System Size, Lock-in and Network Effects for Patient Records

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Abstract

We examine empirically whether the size of a firm using a network affects the scope of its network usage, and consequently network effects and lock-in within the network. We use the example of hospital information exchange. We find that hospitals in larger hospital systems are more likely to exchange electronic patient information only within their system and less likely to exchange patient information externally. We show that hospitals are also more likely to exchange information externally if others hospitals also do so. This implies that the disinclination of large hospital systems to exchange data externally harms overall levels of network use. Our results highlight that makers of technology policy designed to encourage the optimal use of networks should consider regulating the behavior of network users as well as technology vendors.

Keywords: Network Effects, Lock-In, Technology Policy

1 Introduction

Both empirical and theoretical work has emphasized that larger vendors are more likely to create products which lock network users into a proprietary network (Farrell and Klemperer, 2007). In this paper, we study how the size of the firms who are *users* of a network product affects the scope of their network usage, and how this in turn affects network effects within that network.

We examine this question empirically, using data on the use of electronic medical records (EMRs) and the exchange of health information within a local health network. EMRs allow health providers to store and exchange health information electronically. There is evidence that EMRs can save lives and to some extent save money (Bower, 2005; Walker et al., 2005; Miller and Tucker, 2008, 2009a). The federal government in the United States has therefore pushed to ensure widespread EMR adoption, providing $19 billion in financial incentives to healthcare providers under the 2009 HITECH Act. However, these newly adopted electronic systems must fulfill a government criterion of "meaningful use", meaning that they must incorporate technological standards that enable them to exchange patient information.

The federal emphasis on interoperable technological standards reflects a belief that costs will be lower if all providers treating a patient can exchange information about her, even if the providers are in more than one location. Hospitals themselves have financial incentives to exchange patient information, under prospective payment systems that reimburse hospitals a flat amount per diagnosis group, rendering expensive duplicate tests undesirable. This is also the case for emergency rooms, where in addition to Medicare and Medicaid many private insurers pay a fixed fee.[1] In addition to lowering hospital costs, sharing information can improve the quality of hospital care, especially for patients with chronic conditions who are seeing a new specialist, or in emergency situations who are unable to communicate

[1]Doctors have suggested that situations, such as one where a patient had seven computed tomography (CT) scans and five ultrasounds in 2007 in various hospital emergency rooms, could have been avoided with electronic health information exchange (Calcanis, 2005).

their medical history or allergies (Brailer, 2005). Nevertheless, despite potential for cost reduction and quality improvement, it may not be advantageous to a hospital system to exchange patient information routinely with external hospitals. Either they may assume there is little demand from their patients for care outside of their system or they may fear that easily portable records would reduce patients' switching costs, making it easier for them to receive future care at another hospital.

In this paper, we investigate how the size of a hospital's system influences whether it exchanges patient information only with other hospitals in its system or with hospitals outside its system. Economies of scope for IT systems may make it cheaper for hospitals in larger systems to exchange data externally. On the other hand, hospitals in larger systems may believe either that there is little gain to sharing patient records or even fear that there will be a net outflow of patient data if patients seek more follow-up care in stand-alone or community hospitals which may offer more convenience or lower costs to patients whose insurance imposes substantial deductibles (Melnick and Keeler, 2007). Since a hospital system's size could influence its decision to exchange information in either direction, we analyze this question empirically.

We use new data from a recent American Hospital Association survey, which asked hospitals whether they exchanged patient information only within their hospital system, or outside their hospital system. These data represent a new opportunity in research into empirical network effects and lock-in. Researchers often have data on adoption of network goods, but far less commonly have observations on how network users approach using a network after adoption.[2]

We find that hospitals with more other hospitals in their system are more likely to exchange information only internally, and less likely to exchange information externally.

[2]Papers such as Tucker (2008) exploit network usage data to identify network effects, but we know of no papers on network effects that measure strategic decisions to interact or not over a network after adoption.

This decision to exchange information externally does not seem to be driven by which EMR vendor the hospital chose or the date the EMR system was installed, but instead by other factors.

