



Management Science

Publication details, including instructions for authors and subscription information:
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To cite this article:

Amalia R. Miller, Catherine Tucker, (2009) Privacy Protection and Technology Diffusion: The Case of Electronic Medical Records. Management Science 55(7):1077-1093. <http://dx.doi.org/10.1287/mnsc.1090.1014>

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

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This paper quantifies the effect of state privacy regulation on the diffusion of electronic medical records (EMRs). EMRs allow medical providers to store and exchange patient information using computers rather than paper records. Hospitals may be more likely to adopt EMRs if they can reassure patients that their confidentiality is legally protected. Alternatively, privacy protection may inhibit adoption if hospitals cannot benefit from easily exchanging patient information. We find that state privacy regulation restricting hospital release of health information reduces aggregate EMR adoption by hospitals by more than 24%. We present evidence that suggests that this is due to the suppression of network externalities.

Key words: technology; privacy protection; health IT; network externalities; network effects; hospitals

History: Received May 2, 2008; accepted February 16, 2009, by Ramayya Krishnan, information systems.

Published online in *Articles in Advance* May 7, 2009.

1. Introduction

Electronic medical records (EMRs) allow medical providers to store and exchange medical information using computers rather than paper records. Although EMRs were invented in the 1970s, by 2005 only 41% of U.S. hospitals had adopted a basic EMR system. This is troubling, given estimates that widespread adoption could reduce America's annual health-care bill by \$34 billion through higher efficiency and safety (Hillestad et al. 2005).¹ Anecdotal evidence suggests that privacy protection may partially explain this slow pace of 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

This paper pursues a three-pronged empirical strategy to provide the first quantitative estimates of the effect of state-level privacy protection on hospital EMR adoption. We start by identifying how network effects shape the adoption of EMRs, and how these network effects vary by whether or not states have privacy legislation. We then examine how privacy legislation affects overall adoption. Finally, we present evidence that suggests that privacy legislation

primarily reduces demand for EMRs via the suppression of network effects. We discuss these three empirical strategies in turn in the remainder of this introduction.

Network effects may shape the adoption of EMRs because hospitals derive network benefits from EMRs when they can electronically exchange information about patient histories with other health providers. Exchanging EMRs is quicker and more reliable than exchanging paper records by fax, mail, or patient delivery. It is especially useful for patients with chronic conditions who want to see a new specialist who requires access to previous tests. It is also useful for emergency room patients whose records (containing information about previous conditions and allergies) are stored elsewhere. Exchanging EMRs with another hospital can also be profitable. Under the prospective payment system, where Medicare and many state Medicaid programs reimburse hospitals a flat amount per diagnosis group, hospitals have large financial incentives to avoid expensive duplicate tests. Such network benefits may lead to "network effects," where the adoption of EMRs by one hospital depends on the adoption by other hospitals. This paper defines network effects as the economic externality produced from one hospital's adoption decision on the profitability of EMR adoption for other hospitals.

Privacy protection may affect the network benefit of EMRs to hospitals and, by implication, alter

¹ These rough calculations of annual net savings are based on a 15-year period and 90% EMR adoption.

² SBCCDE was formed in 1999 to exchange health information between providers in Santa Barbara (Robinson 2007).

how much one hospital's decision to adopt EMRs is affected by another hospital's adoption. The direction of this effect is not clear. Privacy protection could increase the network benefits to hospitals of exchanging information electronically if patients are reassured that their medical information will be treated confidentially, consequently making them more likely to report accurate medical information. On the other hand, privacy protection also makes the electronic exchange of information more expensive, and that could reduce net network benefits. These concerns apply to all records, but are heightened for electronic records, because a major advantage of EMRs over paper records is that they facilitate the dissemination of information.

Measuring such network effects is challenging in any setting. Adoption may be correlated within a local health service area (HSA), even absent network effects, due to common shocks. We exploit variables that affect the preexisting information technology (IT) infrastructure and policy of other hospitals in the local HSA as sources of exogenous variation for the installed base. These instrumental variables (IVs) proxy for whether other local hospitals' adoption is reduced by legacy infrastructure and physician resistance.

The decision to enact privacy legislation may itself be correlated with unobservables that have an influence on the adoption decision, so in our first analysis we seek to identify how local network effects shape adoption for states with and without privacy legislation by running separate regressions for each of these groups. In states without hospital privacy legislation, EMR adoption by one hospital increases the probability of a neighboring hospital's adoption by 7% overall in the cross section using cross-sectional data and by 2% every three years using panel data. In states with hospital privacy protection, there is no measurable effect from one hospital adopting EMRs on another hospital. Privacy protection reduces the net installed base effect, which suggests that the installed base effect is driven by network effects and can be attributed to the exchange of information rather than to other supply-side spillovers, such as learning by doing or agglomeration of technological expertise, that are not directly affected by privacy protection. We provide some validation for the empirical approach using a falsification exercise. We show that although EMR adoption exhibits positive and significant responses to the installed base in states without privacy laws, there are no such effects for a software that has no network benefits.

Having uncovered a mechanism by which privacy protection may affect EMR adoption, we estimate the overall effects of the laws on EMR diffusion. We

implement several complementary empirical strategies, using cross-sectional and panel data and two sets of IVs. The panel model includes hospital fixed effects (FEs), and uses compositional shifts in state legislatures to instrument for changes in privacy laws. The cross-sectional strategy uses variation in local tastes for privacy and regulation to separate the effects of the laws from confounding factors such as education levels or tastes for technology. Both sets of IV estimates indicate that state privacy protection (reflecting tastes for privacy) reduces adoption by 24% overall using cross-sectional data and 11% per three-year time period using panel data. We repeat the falsification test and find no evidence that privacy laws inhibit adoption of a placebo technology that privacy laws do not cover. We conclude by presenting some suggestive three-stage least squares (3SLS) estimates that incorporate the panel data and the full set of instruments to estimate direct effects of privacy laws on adoption and effects that are mediated through network considerations and the installed base.

Our results suggest there is a trade-off between EMR adoption and privacy protection. We do not, however, quantify the overall benefits of either EMR adoption or privacy protection. For example, the overall benefit of privacy protection might be positive if other spillovers, such as a reduction in medical identity theft, outweigh the costs of delayed EMR adoption.

Although we study just one technology and one type of regulation, our results illuminate the broader debate about the potential implications of privacy protection for speedy adoption of other 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 radio-frequency identification (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 that allow companies and individuals to exchange information online, such as e-wallets and online supplier electronic data interchange (EDI) systems. Our results support work by economic scholars such as Posner (1981) and Varian (1997), which suggests that there are efficiency costs to privacy protection.

Our paper is organized as follows. Section 1.1 discusses more broadly how our research contributes to the health and IT literature. Section 2 sets out our conceptual model, whereas §2.1 discusses the legal context of state variation in privacy protection. Section 3

describes the data. Section 4 studies how network effects shape the adoption of EMRs, and how these network effects differ for states with and without privacy legislation. Identification in this analysis arises from variation in the number of adopters within a local HSA. Instrumental variables are used because there may be unobserved demandside shocks within a local HSA that have an influence on all adopters. Section 5 examines how passing privacy legislation influences adoption, without studying how it affects the network benefits of adoption. Here identification arises from variation in legislation within a state over time, and again we instrument the law because demand for privacy protection may be correlated with propensity to adopt EMRs. Section 6 combines these two types of estimation and exploits variation in policy and local adopters to see whether the privacy legislation reduces demand for EMRs primarily through decreasing the network benefit. Section 7 concludes the paper.

