medical information. (Varian, Wallenberg, and Woroch 2005) describes the summary statistics for this data. In appendix table **??**, we report the summary statistics for each of our covariates and the dependent variable by whether that hospital's state is above or below the median DNC sign-up. These sign-ups are driven by consumers rather than reflecting privacy efforts on the part of states. It seems plausible that variations in sign-ups to the list are unrelated to hospital demand or returns to technology investment in healthcare, and should have no independent effect on EMR adoption. In addition to the use of the DNC costs to capture residents' tastes for privacy, we also include variables to capture resistance to privacy type protection in that state's legislative system. To do this we study the passage (or lack of passage) of various measures designed to "opt out" of the federal "Real ID" Bill. This is a bill that would require all states to verify federal immigration documents and birth certificates before issuing federally recognized drivers' licenses to its residents. We use as an instrument a variable that captures whether a bill was set in motion against the "Real ID" bill, but not passed into law. We also include a variable that measures whether a state has successfully opted out of the RealID system.[18]

These instruments do not vary across time so we analyze purely the cross-sectional data from 2005. The dependent variable is whether or not the hospital has adopted enterprise EMR by 2005.

The first column of Table 2 reports results from a basic probit of hospital EMR adoption, treating privacy protection as exogenous. The estimates in the second column are from a GMM probit with instruments that treats privacy protection as endogenous.[19] The effect of hospital privacy protection goes from positive (0.01**) to negative (-0.6*) and significant

[18] These data come from the ACLU website www.realnightmare.org

[19] A linear probability model produced similar results. We also estimated a regression where we put our instrument directly into the regression and obtained similar results.

at the 10% level. A separate calculation based on the reported estimates of the marginal effects calculated at the sample mean implies that a state privacy law reduces a hospital's propensity to adopt EMR by 27.0%.

For the "Do Not Call" and "RealID" instruments to be valid, they need to be correlated with state privacy protection, while being uncorrelated with other influences at the state level on hospital technology adoption. The first stage of the GMM regressions shows that, reassuringly, the proportion of sign-ups to the do-not-call list was a strong and significant predictor of state privacy protection. In addition, failed opposition to Real ID laws was a strong predictor that state privacy protection was not enacted. An F-test on the joint significance of the instruments strongly rejects zero for each of the technologies. Hence, the instruments satisfy the first necessary condition for validity.

To ensure that our instruments were uncorrelated with other influences at the state level of hospital technology adoption we took two actions. First, we performed the usual statistical tests for over-identification, such as (Basmann 1960). The Hansen J-statistic and its associated P-value are reported below each of the main IV results. These tests fail to reject the null hypothesis that the instruments are valid, under the assumption that at least one is exogenous. We also checked various potential correlates and found little evidence of correlation between our instruments and factors that affect EMR adoption (See appendix for a further discussion).

Second, we conducted a falsification exercise in which we examined another technology that should not be affected by the interaction of privacy protection and network effects, and checked that privacy protection had a negligible effect on such a technology. We chose to examine stand-alone software/hardware systems for intensive critical care units that monitor patients' vital signs. This information is useful for alerting doctors and nurses if a patient's condition is deteriorating, but it is typically never stored or transferred between providers. Figure 6 shows that the adoption pattern for these IT systems is similar to that of EMR in

Figure 4.

The second two columns of Table 2 show the results of the same IV specification as the first two columns for this alternative technology. Similar to EMR, the basic probit estimate for HospPrivacyLaw is positive and significant. Unlike EMR, however, the IV probit estimate is statistically insignificant. This provides some evidence against the presence of a general force underlying both a state's decision to enact privacy protection and causing hospitals in that state to be less likely to adopt Healthcare IT technologies. However, the imprecision of the estimates prevents more a conclusive interpretation.

We repeated this falsification test by studying the adoption of IT systems for neo-natal intensive care units and obtained similar results. Though it would be ideal to conduct a falsification test with a broader group of new hospital IT technologies, we are limited because a condition for a falsification test is that the technologies' usefulness should not be affected by the network benefits conferred by EMR (or the interference of these benefits by privacy protection). For example, it would not be illuminating to study the diffusion of PET/SPECT/MRI type devices, because the usefulness of these devices would increase when hospitals can use EMR successfully to import and export images and reports from these technologies. Only a very few IT-type technologies do not fall under this critique, because the primary function of EMR is to compile data and records and allow them to be transferred across hospitals. ICU/NICU IT systems are unusual in the extent that the information they collect is used only at the time and is not useful when it is transferred.

6 Network Effects

After controlling for the endogeneity of the decision to enact, we find privacy laws appear to reduce adopt of EMR. To pinpoint the mechanism underlying this negative effect, in this section, we explore the comparative magnitude of network effects from the installed base in states which have privacy protection and those that do not.

Identifying network effects from an installed base measure is an empirical challenge. 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. 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. We do this by exploiting variables that affect the IT adoption environment in these neighboring hospitals but that are plausibly not correlated with the hospital's own adoption decision. Our first instrument is whether neighboring hospitals are part of a system of hospitals that extends into other regions (which resembles the (Gowrisankaran and Stavins 2004) identification strategy for electronic payments adoption). Our second set of instruments covers the type of relationship neighboring hospitals have with their physicians.[20] This captures physician resistance, which is documented as a major driver of EMR adoption by hospitals ((Groopman 2007)). For example, Brian Patty, Medical Director for Information Systems at Fairview Ridges Hospital, MN, 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)). The less integrated the relationship. the less involvement physicians have with the technology roll-out decisions. This can explain why estimates in Table 2 suggest that hospitals that have independent practice association type relationships are more likely to adopt than those that practice an integrated salary model.

For the estimates to be valid, the exclusion restriction must hold that the characteristics of neighboring hospitals have no direct impact on the EMR adoption decisions. The disadvantage of these instruments is that again they do not vary across time sufficiently to allow us to identify time effects and state effects so we report the results for cross-sectional

[20]See (?) for a discussion on how these different doctor-physician affiliations can change the power-structure in hospitals.

variation rather than exploiting our panel data. We divide our cross-sectional data for 2005 into two separate data-sets by whether that state has a state privacy law.

We first obtain estimates for hospitals in states without hospital privacy protection, using a GMM probit with instrumental variables model to address the endogeneity of InstalledHSA. These results are presented in Table **??**, alongside the results of the basic probit on the same hospital sample.

The basic probit estimate of InstalledHSA is more precisely estimated than the IV estimate, but both are large and statistically significant at the 10% level. The marginal effect calculated at the sample mean suggests that the addition of one more hospital that has installed EMR to the installed base increases adoption propensities in the states which have no state privacy protection by 7.06 percent. 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 find evidence of upward bias in the basic probit. The IV estimate of InstalledHSA is reduced from 0.063 to a negative and statistically insignificant -0.103 (standard error of 0.122). Together, these results show that network effects do indeed promote EMR diffusion, but that the gains are virtually eliminated by state privacy protection. 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).