1.1. Literature Review

Our findings are directly relevant for a growing literature that studies the diffusion of health-care IT. The primary motivation of this literature is to identify impediments to the diffusion of IT among health-care providers in the United States. For example, Borzekowski (2002) investigates how cost-saving incentives created by the U.S. health-care finance system affected the adoption of health-care information systems over time. Reflecting the national policy importance of EMRs, there have been multiple studies that examine correlates of its diffusion. Simon et al. (2007) evaluate the role of practice size in the diffusion of EMRs in doctors' offices in Massachusetts. Kazley and Ozcan (2007) emphasize the importance of both a hospital's organizational (size, ownership, system affiliation, public payer mix, teaching status, financial resources) and environmental characteristics (competition, rurality, per capita income, change in unemployment rate) for EMR adoption. Angst et al. (2008) investigate the role of "celebrity status" and spatial proximity in the diffusion of EMRs, taking a mimetic adoption perspective. Miller and Tucker (2009) investigate whether the risk of an electronic "paper trail" in medical malpractice cases inhibits adoption of EMRs. Vetter (2009) discusses the legal issues that have been hampering the development of open-source technologies for health IT. This paper is the first empirical investigation of the role of privacy protection in the diffusion of health-care IT and the implications this has for the network effects and network benefits of the technology. This empirical evidence is valuable given the legal issues surrounding optimal privacy policy for a new national-level EMR system (Hoffman and Podgurski 2008).

This emphasis on privacy protection contributes more broadly to the literature on interorganizational IT. There is a growing literature that studies the role of network effects in technology adoption by organization, such as the theoretical model of buyer and supply networks by Riggins et al. (1994), the empirical study of the role of network externalities in electronic banking adoption by banks by Kauffman et al. (2000), the study of the adoption of automated clearing house technology by banks by Gowrisankaran and Stavins (2004), and the study of the role of network externalities in EDI adoption by firms by Chwelos et al. (2001). However, this is, to the best of the authors' knowledge, the first paper to examine how network effects, and consequently technology adoption decisions, are affected by privacy protection. These results highlight the importance of regulation and the regulatory environment for network industries, a factor often omitted in studies of IT adoption.

A consistent theme of this literature on network effects in the diffusion of IT has been overcoming the challenge of identifying causal network effects when there are unobservable differences in tastes and institutions across networks, which could also explain correlated adoption decisions. To overcome this challenge, previous works such as those of Tucker (2008), Rysman (2004), and Gowrisankaran and Stavins (2004) have focused on finding exogenous shifters for the stand-alone benefits of adoption to study the causal effect of one agent's adoption on another. By contrast, we infer network effects from an exogenous shift in the ability of agents within a network to transfer information across a network. This is the first research to take the direct approach of exploiting exogenous variation in the ability to use a network to identify network effects.

2. Conceptual Model of Hospital EMR Adoption

In this section, we set up our conceptual model of the drivers of EMR adoption by hospitals. In §2.1, we discuss why these drivers of adoption may be affected by privacy legislation enacted by the state. We model the net gain to hospital i in a regional health network j from EMR adoption at time t as the sum of the net network and stand-alone gains from adoption:

$$\begin{aligned} adopt_{ijt}^* &= f(\text{NetworkNetBenefitsEMR}_{ijt}, \\ &\quad \text{Stand-AloneNetBenefitsEMR}_{it} | \text{PrivacyLaw}_{it}). \quad (1) \end{aligned}$$

This is a latent variable setting. If this net gain from electronic records, defined relative to the alternative technology of paper records, is positive, a hospital will adopt EMRs.

The net network and stand-alone gains from EMRs can be decomposed into network and stand-alone costs and benefits. We subscript the network variable with the regional-network indicator j to highlight the dependence on decisions made by other hospitals. The network benefits of EMRs are based on the ability to transfer and exchange patient information quickly and electronically with other hospitals. Hospitals can exploit the expanded access to patient information to provide better care to patients with chronic conditions who are seeing a new specialist, or in emergency room situations where patients cannot communicate their medical history or allergies.³ Under the prospective payment system, where Medicare and many state Medicaid programs reimburse hospitals a flat amount per diagnosis group, hospitals have large financial incentives to avoid expensive duplicate tests. This is also the case for emergency rooms, where in addition to Medicare/Medicaid, many private insurers pay a fixed fee.⁴ These network benefits are contingent on (1) whether patients are willing to reveal health information and subsequently have this information transferred electronically across health-care providers and (2) whether there are other health providers with whom it is possible to exchange health information. Hospitals set these network benefits against the cost of transferring information across the network.⁵

The stand-alone benefits from EMR adoption that are independent of what other regional hospitals do stem from improved quality of internal patient care (for example, ensuring information is easily accessible when transferring patients between a recovery ward and a long-term ward) and lower administrative costs. Stand-alone benefits also 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 our econometric analysis we capture these benefits with a vector X_{it} of hospital characteristics. The potential costs of installing EMRs include the up-front costs of software and hardware installation, as well as training and ongoing maintenance. In this model, the net benefits from EMRs may change over time, owing to changes in EMR system prices and functionality, even if hospital characteristics remain stable. The price of EMR systems is not publicly available, because contracts

are individually negotiated and are complicated by vendors who subsidize the up-front costs in the hope of profiting from high support fees. A 2007 American Hospital Association (AHA) survey put the median capital spending per bed for health-care IT at \$5,556.⁶ For operating costs, the median cost per bed was \$12,060 (Welsh 2007). This total median cost per bed of \$17,616 translates to annual costs of \$3,188,496 for an average hospital in our data set that has 181 beds. The same survey suggests that the costs of EMR systems (unlike most new technologies) have actually increased slightly over time. A vector of time FE γ_i captures these changes over time in the panel data specifications. As with network benefits, we do not attempt to measure the stand-alone benefits and costs separately.

Both stand-alone and network benefits can increase the quality of patient care and reduce administrative costs. Higher demand resulting from higher quality and lower costs should increase hospital profits. Improved patient care may also directly enter into the hospital's objective function. Over 80% of hospitals are nonprofit or government owned, so it may be appropriate to think of hospitals as maximizing an objective function that increases separately with patient care quality and with profits.

2.1. How Privacy Laws May Affect EMR Adoption

Privacy concerns regarding EMRs can be divided into two categories: issues of data security, or how easily hospital data systems can be breached by outsiders; and issues of confidentiality, regarding how the hospital will intentionally share their information. Laws that are intended to protect patient confidentiality by governing the procedures by which hospitals can disclose information can also provide incentives for data security. For example, California fined Kaiser Permanente \$200,000 after an employee posted patient details on her blog. The fine was imposed because this violated a provision in state law that governed the confidentiality of medical information, which requires patients to authorize such releases of data (Vrana 2005). In some cases, the regulation includes explicit security standards (see, for example, the text of the Florida law in SEC.2 in the e-companion⁷).

In theory, privacy laws can increase the network costs or the network benefits from EMR adoption. Privacy laws may increase network benefits because they improve patient compliance by

³ The potential for such gains is described by Brailer (2005).

⁴ Doctors have suggested that situations such as that where one patient had seven computed tomography scans and five ultrasounds in 2007 in various hospital emergency rooms could have been avoided with effective EMRs (Calcanis 2005).

⁵ There is also the potential for there to be a negative effect from multiple hospitals adopting if it makes it more likely that patients can easily leave a hospital and seek treatment elsewhere. Such a "competition" effect would reduce the estimated net network benefits.

⁶ This estimate also includes other applications such as radiology support systems.

⁷ An electronic companion to this paper is available as part of the online version that can be found at <http://mansci.journal.informs.org/>.

reassuring patients that their records will be treated confidentially and securely when transferred among health providers. In an online poll, 8% of patients surveyed said that they felt that a hospital or clinic had improperly disclosed their personal medical information (Westin 2005). Such worries have led 13% of patients to admit to engaging in privacy-protecting behaviors (such as avoiding embarrassing medical tests) for their medical information (California HealthCare Foundation 2005). These concerns are particularly salient for the electronic exchange of health information. It was found that 69% of survey respondents state that they are very concerned or somewhat concerned that an EMR system could lead to “more sharing of your medical information without your knowledge” (Westin 2005); 65% of respondents were concerned that EMRs would make it more likely that others would not disclose sensitive but necessary information to doctors and other health-care providers because of worries that it would go into computerized records (Westin 2005). With a privacy law in place, these patients may be more willing to candidly share their health information and risk factors or undergo testing, making the exchange of information by hospitals using EMRs more useful for improving the quality of care.