The first-stage regressions presented in Table **??** suggest that the instrumental variables are significant predictors of adoption at the HSA level, satisfying a necessary condition for their validity. Hospitals with physicians working in IPAs are more likely to adopt EMR and multi-HSA hospitals are less likely to adopt. The first-stage estimates regarding hospital age, and multi-region and size are consistent with earlier estimates. Since the exclusion restriction on the instrumental variables cannot be tested directly, we conduct a series of indirect tests using an alternative medical information technology that had similar adoption rates to EMR but no network benefits: the stand-alone software/hardware systems for intensive critical care units that monitor patient vital signs. While the information maintained by such systems is useful for alerting doctors and nurses if a patient's condition is deteriorating, it is typically never stored or transferred between providers. By 1999, 13% of hospitals in the sample had adopted the "placebo" technology for ICU, and 15% had adopted EMR.[21]

The first column of Table 4 shows significant correlations between installed base of ICU systems and new adoption of ICU systems using a probit model for the period 1999-2005. In these regressions, the sample of potential new adopters is modified to include all hospitals who had not previously adopted ICU rather than EMR. In the first two columns, we report probit and IV probit estimates of the effect of EMR installed base on ICU adoption. The installed EMR adoption base is not significantly related to ICU adoption in either probit or IV-probit models. Since data from ICU systems are not shared across hospitals, the positive correlation in the simple probit model in the third column is likely capturing unobservable factors that are common to hospitals within an HSA, such as healthcare demand. Reassuringly, when the instrumental variables are used to predict ICU installed base, the spurious network effects are eliminated. This provides some support that the instrumental variables are valid, and that the relationships in the previous table are not merely capturing the effect of omitted variables that are correlated with information technology adoption in healthcare.

7 Combined Estimation

We conclude by combining both the panel data and the cross-sectional instrumental variables, to provide some rough estimates for the combined effect of changes in laws over time and

[21] In theory, a more stringent placebo test could be conducted using a form of health IT that has network effects across hospitals, but no network effects with EMR. However, in practice, since EMR comprises the backbone of a hospital's health records system, any other network technology in our data will also interact with EMR. To avoid this source of contamination, we chose a technology without network effects.

the instrumented installed base and law measures. We present these estimates as supporting evidence rather than robust evidence since the number of endogenous equations requires a linear probability model to obtain convergence. Our estimates are also unlikely to be precise given our use of non-time varying instruments despite a panel data setting. The data for each hospital again covers 1999, 2002, and 2005, matching the years for our data on the status of privacy protection.

Table **??** presents the results of a 3SLS model. The main specification contains a set of state and year dummy variables to capture permanent geographic features and secular adoption trends. The endogenous equations include all the instruments discussed in Sections 4 and **??**, as well as their interactions. We interpret HospPrivLaw*InstalledHSA as capturing the extent to which state privacy protection reduces a hospital's benefits from an installed base of other hospitals with which it can exchange health information. The interaction term HospPrivLaw*InstalledHSA is negative and significant. The coefficient ranges from -0.024 to -0.030, implying that privacy protection reduces the positive effect of another local hospital's adoption by 27 to 32 percent. The privacy law level effects are also negative, but not statistically significant. The suppression of network effects led to an overall reduction of EMR adoption from privacy protection of about 30 percent, comparable to (though slightly higher than) the estimates in Section 4. Consistent with Section **??**, the channel appears to be the inhibition of network benefits.

8 Conclusion

This paper examines how tastes for privacy and privacy protection interact with the diffusion of an inherently inter-dependent technology. We present evidence from panel data that the enactment of state privacy protection reduces the responsiveness of electronic medical records adoption to the size and compatibility of the installed base. This suggests that privacy protection inhibits network effects that would otherwise have promoted hospital adoption of electronic medical records. To identify the effect of state privacy protection that stems from tastes for privacy rather than alternative confounding factors, we use sign-ups to the "Do Not Call" list and opposition to the "Real ID" bill as instruments. We find that privacy protection of hospital medical disclosure is inhibiting adoption by about 24 percent in those states that have it. Additionally, instrumental variable estimates suggest that in states without hospital privacy protection, one hospital's adoption increases the propensity of other area hospitals to adopt by 7.06 percent. Network effects are not detected in states with privacy protection. For identification of the effect of the installed base, we use variables that pick up both the likelihood of a neighboring hospital having a hard-to-integrate DOS-based IT system and the neighboring hospital encountering physician resistance to the adoption of the technology.

Our evidence shows that, while there may be many reasons for states to restrict medical providers' ability to disclose information, these restrictions may lead to less adoption of EMR and the adoption of less compatible systems. This could hinder the federal government's goal of having a national health IT network by 2014. It is estimated that a national IT network will cost the US $156 billion in capital investment over 5 years.[22] This large sum makes it crucial that future efforts at protecting privacy recognize the tradeoffs between technology diffusion and privacy.[23] Politicians find EMR's unusual combination of "Saving Lives and Saving Money"[24] attractive, but there has been little rigorous measurement until now of how privacy protection affects EMR diffusion.[25] Our study hopes to complement such qualitative

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

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

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

[25]Research efforts have been almost entirely qualitative, as in the AHCQ interview-based 3-year $17.3 million "Health Information Security and Privacy Collaboration" study (www.rti.org/pubs/nationwide_summary.pdf)

research by empirically quantifying how a hospital's decision to adopt EMR is affected by whether state privacy protection restricts a hospital's ability to disclose information.

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. 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. 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 (**?**) and (Gowrisankaran and Stavins 2004), has focused on finding exogenous shifters of adoption to study the causal effect of one agent's adoption on another.[26] We infer network effects from an exogenous shift in the ability of agents within a network to transfer information across a network.[27] Our 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 it being the closest approach to identifying network effects based on actual usage of the network.

Our research provides some initial evidence about how tastes for privacy and privacy protection can adversely affect the diffusion of technologies that are intended to be inter-dependent. This reflects statements by those affected by privacy protection such as the American Clinical Laboratory Association which has gone on record, saying that the "patchwork of state privacy laws is an impediment to health information exchange". Further research is needed to investigate the extent to which privacy protection can be optimized (or at least integrated) to minimize disruption to the diffusion and use of inter-dependent technologies. For example, it would be valuable to find out whether IT-based privacy protection (us-

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

[27]This contrasts with the approach of (**?**), who uses exogenous variation in the stand-alone benefit of a technology to identify network effects.

ing methods such as those proposed in (?), (?) and (?)) can provide a welfare-enhancing alternative in the future to rules-based privacy protection.

References

Acemoglu, D. and A. Finkelstein (2006). Input and technology choices in regulated industries: Evidence from the health care sector. Technical report, NBER Working Paper No. 12254.

Ai, C. and E. C. Norton (2003, July). Interaction terms in logit and probit models. *Economics Letters 80*(1), 123–129.

Baker, L. C. and C. S. Phibbs (2002, Autumn). Managed care, technology adoption, and health care: The adoption of neonatal intensive care. *RAND Journal of Economics 33*(3), 524–548.

Baldwin, G. (2005, September). Roundtable: Information technology and the community hospital. Technical report, Health Leaders.

Basmann, R. L. (1960). On finite sample distributions of generalized classical linear indentifiability test statistics. *Journal of the American Statistical Association 55*, 650–659.

Bower, A. G. (2005). *The Diffusion and Value of Healthcare Information Technology.* RAND.

Brailer, D. (2005). Interoperability: The key to the future health care system. *Health Affairs*.

Covich Bordenick, J., J. Marchibroda, and E. Welebob (2006). Improving the quality of healthcare through health information exchange. Technical report, eHealth Initiative.

Dafny, L. (2005, December). How do hospitals respond to price changes? *American Economic Review 95*(5), 1525–1547.

Dranove, D., M. Shanley, and C. Simon (1992, Summer). Is hospital competition wasteful? *RAND Journal of Economics 23*(2), 247–262.

Farrell, J. and G. Saloner (1985). Standardization, compatibility, and innovation. *RAND Journal of Economics 16*, 70–83.

Fonkych, K. and R. Taylor (2005). The state and pattern of health information technology adoption. Technical report, RAND.

Gostin, L., Z. Lazzarini, and K. Flaherty (1996). Legislative Survey of State Confidentiality Laws, with Specific Emphasis on HIV and Immunization. Technical report, Report to Centers for Disease Control and Prevention.

Gowrisankaran, G. and J. Stavins (2004). Network externalities and technology adoption: lessons from electronic payments. *RAND Journal of Economics 35*(2), 260–276.

Groopman, J. (2007). *How Doctors Think*. Houghton Mifflin Company.

Hamilton, B. and B. McManus (2005). Technology Diffusion and Market Structure: Evidence from Infertility Treatment Markets. Mimeo, Washington University.

Hillestad, R., J. Bigelow, A. Bower, F. Girosi, R. Meili, R. Scoville, and R. Taylor (2005, Sep-Oct). Can electronic medical record systems transform health care? Potential health benefits, savings, and costs. *Health Affairs 24*(5), 1103–17.

Katz, M. L. and C. Shapiro (1985). Network externalities, competition, and compatibility. *American Economic Review 75*(3), 424–40.

Kaushal, R., D. Blumenthal, E. G. Poon, A. K. Jha, C. Franz, B. Middleton, J. Glaser, G. Kuperman, M. Christino, R. Fernandopulle, J. P. Newhouse, and D. W. Bates (2005). The costs of a national health information network. *Annals of Internal Medicine*.

Lenzo, J. (2005). Market Structure and Profit Complementarity: The Case of SPECT and

PET. Mimeo, Northwestern University.

Makuc, D., B. Haglund, D. Ingram, J. Kleinman, and J. Feldman (1991). Health Service areas for the United States. Technical report, National Center for Health Statistics, Vital Health Statistics. DHHS Publication No. (PHS) 92-1386.

Posner, R. A. (1981). The economics of privacy. *The American Economic Review 71*(2).

Pritts, J., A. Choy, L. Emmart, and J. Hustead (2002). The State of Health Privacy: A Survey of State Health Privacy Statutes. Technical report, Second Edition.

Pritts, J., J. Goldman, Z. Hudson, A. Berenson, and E. Hadley (1999). The State of Health Privacy: An Uneven Terrain. A Comprehensive Survey of State Health Privacy Statutes. Technical report, First Edition.

Rysman, M. (2004, April). Competition between networks: A study of the market for yellow pages. *Review of Economic Studies 71*(2), 483–512.

Schmidt-Dengler, P. (2006). The Timing of New Technology Adoption: The Case of MRI. Mimeo, LSE.

Varian, H. (1997). Economic aspects of personal privacy.

Varian, H., F. Wallenberg, and G. Woroch (2005). The demographics of the do-not-call list. *IEEE Security and Privacy 3*(1), 34–39.

A Data Processing

The HIMSS database gives 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 protection, we dropped the 537 observations where no information about timing was provided.[28]

The annual American Hospital Survey covers over 6,000 hospitals. We matched these to the HIMSS database using Medicare ID numbers where available and names and cities where not. We were able to match all but 193 of our the hospitals in the HIMSS database. The hospitals we could not match were largely hospitals that were split into two campuses in the HIMSS database but reported as a single campus in the AHA database. In all we were left with 2935 observations, of which 25 had missing AHA data so were dropped. This left us with 2910 observations for our regressions. The hospitals that were not matched were smaller than those that were. They had 118 beds as compared to 208 beds for the matched hospitals. They also spent 14 million on total payroll as compared to 38 million for the matched hospitals. 38 percent of the unmatched hospitals reported they were part of a healthcare system, compared to 62 percent of the matched hospitals. Given that adoption decisions are positively correlated with these variables, it seems likely that if we did have data on these unmatched hospitals they would have adopted less than the ones we study.

B Robustness Checks

B.1 "Privacy" Instruments

(Varian, Wallenberg, and Woroch 2005) exhaustively report the various correlates of households signing up for the do-not-call list. Of these, they report that the most significant are county-level education, race, income and age. These are not significant correlates of hospital EMR adoption. In fact, as shown in Table **??**, higher HSA household income actually has an insignificant and negative effect on technology adoption, as opposed to the positive and

[28]Results where we just look at adoption in 2005 show little change whether we include or exclude these 537 observations.

significant effect it has on sign-ups to the do-not-call list. A demographic variable that has significant influence on adoption in Table **??** is the population density in an HSA. However, population density has an ambiguous effect on sign-ups for the do-not-call list. Urban clusters have high sign-up rates, but farming communities have the highest sign-up rate. Table **??** shows how hospital and demographic characteristics vary by whether or not there are high or low do not call signups.

C Legal Context

C.1 Text of State Disclosure Law

There are many regulations that cover the disclosure of health information. 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. In this paper we simply divide states by whether they have regulation that limits the disclosure of information by hospitals. However, the following extracts for the state law pertaining to disclosure by hospitals in Florida and New Hampshire, show that the laws are not always worded the same and that each state law has its own nuances. For example, the New Hampshire law explicitly includes electronic records while the Florida law refers to health records in more general terms. Also the Florida state law explicitly allows facility personnel and attending physicians within that hospital to access the records without written consent, while the New Hampshire law requires written consent for all releases of information except those required by law. This suggests that by state there may be slight differences in the stand-alone benefits for the use of EMR within a hospital. Such differences are controlled for in the specifications that contain state fixed effects, and the similarity of the results for cross-sectional and panel results suggests that they are not overly important.

Health Disclosure Rules for Hospitals in Florida

Hospitals and licensed entities are subject to restrictions on disclosure of patient records and information similar to those applicable to health practitioners. [Fla. Stat.5 Ann. 395.3025.] In general their patient records may not be disclosed without the patients consent, except under the circumstances specified in the statute. [Id.] These include: to licensed facility personnel and attending physicians for use in connection with the treatment of the patient; to licensed facility personnel for administrative purposes or risk management and quality assurance functions; pursuant to a subpoena in any civil or criminal action, unless otherwise prohibited by law; and to various state agencies and other entities for purposes specified in the statute. [Id.] The Health Department is explicitly authorized to examine a licensed facility's patient records, whether held by the facility or the Agency for Health Care Administration, to conduct epidemiological investigations. [Id.] Recipients of information lawfully disclosed may use it only for the purpose for which it was provided and may not further disclose it, except upon the written consent of the patient. [Id.] A general authorization for the release of medical information does not authorize re-disclosure. [Id.]