At the same time, privacy laws may impose additional network costs on hospitals who wish to transfer information electronically, for example, by demanding more of a paper trail, or by requiring more robust software. The design of networked EMR systems with strong security and confidentiality protections involves well-known challenges. Individual consent requirements that can be limited to particular types of information and provider destinations demand a flexibility that is costly to implement (Win and Fulcher 2007). It is more expensive to design a system that has the additional flexibility to limit the flow of information by the type of detail in a patient medical record and by the type of external destination, irrespective of how many patients refuse to have their records shared. Confidentiality protection that demands prior patient consent, which can be revoked at any time, also increases the costs of information exchange. McCarthy et al. (1999) give details of how privacy legislation that requires subjects to give their consent for each study used in research led to lower response rates. When individual consent was required by state law, it was granted by 19% of individuals, as opposed to 93% of patient records made available directly by providers in states without this privacy protection. Finally, in addition to the fixed costs that are added to the complexity of designing the EMR system, the laws require additional documentation, and that burden increases with the flow of information between providers. Theoretically, therefore, privacy regulation can affect the fixed or the variable

costs of EMR adoption, and without detailed breakdowns of the costs involved, we cannot distinguish between the two.

Privacy protection inhibits EMR diffusion not by creating a different legal requirement for different record types, but by raising compliance costs. Complying with privacy laws increases the costs of electronic record systems and, in particular, the costs of sharing information. This is particularly important if one of the key benefits of EMRs is the reduced costs of sharing information as compared with paper records. In this sense, the laws may pose an institutional barrier to information flow, which in turn reduces the potential benefits to hospitals from the adoption of EMRs, a technology that would otherwise reduce the physical barriers to information exchange.

Although it would be desirable to estimate the effects of privacy regulation on network costs and benefits separately, we observe neither of these outcomes. Using data on adoption decisions, we can identify only the net effect of privacy law on network benefits.

3. Data

3.1. Health IT Data

We use technology data from the 2005 release of the Healthcare Information and Management Systems Society (HIMSS) Analytics™ Database (HADB). 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 et al. (2005), and Bower (2005), as well as in Angst et al. (2008). Although these studies did not evaluate the role of privacy protection, (Bower 2005, p. 51) did note that, “Conceivably, privacy demands could forestall benefits of networked technology.” We matched the HADB data with the AHA survey, and were left with data on the timing of technology adoption decisions of 2,910 hospitals. These hospitals were larger and more urban than hospitals that we could not match. Further details about the matching process of these hospitals and likely representativeness are reported in the e-companion. Table 1 describes the main variables in our regressions, including the multiple controls (such as number of patients, organizational type) that we use for variation in stand-alone benefits.

We measure EMR adoption by whether a hospital has installed or is installing an “enterprise EMR” system.⁸ This software is a basic EMR system that underlies other potential add-ins such as clinical decision support, a clinical data repository, and order entry.

⁸ Alternative specifications excluding the 185 observations where adoption is incomplete give similar results.

Table 1 Summary Statistics

			Data set			
			Panel		Cross-section (2005)	
			Mean	Std. dev.	Mean	Std. dev.
Description			Source			
Dependent variables						
EMR adopt	Indicator for whether a hospital adopts enterprise EMRs	HADB	0.17	0.37	0.41	0.49
False adopt	Indicator for whether hospital adopts ICU software	HADB	0.18	0.38	0.3	0.46
Endogenous variables						
<i>HospPrivLaw</i>	Indicator for whether a state had privacy law covering hospitals	Georgetown privacy project	0.61	0.49	0.56	0.5
<i>InstalledHSA</i>	Number of hospitals in HSA that had installed EMRs	HADB	2.89	4.83	4.31	6.45
False <i>InstalledHSA</i>	Number of hospitals in HSA that had installed ICUs	HADB	2.17	4.08	3.27	5.53
Independent variables						
No. hospitals HSA	Number of hospitals in HSA	AHA/HADB	10.1	14.38	10.34	14.94
Academic	Indicator for whether a hospital is an academic research institution	AHA	0.08	0.26	0.08	0.28
Years opened	Number of years hospital has been open	AHA	31.73	34.65	32.52	35.19
No. out-of-reg. system hosp.	Number of hospitals that are part of a system that has hospitals outside HSA	HADB/AHA	15.3	29.68	14.12	28.68
Independent practice association	Indicator for whether hospital is an independent practice association	AHA	0.17	0.38	0.14	0.35
Physician hospital organization	Indicator for whether hospital is a physician hospital organization	AHA	0.32	0.47	0.3	0.46
Fully integrated organization	Indicator for whether hospital is a fully integrated organization	AHA	0.25	0.43	0.26	0.44
Member system	Indicator for whether hospital is a member of a system	AHA	0.6	0.49	0.64	0.48
Member network	Indicator for whether hospital is a member of a network	AHA	0.33	0.46	0.33	0.47
Total payroll (USDm)	Total annual hospital payroll in millions of U.S. dollars	AHA	35.3	47.24	44.48	58.1
Staffed beds (000)	Thousands of staffed beds at hospital	AHA	0.2	0.17	0.2	0.18
Nursing home unit	Indicator variable for whether hospital has nursing home unit	AHA	0.32	0.47	0.28	0.45
Total outpatients (000)	Thousands of annual outpatients seen at hospital	AHA	11.69	14.4	13.8	16.66
Births (000)	Thousands of births that take place at hospital	AHA	0.95	1.25	1	1.34
Medicare patients (000)	Thousands of Medicare patients seen by hospital annually	AHA	3.11	2.94	3.57	3.37
Medicaid patients (000)	Thousands of Medicaid patients seen by hospital annually	AHA	1.28	1.86	1.53	2.09
HMO	Indicator for whether hospital accepts HMO insurance	AHA	0.21	0.4	0.16	0.37
Fee for service	Indicator for whether hospital accepts fee-for-service insurance	AHA	0.08	0.27	0.05	0.23
PPO	Indicator for whether hospital accepts PPO insurance	AHA	0.25	0.44	0.2	0.4
Population HSA	Number of households in HSA (100,000)	Census	1.51	2.7	1.48	2.61
Income median HSA (000)	Average income in HSA in thousands of U.S. dollars	Census	25.26	7.28	25.29	7.4
Medicare HSA	Average proportion of households receiving Medicare in HSA	Census	0.2	0.36	0.2	0.35
Number of observations			7,139		2,935	

The columns in Table 1 reflect our use of both panel and cross-sectional data in our empirical specifications. In our panel, we group the technology adoption data into three periods, ending in 1999, 2002, and 2005, based on when we have data on changes to state statutes. The dependent variable is whether the hospital has adopted EMRs by that year. In the cross-sectional data, the dependent variable is whether or not the hospital has adopted EMRs by 2005.

We capture the network benefit by a count of the total number of *other* hospitals in the local HSA who have adopted EMRs.⁹ To define a regional-health network we need an area that encompasses all of the local hospitals that are likely to exchange

patient histories. Fortunately, Makuc et al. (1991) have developed the HSA measure. An HSA is one or more counties that are relatively self-contained with respect to the provision of routine hospital care. On average, each of the 815 HSAs spans 3.85 counties, although in our sample only 2.14 of these counties have hospitals. An HSA's mean radius is 36.1 miles.¹⁰ We also estimated results for 392 "labor market areas" as defined by the 1990 census using commuting data, obtaining similar results. In our regressions we exclude from our observations hospitals that have previously adopted EMRs, although we include these adoptions in the installed base. Adoption decisions before 1996 are not studied in the panel framework, but are included in the installed base measures.

⁹ 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.

¹⁰ There is, however, large variation in HSA size, as shown in Figure EC.1 in the e-companion.

Conversations with industry specialists reassure us that, once adopted, divestiture of an EMR system is rare. Indeed, in our data only 2.4% of EMR systems were replaced. We assume that hospitals consider only past adoption, not forecasts of future adoption, in their decisions. If this assumption does not hold, then our estimates of network effects capture only part of the expected network gain.