(Pritts, Choy, Emmart, and Hustead 2002) summary of www.leg.state.fl.us

Health Disclosure Rules for Hospitals in New Hampshire

A patient of a health facility must be ensured confidential treatment of all information contained in the patients personal and clinical record, including that stored in an automatic data bank. [N.H. Rev. Stat. 151:21(X).] The patient's written consent is required for the release of information to anyone not otherwise authorized by law to receive it. [Id.] This provision *applies to any licensed hospital, infirmary or health service maintained by an educational institution, laboratory performing tests or analyses of human samples, outpatient rehabilitation clinic, ambulatory surgical center, hospice, emergency medical care center, drop-in or walk-in care center, dialysis center, birthing center, or other entity where health care associated with illness, injury, deformity, infirmity, or other physical disability is provided, whether operated for profit, for free or at a reduced cost, and others. [N.H. Rev. Stat. 151:19 (defining facility); 151:2 (detailing facilities that must be licensed).]*

(Pritts, Choy, Emmart, and Hustead 2002) summary of gencourt.state.nh.us/ns

C.2 Penalties for breaking state law

We describe the penalties for breaking the state law below. On face value, they do not appear particularly harsh. Conversations with IT professionals suggest, however, that hospital IT departments are eager to ensure there IT systems fully comply with state law as the potential harm from negative publicity is far greater than that implied by state statute.

Remedies and Penalties (Florida)

Fines and Penalties. Unauthorized disclosure of any information that would identify an individual by agents of the Health Department is a misdemeanor of the first degree, punishable as specified by statute. [Id.]

(Pritts, Choy, Emmart, and Hustead 2002) summary of www.leg.state.fl.us

Fines and Penalties (New Hampshire)

A facility that violates this provision is liable for the sum of $50 for each violation per day or part of a day or for all damages proximately caused by the violations, whichever is greater.

[Id.] If a facility is found to be in contempt of a court order issued under this section, the facility is liable for the plaintiffs reasonable attorney fees and costs. [Id.]

(Pritts, Choy, Emmart, and Hustead 2002) summary of gencourt.state.nh.us/ns

C.3 HIPAA

Another significant change between 1996 and 2005 is the introduction of the Federal Privacy Rule in 2003 stemming from the 1996 HIPAA law.[29] Although HIPAA provides a uniform minimum standard of federal privacy protection for *documenting* how health information is used, actual standards about usage continued to vary from state to state. 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 further weakened by its dependence on consumer complaints to initiate actions. In our panel estimates, HIPAA's effect on the level of adoption is captured by a series of national-level time dummies. For robustness, we repeated our estimation separately for before and after the introduction of HIPAA. Reassuringly, our results did not qualitatively change. However, this does mean that our estimates measure the incremental effect of state privacy protection beyond existing federal regulation.

C.4 Breakdown of co-variates by Law

Table **??** describes the differences in our regression covariates by state privacy law. The most noticeable difference is that total payroll for hospitals is substantially higher in states that have privacy laws, while hospital size measured in beds is only slightly higher. A close inspection of Figure 1, however, suggests that this is probably reflective of generally higher wages in the states that have privacy laws.

[29]Sections 261 through 264

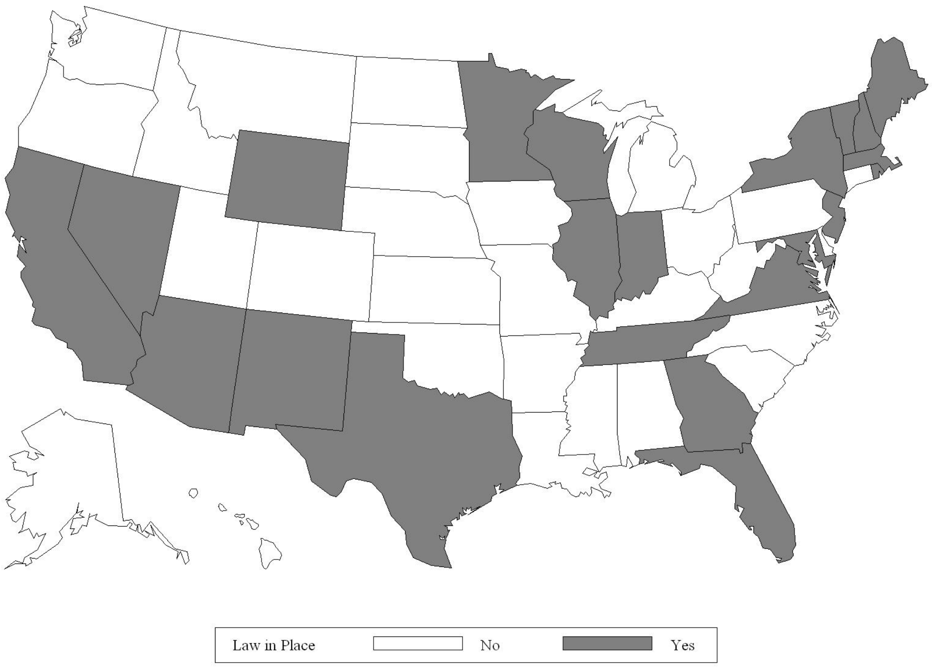

Figure 1: Map of States with Hospital privacy protection: 2002

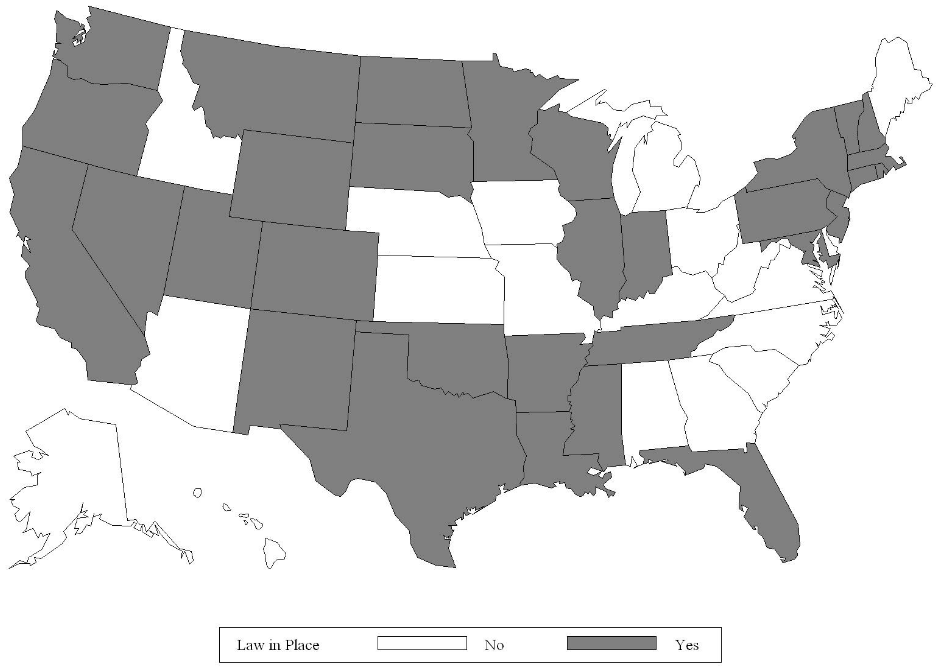

Figure 2: Map of States with Hospital privacy protection: 1996

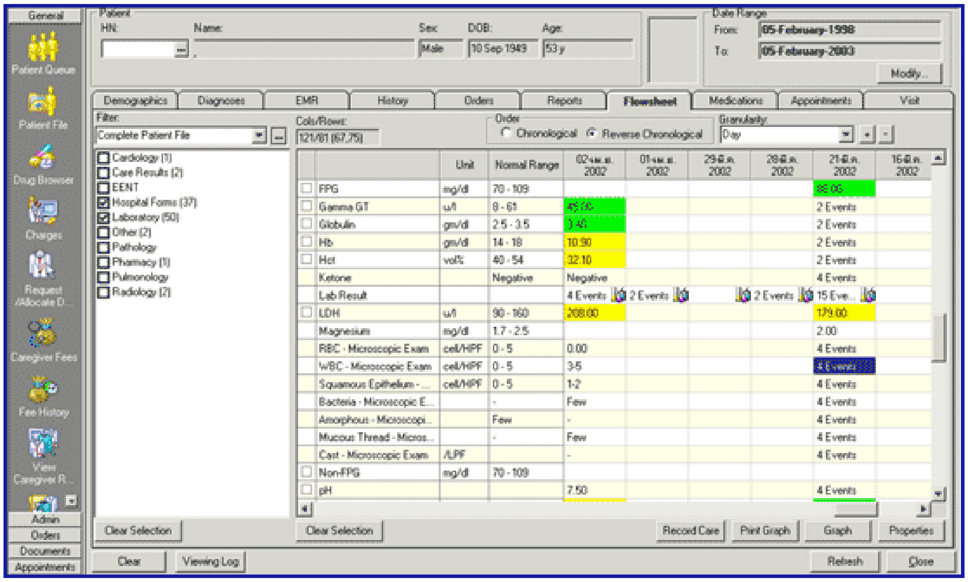

Figure 3: Screen Capture

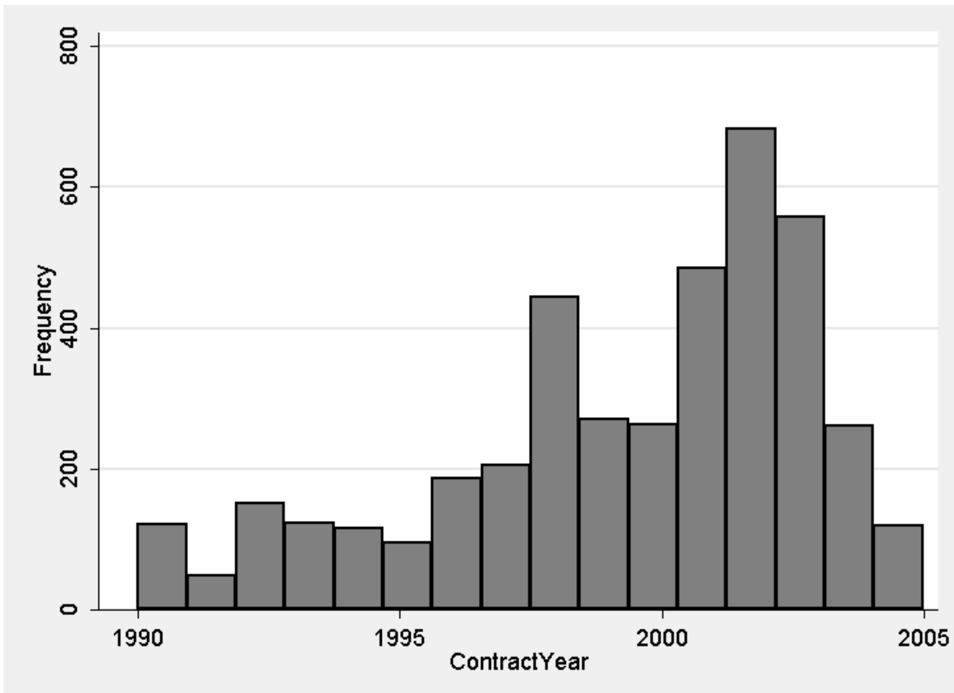

Figure 4: New Adoptions of EMR by Year

Observations are censored before 1990. Adoption in 1990 means before or during 1990.

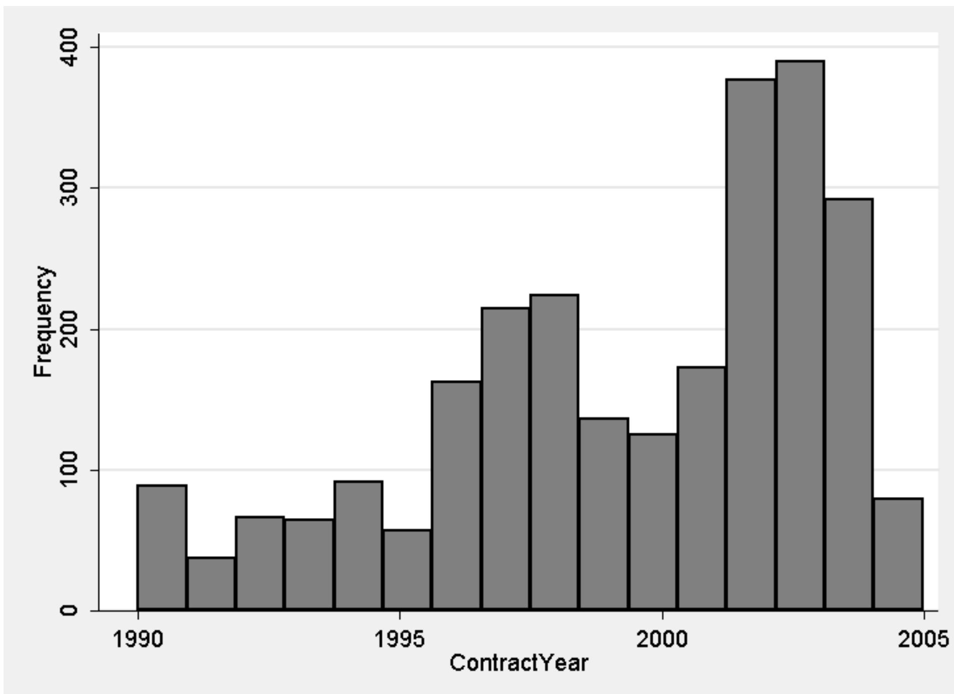

Figure 5: New Adoptions of ICU IT by Year

Observations are censored before 1990. Adoption in 1990 means before or during 1990.