An installed base of hospitals is only a necessary, but not a sufficient, condition for the transfer of health information. There also needs to be a mechanism for cooperation and coordination across hospitals, such as a local regional health information organization (RHIO). A 2006 eHealth Initiative survey (Covich Bordenick et al. 2006) identified over 165 active Health Information Exchange initiatives in the United States, of which 45 were being implemented and 26 were fully operational. This slow implementation may explain why, in 2005, only 38% of hospitals reported that they shared electronic patient data with other hospitals, which is lower than the 41% adoption rate of EMRs (Welsh 2007). 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.

3.2. Legal Data

Our main source for changes in state privacy protection is a series of surveys of state health privacy statutes (Gostin et al. 1996; Pritts et al. 1999, 2002) produced by the Health Privacy Project at Georgetown University. They determine state privacy protection by examining state statutes governing medical privacy. This approach excludes refinements to privacy law stemming from case law or administrative law. 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 according to the Health Privacy Project. We also verified the laws themselves to confirm the accuracy of their reporting. 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. In SEC.2 in the e-companion, we discuss in detail the nuances of some sample text from these laws, and the penalties associated with their violation.

Our state law panel begins in 1996, covering the great bulk of the relevant period of EMR adoption. During that period, we observe 19 changes in laws: 4 changes to increase privacy protection and 15 to decrease it. Figure 1 displays privacy protection in 1996. The 19 changes in laws between 1996 and 2002 allow us to use time series as well as cross-sectional variation to study the effect of state privacy protection.

Figure 1 Map of States with Hospital Privacy Protection: 1996

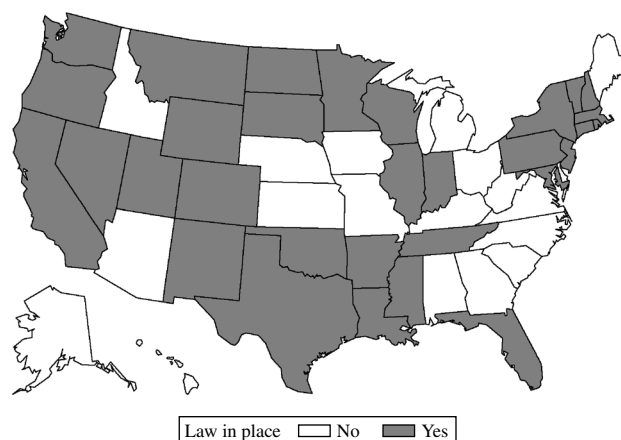
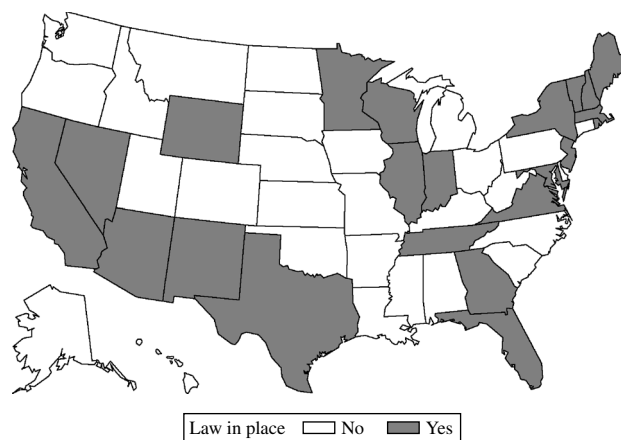


Figure 2 shows that by 2002, about half of the states in the United States had laws that cover hospital behavior. Each of the nine census divisions includes at least one state with and one without hospital coverage. States with hospital privacy protection are significantly larger, have higher incomes, have higher rates of managed care, and are more populous than other states, but have statistically indistinguishable population densities and numbers of hospitals. Because these factors may also affect adoption, we include them as controls in our regressions.

Changes in EMR adoption rates over the sample period varied by privacy regime. Hospitals in states that shed their laws experienced a 21% gain in adoption rates around the years the law changed, compared with an 11% gain in adoption rates for hospitals that maintained their privacy laws. Hospitals located in states that adopted new privacy laws had a similar 11% difference between their level of adoption before the law and in the years after. These numbers are difficult to interpret without considering other factors that vary across states and affect EMR adoption rates.

Figure 2 Map of States with Hospital Privacy Protection: 2002



Therefore, in the following sections, we develop and estimate a model that addresses these factors to estimate the impact of privacy laws on EMR adoption.

4. Network Effects

This section aims to determine the importance of network effects in EMR adoption decisions for hospitals in states with and without privacy laws. Building on our conceptual model in Equation (1), we estimate a discrete-time hazard model of EMR adoption. Discrete survival time models can be estimated using standard binary choice methods if the panel is limited to time periods for each firm when it is still at risk of the event (Allison 1982). We model adoption as an irreversible state and exclude hospitals that have previously adopted from the sample. The latent propensity to adopt EMRs in period t is a function of the installed base in area j and privacy regime:

$$\text{adopt}_{ijt} = f(\text{InstalledbaseHSA}_{ijt}, X_{it}, \alpha_i, \gamma_t, \epsilon_{it} | \text{PrivacyLaw}_{it}), \quad (2)$$

where adopt_{ijt} is a hospital-year level indicator for adoption and implementation in 1999, 2002, and 2005. We do not separately identify costs and benefits, but instead measure how each variable affects a hospital's adoption propensity overall.

Our primary variable of interest is *InstalledbaseHSA_{ijt}*. This measures the responsiveness of one hospital's EMR adoption to past adoption by other local hospitals. Greater adoption by other hospitals should lead to greater network benefits from EMRs, as described in §2. It may also lead to learning effects (such as those estimated by Karshenas and Stoneman 1993). Unlike learning spillovers, network benefits also depend on the costs or ease of transferring information across the network. We estimate the model separately for hospitals in states with and without privacy laws. This flexibility allows the privacy regime to affect stand-alone and network benefits from EMRs. Here γ_t is a series of year FE, X_{it} is a vector of time-varying hospital characteristics, ϵ_{it} is an independent and identically distributed random error term, and α_i is a vector of hospital-level FE that absorbs all permanent hospital and location features. Including these FEs ensures that identification of key parameters is based on within-hospital variation over time, rather than cross-hospital variation. However, as discussed by Allison and Christakis (2006), one can only estimate conditional individual-level FEs in a discrete-time hazard model with baseline controls such as ours. Reassuringly, the results are similar when we repeat the panel estimation using FEs at the HSA or state level using full-information maximum likelihood.

We estimate a linear probability model of EMR adoption separately for hospitals in states with and

without privacy laws. The linear probability model allows us to circumvent the incidental parameters problem that would lead to inconsistency in a probit model with FEs. The linear model has the disadvantage that predicted values will not be constrained to lie between zero and one. However, Angrist (2001) provides evidence that the linear IV model performs similarly to the probit specification with instruments and can be useful for estimating causal effects. To check our specification, we also present results from a cross-sectional probit regression where the endogenous variable is instrumented but there are no hospital FEs. In this cross-sectional regression, we use the full range of hospital and local area controls reported in Table 1.

The positive and significant coefficients on installed base, reported in columns 1 and 4 in Table 2, indicate positive responsiveness to nearby adoption and suggest the presence of network effects. However, the coefficients will be biased estimates of true network effects if the installed base is correlated with omitted factors that also predict adoption. For example, neighboring hospitals may share a taste for technology. Hospital FEs will eliminate bias from any permanent differences in tastes, but bias will persist if tastes for technology are changing in a correlated way.