Table 1: Summary statistics (2005)

Variable	Mean	Std. Dev.	Min.	Max.
EMR Adoption	0.41	0.49	0	1
Inter-Operable EMR Adoption	0.22	0.41	0	1
Non Inter-Operable EMR Adoption	0.07	0.38	0	1
Meditech EMR Adoption	0.12	0.33	0	1
ICU Adoption	0.21	.41	0	1
Hosp Privacy Law	0.56	0.50	0	1
Academic	0.08	0.28	0	1
Years Opened	32.52	35.19	0	187
Numb Hospitals HSA	10.34	14.94	0	76
No Out-of-Reg. System Hosp	14.12	28.68	0	128
Independent Practice Association	0.14	0.35	0	1
Physician Hospital Organization	0.30	0.46	0	1
Fully Integrated Organization	0.26	0.44	0	1
Member System	0.64	0.48	0	1
Member Network	0.33	0.47	0	1
Total Payroll (USDm)	44.48	58.10	0.62	879.81
Staffed Beds (000)	0.20	0.18	0.01	1.84
Nursing Home Unit	0.28	0.45	0	1
Total Outpatients (000)	13.80	16.66	0	253.35
Births (000)	1.00	1.34	0	16.01
Medicare Patients (000)	3.57	3.37	0	28.27
Medicaid Patients (000)	1.53	2.09	0	23.97
HMO	0.16	0.37	0	1
Fee for Service	0.05	0.23	0	1
PPO	0.20	0.40	0	1
Population HSA	1.48	2.61	0	15.98
Income Median HSA (000)	25.29	7.40	0	58.25
Medicare HSA	0.20	0.35	0	2.90
Observations		2935		

Table 2: The effect of state privacy protection on hospital adoption of InterOperable EMR systems 1999-2005

	OpenLoop Technology	**ClosedLoop Technologies**	**Meditech Technology**
Hosp Privacy Law	0.039	0.735***	0.228
	(0.185)	(0.262)	(0.251)
Installed Open-Loop HSA	0.259***	0.177***	-0.008
	(0.038)	(0.058)	(0.073)
Hosp Priv Law*Installed Open-Loop HSA	-0.084**	-0.019	-0.056
	(0.042)	(0.065)	(0.082)
Installed Closed-Loop HSA	-0.040	0.171	0.107
	(0.071)	(0.117)	(0.128)
Hosp Priv Law*Installed Closed-Loop HSA	0.050	-0.078	-0.030
	(0.079)	(0.122)	(0.136)
Installed Meditech HSA	-0.142	0.157	0.487***
	(0.100)	(0.131)	(0.100)
Hosp Priv Law*Installed Meditech HSA	0.282***	-0.043	-0.327***
	(0.103)	(0.139)	(0.105)
Academic	0.296*	0.152	-0.054
	(0.175)	(0.254)	(0.303)
Years Opened	0.000	0.006***	0.007***
	(0.001)	(0.002)	(0.002)
Numb Hospitals HSA	-0.052***	-0.040***	-0.027***
	(0.009)	(0.011)	(0.010)
No Out-of-Reg. System Hosp	-0.064***	-0.011	-0.088***
	(0.011)	(0.012)	(0.021)
Independent Practice Association	-0.163	-0.452**	0.138
	(0.123)	(0.181)	(0.149)
Physician Hospital Organization	0.310***	-0.356**	-0.077
	(0.092)	(0.144)	(0.131)
Fully Integrated Organization	0.022	-0.219	0.110
	(0.102)	(0.147)	(0.134)
Member System	0.535***	-0.168	0.165
	(0.103)	(0.136)	(0.131)
Member Network	0.006	-0.100	0.011
	(0.094)	(0.137)	(0.128)
Total Payroll (USDm)	0.002	0.004*	-0.017***
	(0.002)	(0.002)	(0.005)
Staffed Beds (000)	-0.336	-0.659	1.525*
	(0.578)	(0.828)	(0.861)
Nursing Home Unit	-0.011	-0.273*	0.001
	(0.101)	(0.144)	(0.131)
Total Outpatients (000)	0.011***	0.008	0.015**
	(0.004)	(0.005)	(0.007)
Births (000)	-0.041	-0.007	0.125*
	(0.046)	(0.065)	(0.075)
Medicare Patients (000)	0.023	-0.006	0.022
	(0.026)	(0.039)	(0.045)
Medicaid Patients (000)	0.034	-0.041	-0.062
	(0.034)	(0.045)	(0.065)
HMO	-0.005	0.321*	-0.418**
	(0.122)	(0.173)	(0.190)
Fee for Service	-0.171	-0.027	-0.898***
	(0.173)	(0.247)	(0.310)
PPO	0.246**	-0.164	0.227
	(0.117)	(0.178)	(0.161)
year==2002	0.441***	-0.518***	-0.536***
	(0.109)	(0.152)	(0.142)
year==2005	-0.148	-0.463***	-0.984***
	(0.132)	(0.167)	(0.184)
Constant	-2.406***	-2.348***	-2.640***
	(0.271)	(0.361)	(0.370)
Observations	7139		
Log-Likelihood	-4407.447		

State Dummies Not Reported
Sample: Adoption decisions for different types of Enterprise EMR 1996-2005
Multinomial Logit Estimates for decision to adopt open-loop, closed-loop and Meditech EMR enterprise technology
* p<0.10, ** p<0.05, *** p<0.01

Table 3: Instrumental variables estimates for the effect of hospital privacy protection on hospital adoption

	EMR Technology		**Placebo ICU Technology**	
	Probit	**Probit-IV**	**Probit**	**Probit-IV**
Hosp Privacy Law	0.099*	-0.623*	0.110**	-0.306
	(0.051)	(0.365)	(0.052)	(0.428)
Academic	0.210*	0.166	0.149	0.126
	(0.108)	(0.110)	(0.110)	(0.112)
Years Opened	0.002***	0.003***	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Numb Hospitals HSA	-0.003*	0.002	0.001	0.004
	(0.002)	(0.003)	(0.002)	(0.003)
No Out-of-Reg. System Hosp	-0.013***	-0.012***	-0.005***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Independent Practice Association	0.087	0.143**	-0.162**	-0.124
	(0.069)	(0.072)	(0.073)	(0.083)
Physician Hospital Organization	-0.019	-0.039	0.053	0.040
	(0.054)	(0.054)	(0.056)	(0.057)
Fully Integrated Organization	-0.114**	-0.160***	-0.033	-0.063
	(0.056)	(0.058)	(0.058)	(0.065)
Member System	0.156***	0.176***	0.077	0.092
	(0.057)	(0.056)	(0.059)	(0.060)
Member Network	-0.094*	-0.105**	0.008	-0.002
	(0.054)	(0.053)	(0.055)	(0.055)
Total Payroll (USDm)	-0.004***	-0.004***	-0.002**	-0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
Staffed Beds (000)	0.784**	0.898***	0.122	0.211
	(0.347)	(0.340)	(0.351)	(0.359)
Nursing Home Unit	-0.112**	-0.128**	-0.028	-0.040
	(0.056)	(0.055)	(0.058)	(0.059)
Total Outpatients (000)	0.008***	0.007***	-0.000	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Births (000)	0.022	0.040	0.018	0.029
	(0.026)	(0.027)	(0.026)	(0.028)
Medicare Patients (000)	0.008	-0.003	0.049***	0.042**
	(0.014)	(0.015)	(0.014)	(0.016)
Medicaid Patients (000)	0.004	0.007	0.003	0.005
	(0.019)	(0.019)	(0.019)	(0.019)
HMO	-0.067	-0.062	0.140*	0.138*
	(0.082)	(0.081)	(0.083)	(0.082)
Fee for Service	0.077	0.061	-0.124	-0.128
	(0.118)	(0.116)	(0.120)	(0.119)
PPO	0.137*	0.087	0.170**	0.143*
	(0.076)	(0.080)	(0.076)	(0.082)
Observations	2935	2935	2935	2935
Log-Likelihood	-1861.500	-3810.283	-1734.710	-3684.737
First-Stage Regressions				
Proportion Signed-Up DNC		0.299***		0.317***
		(0.069)		(0.068)
Failed Opposition RealID		-0.071***		-0.068***
		(0.016)		(0.017)
Opted Out RealID		0.015		0.012
		(0.034)		(0.037)
No Opposition RealID by 2007		-0.011		-0.012
		(0.023)		(0.024)
Over-identification test of instrumental variables				
Hansen J statistic		5.609		5.207
P-value		0.132		0.157
Joint Significance of First Stage variables				
F-Test		2.980		2.980
P-value		0.018		0.018