In order to estimate a causal network effect that will trace the effect of one hospital's adoption on the adoption decisions of neighboring hospitals, we use IVs. These variables affect the IT adoption environment in neighboring hospitals, but are plausibly uncorrelated with the hospital's own adoption decision. Our first instrument is whether neighboring hospitals belong to a system of hospitals that extends into other regions (this resembles the identification strategy for electronic payments adoption of Gowrisankaran and Stavins 2004). Our second set of instruments covers the type of relationship neighboring hospitals have with their physicians. Ciliberto and Dranove (2006) discuss how these different doctor-physician affiliations can change the power structure in hospitals. For the estimates to be valid, the exclusion restriction must hold that characteristics of neighboring hospitals have no direct impact on EMR adoption decisions.

We report results from FE-IV estimation in columns 2 and 5 in Table 2. For hospitals under either privacy regime, estimated network effects are smaller under IVs than under ordinary least squares. More importantly, the installed base effect is positive and significant for hospitals without privacy laws and zero for those with privacy laws. These measures are significantly different at the 5% level. Absent privacy protection, we estimate a 2% increase in the propensity to adopt EMRs during each three-year time period for each additional hospital in the HSA who adopts EMRs.

Table 2 Hospitals Considering Adopting EMRs Respond Differently to the EMR Installed Base in States That Have Privacy Laws and Those That Do Not

Model	States with no privacy law			States with privacy law		
	1	2	3	4	5	6
Data	Panel	Panel	Cross-sectional	Panel	Panel	Cross-sectional
Hospital fixed effects	Yes	Yes	No	Yes	Yes	No
Instrumental variables	No	Yes	Yes	No	Yes	Yes
<i>InstalledHSA</i>	0.025*** (0.005)	0.023** (0.009)	0.071* (0.039)	0.013*** (0.004)	−0.009 (0.011)	0.007 (0.046)
Year 2002	0.126*** (0.014)	0.128*** (0.016)		0.174*** (0.013)	0.196*** (0.016)	
Year 2005	0.158*** (0.016)	0.161*** (0.019)		0.199*** (0.015)	0.243*** (0.025)	
No. hospitals HSA	0.004 (0.021)	0.006 (0.021)	−0.030 (0.021)	−0.019** (0.009)	0.025 (0.022)	−0.003 (0.019)
No. out-of-reg. system hosp.	−0.022 (0.051)	−0.023 (0.051)	−0.011** (0.004)	−0.040** (0.018)	−0.043** (0.019)	−0.011*** (0.002)
Academic (d)			0.073 (0.070)			0.121* (0.065)
Years opened			0.001*** (0.000)			0.001*** (0.000)
Independent practice association (d)			0.113** (0.047)			−0.012 (0.034)
Fully integrated organization (d)			−0.061*** (0.031)			−0.003 (0.031)
Total payroll (USDm)			−0.002** (0.001)			−0.001** (0.001)
Total outpatients (000)			0.004** (0.002)			0.003*** (0.001)
Observations	2,811	2,367	1,281	4,328	3,446	1,654
Log-likelihood	1,027.173	661.266	−2,904.155	1,020.762	390.880	−4,418.995
Excluded first-stage regressions variables						
Prop. other hosp. multi-HSA		−3.726*** (0.186)	−0.237*** (0.044)		−2.435*** (0.148)	−0.073*** (0.018)
Proportion IPA in HSA		0.067 (0.251)	1.038*** (0.262)		−0.956*** (0.260)	0.180 (0.218)
Proportion integrated in HSA		−0.519*** (0.158)	−0.012 (0.094)		−0.355 (0.227)	0.775*** (0.151)
Overidentification test of instruments						
Hansen <i>J</i> -statistic		4.607	2.107		1.118	2.761
<i>p</i> -value		0.100	0.349		0.572	0.251
Significance of first-stage regressions						
LM-statistic		341.762	33.847		258.924	43.121
<i>p</i> -value		0.000	0.000		0.000	0.000

Notes. Multiple hospital and HSA-level control variables not reported. See the e-companion for full specification. Linear probability model estimates reported for panel. Probit GMM estimates for cross section reported as marginal effects calculated at mean. (d) indicates that the marginal effect is calculated as the discrete change in *y* as the dummy variable changes from zero to one. Test statistics for cross-sectional data calculated for identically specified linear probability model to ensure comparability.

p* < 0.10; *p* < 0.05; ****p* < 0.01. Robust standard errors are reported in parentheses below the estimate.

These results from panel estimation provide evidence of the presence of network benefits from EMRs that are diminished by privacy laws. However, with only three time periods in the sample, we hesitate to rely solely on time-series variation. As a robustness check, we estimate a cross-sectional IV model of adoption:

$$adopt_{ij} = f(InstalledbaseHSA_{ij}, X_i, \epsilon_i | PrivacyLaw_i), \quad (3)$$

where $adopt_{ij}$ is a hospital-year level indicator for adoption by 2005. We use a generalized method of moments (GMMs) to estimate an IV-probit model that addresses the potential endogeneity of *Installed-baseHSA_{ij}*. Results are reported (as marginal effects at the sample means) in columns 3 and 6 in Table 2 for hospitals with and without privacy laws, respectively.

For states without privacy laws, the cross-sectional evidence confirms the panel IV finding of positive

network effects. The marginal effect implies that the addition of one more hospital that has installed EMRs to the installed base increases propensity to adopt EMRs by 2005 by 7%. 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 that privacy laws inhibit network benefits, because the effect of *InstalledHSA* is again negligible and statistically insignificant. Together, these results show that network effects promote EMR diffusion, but that these network benefits are suppressed by the state privacy rules we study. Given that network externalities can lead to multiple equilibria, the coefficient estimate for *InstalledHSA* should be interpreted as an equilibrium effect, rather than a structural effect, as in Gowrisankaran and Stavins (2004).

The regressions in Table 2 include numerous covariates that capture differences across hospitals and local markets. *MultiHSAHosp* is an indicator variable for whether a hospital is part of a multiregional chain. Such hospitals are less likely to adopt EMRs. Multi-region hospitals are more likely to have an old, DOS-based server infrastructure, which is harder to update and interface with EMRs. In the cross-sectional regressions, where there are no hospital FEs, we also include variables that capture the organizational structure at the hospital. In the cross-sectional data, hospitals that are built around independent practice associations (IPAs), where doctors are essentially independent contractors, are more likely to adopt EMRs than hospitals that are fully integrated organizations where doctors are paid wages. There is some evidence that academic hospitals and older hospitals are more likely to adopt EMRs. The coefficient estimates on total payroll and total outpatients suggest that hospitals with more patients but smaller payrolls are more likely to adopt EMRs. The number of area hospitals, whether the hospital is a member of a network, and health insurance and managed-care variables are not generally significant.

The first-stage regressions presented in Table 2 show that the IVs are significant predictors of adoption at the HSA level, satisfying a necessary condition for their validity. Multi-HSA hospitals are less likely to adopt EMRs. Hospitals with physicians working in IPAs are less likely to adopt in the panel regressions and more likely to adopt in the cross-sectional regressions. The negative coefficient in the panel regression likely captures physician resistance, which is documented as a factor limiting EMR adoption by hospitals (Groopman 2007). For example, Brian Patty, medical director for information systems at Fairview Ridges Hospital, Minnesota, reports a frequent physician complaint about EMRs as being, “I am not a

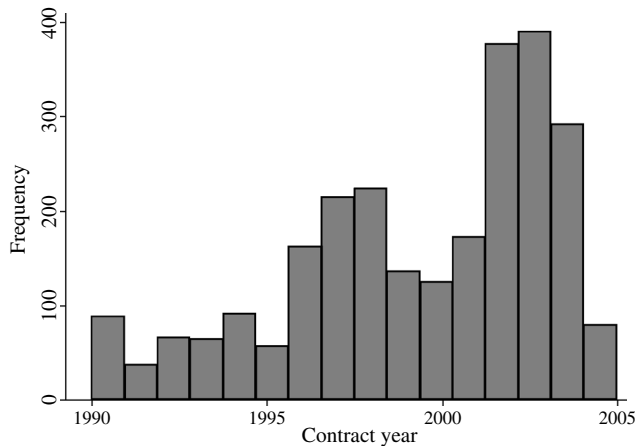
robot. This computer is making me into a robot practicing cookbook medicine” (Baldwin 2005, RT3). The less-integrated the relationship, the less involvement physicians have with technology roll-out decisions. The positive coefficient in the cross section likely reflects the changing profile of IPA hospitals documented by Ciliberto (2006), whereby hospitals that had less success with the IPA system, perhaps because of difficulties in involving doctors in decision making, dropped this form of organization. Hospitals with IPAs at the end of the period may have experienced less internal conflict regarding technology adoption.