Dependent Variable: Whether Hospital has installed Enterprise EMR/ICU technology by 2005
Probit GMM Estimates: Test statistics from identically specified linear probability model
* p<0.10, ** p<0.05, *** p<0.01

Table 4: Instrumental variables estimates for the effect of the installed base on adoption in Privacy and Non-Privacy Law States

	No Privacy Law		**Privacy Law**	
	Probit	**Probit-IV**	**Probit**	**Probit-IV**
Installed HSA	0.120***	0.186*	0.063***	-0.103
	(0.029)	(0.103)	(0.017)	(0.122)
Academic	0.193	0.189	0.277*	0.374**
	(0.178)	(0.178)	(0.147)	(0.156)
Years Opened	0.004***	0.004***	0.004***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Numb Hospitals HSA	-0.047**	-0.079	-0.027***	0.042
	(0.024)	(0.054)	(0.010)	(0.051)
No Out-of-Reg. System Hosp	-0.030***	-0.028**	-0.025***	-0.030***
	(0.011)	(0.011)	(0.005)	(0.005)
Independent Practice Association	0.301**	0.289**	-0.029	-0.032
	(0.117)	(0.118)	(0.087)	(0.085)
Physician Hospital Organization	0.030	0.039	-0.042	-0.022
	(0.085)	(0.085)	(0.073)	(0.074)
Fully Integrated Organization	-0.164**	-0.163*	-0.015	0.009
	(0.084)	(0.083)	(0.077)	(0.078)
Member System	0.155*	0.156*	0.036	0.027
	(0.088)	(0.088)	(0.076)	(0.074)
Member Network	-0.124	-0.117	-0.038	-0.002
	(0.081)	(0.082)	(0.072)	(0.077)
Total Payroll (USDm)	-0.004**	-0.004**	-0.003**	-0.003**
	(0.002)	(0.002)	(0.001)	(0.001)
Staffed Beds (000)	1.040	1.074	0.387	0.285
	(0.669)	(0.673)	(0.418)	(0.430)
Nursing Home Unit	-0.102	-0.098	-0.010	-0.012
	(0.087)	(0.087)	(0.076)	(0.075)
Total Outpatients (000)	0.012***	0.011**	0.007**	0.008**
	(0.004)	(0.004)	(0.004)	(0.003)
Births (000)	0.081	0.081	0.016	-0.006
	(0.051)	(0.051)	(0.031)	(0.038)
Medicare Patients (000)	-0.012	-0.011	0.016	0.024
	(0.025)	(0.025)	(0.018)	(0.019)
Medicaid Patients (000)	0.002	0.001	-0.016	-0.000
	(0.041)	(0.041)	(0.022)	(0.026)
HMO	-0.156	-0.152	0.117	0.127
	(0.124)	(0.123)	(0.114)	(0.112)
Fee for Service	0.124	0.117	0.101	0.069
	(0.176)	(0.174)	(0.166)	(0.166)
PPO	0.128	0.113	0.094	0.134
	(0.111)	(0.114)	(0.108)	(0.107)
Observations	1281	1281	1654	1654
Log-Likelihood	-807.720	-2904.168	-1076.521	-4425.367
First-Stage Regressions				
Prop Other Hosp MultiHSA		-0.236***		-0.078***
		(0.044)		(0.018)
Proportion IPA in HSA		1.055***		0.195
		(0.261)		(0.209)
Over-identification test of instrumental variables				
Hansen J statistic		1.403		0.338
P-value		0.2362		0.854
Joint Significance of First Stage variables				
F-Test		20.305		9.676
P-value		0.000		0.000

Dependent Variable: Whether Hospital has installed Enterprise EMR by 2005
Probit GMM Estimates: Test statistics from identically specified linear probability model
Robust Standard Errors: * p<0.10, ** p<0.05, *** p<0.01

Table 5: Falsification Exercise: Instrumental variables estimates for the effect of hospital privacy protection on hospital adoption of ICU unit technology