The exclusion restriction on the IVs cannot be tested directly, so we conduct a series of falsification tests using an alternative medical technology that should not be affected by the interaction of privacy protection and network effects. In theory, the most stringent placebo test would be conducted using a form of health-care IT that has network effects across hospitals, but no network effects with EMRs. However, in practice, because EMRs comprise the backbone of a hospital’s health records system, any other network technology in our data will also interact with EMRs. To avoid this source of contamination, we chose a technology without any network effects and that is not used as a part of a patient’s permanent health record. There are few such technologies. For example, it would not be helpful to study the diffusion of PET/SPECT/MRI type devices, because the usefulness of these devices would increase when hospitals use EMRs successfully to import and export images and reports from these technologies.

We chose to examine stand-alone software/hardware systems for intensive critical-care units (ICUs) that monitor patients’ vital signs. This information is useful for alerting doctors and nurses on site if a patient’s condition is deteriorating, but it is typically never stored or transferred between providers. Figure 3 shows that the adoption pattern for these IT systems is similar to that of EMRs in Figure 4. By 1999, 13% of hospitals in the sample had adopted the ICU “placebo,” and 15% had adopted EMRs. ICU IT systems are unusual in that the information they collect is used only at the time and is not useful when it is transferred.

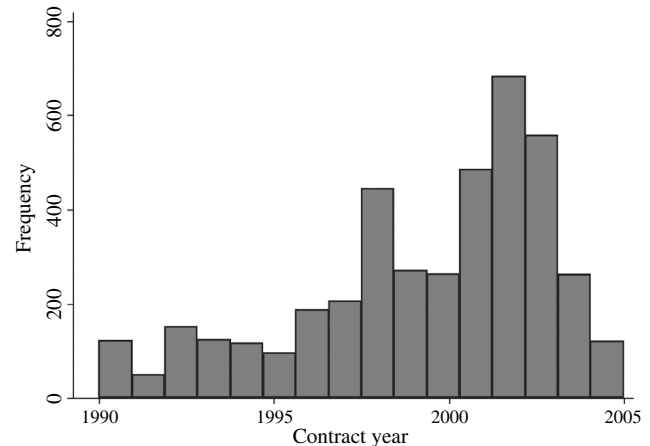
We implement the falsification tests in two stages. First, we estimate the effect of EMR *InstalledbaseHSA* on the adoption of the placebo technology. Next, we measure the effect of installed placebo base on placebo adoption. Corresponding to the main EMR network effect estimates in Table 2, we estimate these effects separately for states with and without privacy protection, using each of the three basic models: panel FE, panel FE-IV, and cross-sectional IV. In the panel regressions, the sample of potential new adopters is all hospitals who had not previously adopted ICUs.

Figure 3 New Adoptions of ICU IT Systems by Year



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

Figure 4 New Adoptions of EMRs by Year



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

The results in Table 3 show that increased adoption of EMRs does not increase adoption of ICU IT at other local hospitals. Although there is a significant correlation in states without privacy laws (column 4), it is eliminated when IVs are used. The IV estimates show no evidence that an increase in the EMR installed base significantly increases ICU IT

adoption. Columns 1 and 3 in Table 4 show significant positive correlations between installed base of ICU IT systems and new adoption of ICU IT systems in the FE model. However, because data from ICU IT systems are not shared across hospitals, this correlation is likely capturing unobservable factors that are common to hospitals within an HSA, such as health-care

Table 3 Hospitals Considering Adopting ICU IT Do Not Respond Differently to the EMR Installed Base in States That Have Privacy Laws and Those That Do Not

Model	States with no privacy law			States with privacy law		
	1	2	3	4	5	6
Data	Panel	Panel	Cross-sectional	Panel	Panel	Cross-sectional
Hospital fixed effects	Yes	Yes	No	Yes	Yes	No
Instrumental variables	No	Yes	Yes	No	Yes	Yes
<i>InstalledHSA</i>	−0.001 (0.004)	−0.015* (0.008)	−0.024 (0.033)	0.006** (0.003)	−0.015* (0.009)	0.018 (0.040)
Observations	2,811	2,367	1,281	4,328	3,446	1,654
Log-likelihood	1,539.726	1,082.533	−2,811.233	1,617.413	858.285	−4,343.334
Excluded first-stage regressions variables						
Prop. other hosp. multi-HSA		−3.726*** (0.186)	−0.237*** (0.044)		−2.435*** (0.148)	−0.073*** (0.018)
Proportion IPA in HSA		0.067 (0.251)	1.038*** (0.262)		−0.956*** (0.260)	0.180 (0.218)
Proportion integrated in HSA		−0.519*** (0.158)	−0.012 (0.094)		−0.355 (0.227)	0.775*** (0.151)
Overidentification test of instruments						
Hansen <i>J</i> -statistic		0.066	2.081		0.264	0.776
<i>p</i> -value		0.967	0.353		0.876	0.679
Significance of first-stage regressions						
LM-statistic		341.762	33.847		258.924	43.121
<i>p</i> -value		0.000	0.000		0.000	0.000

Notes. Multiple hospital and HSA-level control variables not reported. See the e-companion for full specification. Linear probability model estimates reported for panel. Probit GMM estimates for cross section reported as marginal effects calculated at mean. Test statistics for cross-sectional data calculated for identically specified linear probability model to ensure comparability.

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Robust standard errors are reported in parentheses below the estimate.

Table 4 Hospitals Considering Adopting ICUs Do Not Respond in Same Manner as Those Considering Adopting EMRs in States That Have Privacy Laws and Those That Do Not

Model	States with no privacy law			States with privacy law		
	1	2	3	4	5	6
Data	Panel	Panel	Cross-sectional	Panel	Panel	Cross-sectional
Hospital fixed effects	Yes	Yes	No	Yes	Yes	No
Instrumental variables	No	Yes	Yes	No	Yes	Yes
False <i>InstalledHSA</i>	0.024*** (0.008)	−0.145 (0.133)	0.098 (0.138)	0.015*** (0.004)	−0.017* (0.011)	0.036 (0.036)
Observations	2,811	2,367	1,281	4,328	3,446	1,654
Log-likelihood	1,549.415	748.085	−2,705.857	1,631.138	840.155	−4,251.985
Excluded first-stage regressions variables						
Prop. other hosp. multi-HSA		−3.726*** (0.186)	−0.237*** (0.044)		−2.435*** (0.148)	−0.073*** (0.018)
Proportion IPA in HSA		0.067 (0.251)	1.038*** (0.262)		−0.956*** (0.260)	0.180 (0.218)
Proportion integrated in HSA		−0.519*** (0.158)	−0.012 (0.094)		−0.355 (0.227)	0.775*** (0.151)
Overidentification test of instruments						
Hansen <i>J</i> -statistic		1.603	1.552		0.224	0.037
<i>p</i> -value		0.449	0.460		0.894	0.982
Significance of first-stage regressions						
LM-statistic		6.334	13.807		250.865	61.339
<i>p</i> -value		0.096	0.003		0.000	0.000

Notes. Multiple hospital and HSA-level control variables not reported. See the e-companion for full specification. Linear probability model estimates reported for panel. Probit GMM estimates for cross section reported as marginal effects calculated at mean. Test statistics for cross-sectional data calculated for identically specified linear probability model to ensure comparability.

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Robust standard errors are reported in parentheses below the estimate.

demand. Reassuringly, when the IVs are used to predict ICU IT-installed base in the remaining columns of the table, the spurious network effects are eliminated. This suggests that the IVs are valid, and that Table 2 is not merely capturing the effect of omitted variables that are correlated with IT adoption in health care.

5. Effect of State Privacy Protection on Adoption

In this section, we explore the total effect of state privacy protection on the diffusion of enterprise EMRs. In the previous section, we treated state law as exogenously determined, and used IVs to identify network effects from the local installed base, conditional on the privacy regime. In this section, we estimate the overall effect of privacy regulation. When we estimate the impact of regulation, we must acknowledge that laws are not assigned randomly, and may reflect state characteristics, such as wealth or education level, that themselves affect EMR adoption. For example, enacting privacy protection could be positively correlated with the underlying sophistication, lobbying force, and associated financial resources of patients. These unobserved influences on the legislative process could, in turn, affect technology adoption. We

address these concerns using both FE and IV strategies to identify causal effects of the laws.

Because many of the potentially omitted variables that affect privacy laws are stable during the sample period, a natural starting point for estimation is a panel model with hospital FEs. We estimate a modified version of (2) on a pooled sample of hospitals in both privacy regimes, without the installed base effects. We again allow the α_i vector of hospital FEs to absorb permanent geographic variables. The estimated impact of privacy law is thus identified using within-state variation alone. Hospitals in states whose laws are unchanged during the period do not contribute directly to the identification of the *PrivacyLaw* effect, although they can influence the estimate indirectly by changing the effects of the other control variables. Column 1 in Table 5 reports results from the linear FE model. There is no statistically significant relationship between increasing privacy protection and EMR adoption in these raw figures.

However, these results are biased if policy changes are endogenous. Following Besley and Case (2000), we exploit variation in the state political environment over time to instrument for changes in privacy laws. We use the proportions of legislators (as reported in the *Book of States*) in the upper and lower state houses that are Republicans and Democrats to proxy for how

Table 5 Hospitals Considering Adopting EMRs Respond Negatively to State Privacy Laws

Model	EMR adoption			Placebo test		
	1	2	3	4	5	6
Data	Panel	Panel	Cross-sectional	Panel	Panel	Cross-sectional
Hospital fixed effects	Yes	Yes	No	Yes	Yes	No
Instrumental variables	No	Yes	Yes	No	Yes	Yes
<i>HospPrivLaw</i> (d)	0.015 (0.014)	−0.110*** (0.041)	−0.240* (0.138)	0.030*** (0.011)	0.061* (0.034)	−0.107 (0.151)
Observations	7,139	6,524	2,935	7,139	6,524	2,935
Log-likelihood	1,269.401	826.707	−3,810.283	2,481.290	1,985.335	−3,684.737
Excluded first-stage regressions variables						
Proportion dem. upper state house		−2.933*** (0.441)			−2.933*** (0.441)	
Proportion dem. lower state house		−2.349*** (0.838)			−2.349*** (0.838)	
Proportion rep. upper state house		−5.324*** (0.462)			−5.324*** (0.462)	
Proportion rep. lower state house		−1.141 (0.842)			−1.141 (0.842)	
Proportion signed-up DNC			0.318*** (0.077)			0.318*** (0.077)
Failed opposition RealID			−0.068*** (0.018)			−0.068*** (0.018)
Opted out RealID			0.025 (0.036)			0.025 (0.036)
No opposition RealID by 2007			−0.008 (0.025)			−0.008 (0.025)
Overidentification test of instruments						
Hansen <i>J</i> -statistic		1.680	5.294		6.246	7.043
<i>p</i> -value		0.641	0.152		0.100	0.071
Joint-significance of first-stage variables						
LM-statistic		472.304	44.169		472.304	44.169
<i>p</i> -value		0.000	0.000		0.000	0.000

Notes. Dependent variable: whether hospital has installed enterprise EMRs. Multiple hospital and HSA-level control variables not reported. See the e-companion for full specification. Test statistics for cross-sectional data calculated for identically specified linear probability model to ensure comparability. Probit GMM estimates for cross section reported as marginal effects calculated at mean. (d) indicates that the marginal effect is calculated as the discrete change in y as the dummy variable changes from zero to one.

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Robust standard errors are reported in parentheses below the estimate.

favorable the general state climate is to regulation. The omitted group contains independents and vacant seats. Our identifying assumption is that changes over time in tastes for technology adoption are not correlated with the timing of state elections and changes in the composition of state legislatures. The results are reported in column 2 in Table 5. Privacy laws are shown to significantly reduce EMR adoption. The positive bias in the FE estimate in the previous column suggests that the laws are, in fact, positively correlated with unobservable factors that increase the gains from EMRs.

Given the limited number of time periods, we also present cross-sectional results. We estimate a cross-sectional IV model, corresponding to a modified version of (3) without the installed base terms and using the pooled sample. Omitting the hospital FEs compromises the validity of the political instruments. Instead,

we try to exploit tastes for privacy as an exogenous policy shifter. Our first cross-sectional IV is the proportion of people in-state enrolled in the national “Do Not Call” registry.¹¹ Individuals who sign up for the national “Do Not Call” registry do not want telemarketers to contact them at home, and may therefore have stronger tastes for privacy extending beyond medical information. Varian et al. (2005) describe the summary statistics for the data. In Table EC.3 in the e-companion, 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 “Do Not Call” list sign-up. These sign-ups are driven by consumers, not by privacy efforts on the part of states. Variations in sign-ups to the

¹¹ We thank Hal Varian and Fredrik Wallenberg for sharing the data with us.

list are plausibly unrelated to hospital demand or returns to technology investment in health care, and should have no independent effect on EMR adoption. In addition to the use of the “Do Not Call” registry to capture residents’ tastes for privacy, we also include variables to capture resistance to privacy-related 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. 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.¹² These instruments do not vary across time, so we use them only for cross-sectional estimation.

The results from cross-sectional IV estimation are presented in column 3 in Table 5. We present marginal effects at the sample mean from a nonlinear Probit-IV, estimated using GMMs. State privacy laws reduce overall EMR adoption in the sample by 24%. This magnitude is consistent with the 11% per period effect from panel IV methods presented in the previous column. The magnitude is also on par with the estimated reduction in network effects presented in Table 2.¹³ Without privacy laws, another hospital in the local installed base increases propensity to adopt EMRs by 7%. The average installed base is about four hospitals per HSA in 2005, so eliminating this network responsiveness due to privacy protection would reduce overall adoption by around 28%.¹⁴

For the instruments to be valid, they need to be correlated with state privacy protection, but uncorrelated with other state-level influences on hospital technology adoption. The first stage of the regressions shows that the state political variables and the proportion of sign-ups to the “Do Not Call” list are strong and significant predictors of state privacy protection. In addition, failed opposition to Real ID laws is a strong predictor that state privacy protection was not enacted. An *F*-test on the joint significance of the

instruments strongly rejects zero. Hence, the instruments satisfy the first necessary condition for validity.

To ensure that our instruments satisfy the exclusion restriction and are uncorrelated with other influences at the state level of hospital technology adoption, we report the Hansen *J*-statistic and its associated *p*-value below each of the 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 the e-companion for further discussion).

Finally, we conducted a falsification exercise in which we examined another technology that should not be affected by the interaction between privacy protection and network effects, and verified that privacy protection had a negligible effect on it. As in §4, we examined stand-alone software/hardware systems for ICUs that monitor patients’ vital signs. Columns 4–6 in Table 5 show the results of each of the main specifications for this alternative technology: panel FE, panel FE-IV, and cross-sectional IV. Similar to EMRs, the basic panel FE estimate for *HospPrivLaw* is positive. Unlike EMRs, however, the FE-IV estimate is positive and significant.¹⁵ In the cross-sectional framework, the Probit-IV estimate for the placebo technology is negative but insignificant. These estimates provide evidence against the presence of a force affecting the IV that is correlated with the general adoption of health-care IT technologies.