	EMR Base		**Placebo Base**	
	Probit	**Probit IV**	**Probit**	**Probit IV**
Installed HSA	0.025	0.026		
	(0.021)	(0.095)		
False Installed HSA			0.115***	0.026
			(0.018)	(0.120)
Academic	0.174	0.174	0.171	0.177
	(0.115)	(0.114)	(0.119)	(0.116)
Years Opened	0.001*	0.001*	0.001	0.001*
	(0.001)	(0.001)	(0.001)	(0.001)
Numb Hospitals HSA	-0.014	-0.014	-0.039***	-0.012
	(0.010)	(0.039)	(0.006)	(0.038)
No Out-of-Reg. System Hosp	-0.008	-0.008	-0.007	-0.008
	(0.006)	(0.007)	(0.006)	(0.006)
Independent Practice Association	-0.150**	-0.150*	-0.154**	-0.151**
	(0.076)	(0.077)	(0.074)	(0.077)
Physician Hospital Organization	0.053	0.053	0.045	0.052
	(0.058)	(0.058)	(0.058)	(0.059)
Fully Integrated Organization	-0.028	-0.028	-0.019	-0.022
	(0.059)	(0.060)	(0.060)	(0.059)
Member System	0.043	0.043	0.018	0.033
	(0.064)	(0.063)	(0.062)	(0.068)
Member Network	0.009	0.009	0.030	0.015
	(0.063)	(0.062)	(0.061)	(0.067)
Total Payroll (USDm)	-0.002*	-0.002*	-0.002*	-0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
Staffed Beds (000)	0.071	0.072	0.207	0.104
	(0.383)	(0.387)	(0.378)	(0.417)
Nursing Home Unit	-0.014	-0.014	-0.038	-0.019
	(0.060)	(0.060)	(0.058)	(0.066)
Total Outpatients (000)	0.000	0.000	0.001	0.000
	(0.003)	(0.003)	(0.003)	(0.003)
Births (000)	0.015	0.015	0.016	0.011
	(0.026)	(0.031)	(0.028)	(0.029)
Medicare Patients (000)	0.050***	0.050***	0.043***	0.048***
	(0.016)	(0.016)	(0.016)	(0.017)
Medicaid Patients (000)	-0.002	-0.002	0.000	-0.000
	(0.021)	(0.023)	(0.022)	(0.022)
HMO	0.168*	0.168*	0.168*	0.165*
	(0.090)	(0.090)	(0.089)	(0.092)
Fee for Service	-0.119	-0.119	-0.131	-0.125
	(0.135)	(0.135)	(0.133)	(0.136)
PPO	0.161*	0.161*	0.170**	0.170**
	(0.084)	(0.091)	(0.083)	(0.084)
Observations	2935	2935	2935	2935
Log-Likelihood	-1746.680	-7372.059	-1719.960	-7234.910
First-Stage Regressions				
Prop Other Hosp MultiHSA		-0.099		-0.792
		(0.063)		(0.058)
Proportion IPA in HSA		0.623		-0.100
		(0.522)		(0.984)
Over-identification test of instrumental variables:				
Hansen J statistic		0.533		1.100
P-value		0.766		0.577
Joint Significance of First Stage variables				
F-Test		3.523		0.813
P-value		0.0148		0.486

Dependent Variable: Whether Hospital has installed ICU technology by 2005

Probit GMM Estimates: Test statistics from identically specified linear probability model

Robust Standard Errors: * p<0.10, ** p<0.05, *** p<0.01

Table 6: Three-Stage Least Squared Combined Panel Regression

Correlation Structure	**Independent**	**Unstructured**
Hosp Privacy Law	-0.176	-0.194
	(0.205)	(0.202)
Installed HSA	0.074***	0.112***
	(0.020)	(0.020)
Hosp Priv Law*Installed HSA	-0.024*	-0.030**
	(0.013)	(0.013)
Academic	0.045**	0.047**
	(0.023)	(0.023)
Years Opened	0.001***	0.001***
	(0.000)	(0.000)
Numb Hospitals HSA	-0.022***	-0.035***
	(0.006)	(0.006)
No Out-of-Reg. System Hosp	-0.003***	-0.003***
	(0.000)	(0.000)
Independent Practice Association	0.008	0.008
	(0.014)	(0.014)
Physician Hospital Organization	0.015	0.014
	(0.011)	(0.011)
Fully Integrated Organization	-0.017	-0.017
	(0.012)	(0.012)
Member System	0.046***	0.047***
	(0.012)	(0.011)
Member Network	-0.023**	-0.023**
	(0.011)	(0.011)
Total Payroll (USDm)	-0.001***	-0.001***
	(0.000)	(0.000)
Staffed Beds (000)	0.253***	0.252***
	(0.073)	(0.072)
Nursing Home Unit	-0.017	-0.017
	(0.011)	(0.011)
Total Outpatients (000)	0.002***	0.002***
	(0.001)	(0.001)
Births (000)	0.003	0.003
	(0.006)	(0.006)
Medicare Patients (000)	-0.004	-0.004
	(0.003)	(0.003)
Medicaid Patients (000)	0.003	0.003
	(0.004)	(0.004)
HMO	-0.027*	-0.027*
	(0.015)	(0.015)
Fee for Service	-0.042**	-0.042**
	(0.021)	(0.021)
PPO	0.018	0.018
	(0.014)	(0.014)
Population HSA	0.035**	0.059***
	(0.017)	(0.017)
Income Median HSA (000)	-0.005***	-0.006***
	(0.001)	(0.001)
Observations	8601	8601
Log-Likelihood	-4.91e+04	-4.43e+04

Panel data from 1999-2005
State and year fixed effects
Multiple unreported Hospital Level and HSA level controls
Dependent Variable: Whether Hospital has installed Enterprise EMR by that year
3SLS Linear probability model: * p<0.10, ** p<0.05, *** p<0.01

Table 7: Summary statistics by level of DNC

	Low DNC		**High DNC**	
EMR Adoption	0.4	(0.49)	0.42	(0.49)
ICU Adoption	0.22	(0.41)	0.21	(0.41)
Independent Practice Association	0.11	(0.31)	0.17	(0.37)
Physician Hospital Organization	0.32	(0.46)	0.26	(0.43)
Fully Integrated Organization	0.26	(0.44)	0.25	(0.43)
Member System	0.64	(0.48)	0.65	(0.47)
Member Network	0.34	(0.47)	0.31	(0.46)
Total Payroll (USDm)	36.41	(51.76)	52.82	(62.93)
Staffed Beds (000)	0.18	(0.16)	0.22	(0.19)
Nursing Home Unit	0.31	(0.46)	0.26	(0.44)
Total Outpatients (000)	12.16	(15.31)	15.49	(17.79)
Births (000)	0.82	(1.18)	1.18	(1.47)
Medicare Patients (000)	3.23	(3.21)	3.93	(3.5)
Medicaid Patients (000)	1.28	(1.73)	1.8	(2.37)
HMO	0.16	(0.37)	0.16	(0.37)
Fee for Service	0.06	(0.24)	0.05	(0.21)
PPO	0.23	(0.42)	0.17	(0.38)

Table 8: Summary statistics by Privacy Law

	No Privacy Law		**Privacy Law**	
EMR Adoption	0.39	(0.49)	0.43	(0.49)
ICU Adoption	0.22	(0.41)	0.21	(0.41)
Independent Practice Association	0.10	(0.3)	0.17	(0.37)
Physician Hospital Organization	0.31	(0.46)	0.28	(0.44)
Fully Integrated Organization	0.30	(0.45)	0.22	(0.41)
Member System	0.62	(0.48)	0.66	(0.47)
Member Network	0.36	(0.48)	0.31	(0.46)
Total Payroll (USDm)	39.3	(54.68)	48.49	(60.32)
Staffed Beds (000)	0.18	(0.17)	0.21	(0.18)
Nursing Home Unit	0.31	(0.46)	0.27	(0.44)
Total Outpatients (000)	13.23	(16.49)	14.24	(16.78)
Births (000)	0.83	(1.14)	1.13	(1.47)
Medicare Patients (000)	3.40	(3.46)	3.7	(3.3)
Medicaid Patients (000)	1.29	(1.67)	1.72	(2.34)
HMO	0.16	(0.37)	0.16	(0.37)
Fee for Service	0.06	(0.24)	0.05	(0.22)
PPO	0.23	(0.42)	0.18	(0.38)
Population HSA	0.68	(0.99)	2.10	(3.23)
Income Median HSA (000)	23.35	(5.42)	26.79	(8.32)
Medicare HSA	0.10	(0.15)	0.27	(0.43)