6. Further Effects

We conclude by combining both the panel data and the cross-sectional IV to provide some rough estimates for the combined effect of changes in laws over time and the instrumented installed base and law measures. Our main variable of interest in these regressions is the interaction term between the installed base and the presence of a privacy law. As pointed out by Ai and Norton (2003), care is needed when evaluating the significance of interaction terms in nonlinear models. Therefore, we use a linear probability model for estimation. The data for each hospital again cover 1999, 2002, and 2005, matching the years for our data on the status of privacy protection.

Table 6 presents the main results for EMR adoption from a 3SLS model with four equations. The specification contains a set of state and year dummy variables to capture permanent geographic features and secular adoption trends. It was not viable to estimate the full model with hospital FEs in the 3SLS framework.

¹⁵ The difference between *HospPrivLaw* for EMRs and that for ICU IT is statistically significant at the 1% level.

¹² These data come from the American Civil Liberties Union website (<http://www.reallnightmare.org>).

¹³ We only include variables in the cross section for the aggregate effect of the law that are related to the individual hospital, and do not include the HSA-level demographic variables that we used to control for confounds for the installed base in Table 2. Results are qualitatively unchanged (and slightly larger in magnitude) if the variables are included.

¹⁴ Further stratification suggests this negative effect is four times larger for hospitals with below the median number of beds than for hospitals with above the median number of beds.

Table 6 Interaction Between State Privacy Laws and Installed Base Is Negative

Model	1	2
Correlation structure	Independent	Unstructured
Instruments	Cross-sectional and time-varying	Cross-sectional and time-varying
<i>HospPrivLaw</i>	−0.021 (0.057)	0.008 (0.057)
<i>InstalledHSA</i>	0.049*** (0.011)	0.047*** (0.011)
<i>HospPrivLaw * InstalledHSA</i>	−0.029*** (0.011)	−0.030*** (0.011)
Observations	7,086	7,086
Log-likelihood	−3.85 × 10 ⁴	−4.13 × 10 ⁴

Notes. 3SLS linear probability model. Dependent variable: whether hospital has installed enterprise EMRs by that year. Panel data from 1996 to 2005. The coefficient estimates from the endogenous three equations for the variables installed base and privacy law and their interaction are reported in the e-companion (Table EC.8). The coefficients in these equations are individually and jointly significant. The size of the installed base is positively associated with the share of hospitals in multi-HSA groups and negatively associated with the share with IPA arrangements. Privacy laws are more associated with upper-house political representation by party than lower-house representation. Upper-house shares of either major party are associated with significant reductions in the propensity to adopt privacy regulation. The excluded variables have similar effects in the regression predicting the interaction between installed base and privacy regime. State-level and year FEs are in the primary regression. Multiple unreported hospital-level and HSA-level controls.

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Robust standard errors are reported in parentheses below the estimate.

Instead, we use state-level FEs to absorb the primary source of unobserved heterogeneity for measuring the impact of privacy laws. Estimates should be interpreted as measuring within-state changes. A model using two-stage least squares that does not allow for different error structures in the four equations, but does estimate conditional FEs at the hospital level, produces similar results. The three endogenous equations are for installed base, privacy laws, and their interaction. The set of instruments are those discussed in §§4 and 5, as well as their interactions for the interacted endogenous variable. Column 1 assumes that errors are independent across equations, and column 2 allows for arbitrary correlations. We include the interaction term *HospPrivLaw * InstalledHSA* in the adoption equation to capture 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 estimate is −0.3, implying that privacy protection reduces the positive effect of another local hospital's adoption by 60%. The privacy-law level effects are not statistically significant. The suppression of network effects by privacy laws reduced overall EMR adoption by about 9% per period, comparable to the estimates in column 2 in Table 5. The positive

coefficient on *InstalledHSA* could mean that privacy laws reduce the externalities from information transfer, or indicate information spillovers such as learning by doing and increased technological competence.

7. Conclusion

This paper has examined how privacy protection affects the diffusion of electronic medical records. We have found that state privacy protection of hospital medical information is inhibiting EMR adoption by around 11% per three-year period, or 24% overall in states with such laws. The primary channel appears to be that privacy laws reduce the network effects of EMRs, defined as positive externalities experienced by individual hospitals who adopt EMRs when other local hospitals have adopted electronic records. In states without hospital privacy protection, one hospital's adoption increases the propensity of other hospitals in the local area to adopt by 7%. In states with privacy protection, no network effects are detected.

Our evidence has shown that although there may be many reasons for states to restrict medical providers' ability to disclose information, these restrictions do lead to lower adoption of EMRs. 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."¹⁶

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 United States \$156 billion in capital investment over five years (Kaushal et al. 2005). This large sum makes it crucial that future efforts at protecting privacy recognize the trade-offs between technology diffusion and privacy. Politicians find EMRs' unusual combination of "Saving Lives and Saving Money"¹⁷ attractive, but there has been little measurement until now of how privacy protection affects EMR diffusion.¹⁸ Our study complements such qualitative research by quantifying how a hospital's decision to adopt EMRs is affected by whether state privacy protection restricts a hospital's ability to disclose information.

¹⁶ One IT provider we interviewed described privacy compliance as a "terrible" challenge for the roll-out of EMR. Another emphasized that his firm considered privacy regulation to be a crucial impediment to EMR adoption that was "ignored" by government officials.

¹⁷ Former House Speaker Newt Gingrich entitled his book on EMRs "Saving Lives and Saving Money." President Obama described EMRs as a "central pillar of [his] economic recovery plan" that would "save not only jobs but money and lives."

¹⁸ Research efforts have been almost entirely qualitative, as in the Agency for Healthcare Research and Quality (2007) interview-based three-year \$17.3 million health information security and privacy collaboration study.

This paper does not address the overall welfare effects of either EMRs or privacy laws. It merely suggests a trade-off between privacy protection and EMRs. In a separate paper (Miller and Tucker 2008), we examine how the adoption of EMRs affects neonatal outcomes, and calculate that health IT is associated with a cost of \$450,140 per baby saved. However, such specific analysis does not identify the overall opportunity costs of reduced EMR adoption. There may also be alternative benefits achieved by the legislation that are omitted from the current analysis. For example, there may be positive spillovers in the form of increased information security from the increased requirements to protect confidentiality. We also do not evaluate how state privacy protection affects the strategic choices of firms to develop and design EMR systems. These omissions imply that the net welfare effect of such legislation remains undetermined.

Further research is also needed to investigate the extent to which privacy protection can be optimized (or integrated) to minimize disruption to the diffusion and use of interdependent technologies. For example, it would be valuable to determine whether IT-based privacy protection (using methods such as those proposed by Chowdhury et al. 1999, Garfinkel et al. 2002, and Kadane et al. 2006) can provide a welfare-enhancing alternative in the future to rules-based privacy protection. Our findings also support research by information security scholars to pinpoint optimal methods of exchanging data while protecting privacy, such as Boyens et al. (2004) and Angst and Agarwal (2006). Given the diffusion costs imposed by the outright bans of data exchange that we study, systems and techniques such as these may provide a welfare-enhancing alternative for new electronic systems. Future research is also needed to establish whether privacy-protecting systems can be designed that do not add to the variable costs of exchanging patient information. It may, however, be the case that privacy protection affects even the most sophisticated EMR systems after installation, which suggests that the effect and costs of privacy protection will be ongoing.

8. Electronic Companion

An electronic companion to this paper is available as part of the online version that can be found at <http://mansci.journal.informs.org/>.

Acknowledgments

The authors thank HIMSS Analytics for providing the data used in this study. They thank the Networks, Electronic Commerce, and Telecommunications Institute (<http://www.NETinst.org>) and the Bankard Fund for Political Economy for financial support, and the associate editor and two

reviewers for their very helpful comments and suggestions. They thank Susan Athey, Pierre Azoulay, Federico Ciliberto, Leora Friedberg, Wayne-Roy Gayle, Gautam Gowrisankaran, Avi Goldfarb, Bronwyn Hall, Ariel Pakes, Duncan Simester, Scott Stern, Hal Varian, and Birger Wernerfelt for their comments on earlier drafts. The authors also thank multiple discussants and seminar participants for their insights. All errors are the authors' responsibility.

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