The pattern of larger hospital systems being less likely to exchange information externally is stronger for hospital systems that pay their staff high wages. This may be because hospitals whose internal patient records reflect higher-quality medical staff do not wish other hospitals to benefit from these inputs. This would provide support for a lock-in interpretation of these hospitals' choices. The pattern of larger hospital systems being less likely to exchange information externally is also stronger for those that have PPO contracts. Like low-wage hospitals, hospitals without PPO contacts may be of lower-quality, and thus they may see less of a benefit from locking-in patients with chronic conditions who demand various medical services that range in complexity. The difference by PPO status further suggests that hospital systems who have patients whose insurance policies have less stringent rules for referrals, making it easier to transfer hospitals, are less likely to exchange information externally.

If one hospital's decision to exchange patient data or not externally affects other hospitals' decisions to exchange patient data, then there will be consequences for the level of exchange of patient data that will not be internalized by the hospital itself. This may spur policy makers to intervene to increase the level of exchange. To explore the potential for such externalities, we directly explore whether one hospital's decision to exchange data externally or internally affects another hospital's decision to exchange data. Since we want to infer causal relationships, we instrument the ease with which other neighboring hospitals can enter into a data exchange system. We use indicators for whether or not these neighboring hospitals are hampered by legacy internal IT systems that could prevent them from being able to enter into a regional data exchange system. Our findings suggest that a hospital's decision to exchange information externally encourages other hospitals to exchange information externally. Therefore, when a large hospital system chooses to retain records within its system, it also depresses the level of exchange by hospitals outside its system.

The contributions of this paper are three-fold. Policy makers and researchers have focused on questions of encouraging compatibility and inter-operability at the vendor level, but we show that customers may also choose not to exchange information over a network. That means that to be most effective, policies designed to encourage inter-connection may need to be broadened to include customers as well as vendors of technologies. Our empirical analysis implies that the response of potential customers to network effects is more complex than previously supposed. Often empirical work calibrates network effects by measuring the response of customers to the adoption of a network good by other customers. However, this kind of analysis ignores the potential for customers themselves to choose whether to exchange information across a network and influence the future course of adoption.

Second, the finding that larger systems with highly-paid employees and with PPO patients are less likely to exchange patient information with outside hospitals is important in building policy around the 'National Health Information Network' (NHIN). An aim of the NHIN is ultimately to provide a secure, nationwide, interoperable health information infrastructure for health care providers and patients across the country. As of 2009, the Department of Health and Human Services has begun Phase 2 trial implementations of Phase 1 prototype architectures in nine limited regions. Our findings suggest that to succeed in ensuring comprehensive coverage, the federal government will have to address the fact that larger hospital systems that may be producing the best health outputs may also be less willing to to exchange information before moving to the next phase in the roll out.

Last, the finding that larger hospital systems are less likely to share their patient records illuminates arguments used in recent anti-trust cases. Hospital systems have argued that mergers will promote adoption of EMRs and consequently benefit patients and society at large.[3] For example, in the Evanston Northwestern-Highland Park case, one of the claims

[3] This is an example of the "efficiencies defense" commonly used in hospital merger cases (Gaynor and

that Evanston Northwestern made was that it had done much to improve the quality of medical care at Highland Park since the merger, including 'investing millions of dollars in changes [like] new information systems and electronic medical records' (Japsen, 2005). Our analysis indicates that while larger firms are indeed more likely to exchange information on an intra-firm basis, they are less likely to exchange information across an inter-firm network. This means that larger firms, while seemingly associated with higher adoption levels, are actually associated with lower network effects for a technology in the specific sense of promoting information-exchange.

Along with these substantive contributions, we also add to an existing literature that evaluates the role of firm size on compatibility (see Farrell and Klemperer (2007) for a broad overview). The key underlying question that drives such research is whether competition encourages or deters firms that make technology from adopting compatible standards for their technology. Work on standards deployment, such as Augereau et al. (2006)'s RAND paper on ISPs' adoption of modem standards, has documented that ISPs are less likely to choose compatible systems in a symmetric firm setting. Chen et al. (2008) build a dynamic model that can explain why in the long run some firms make their technology compatible despite gaining market dominance. Similarly to the empirical findings in this paper, their model emphasizes that there is a tension for a firm with many in-network customers. Their size may lead them to want to lock customers in, but their size also means they receive a larger aggregate benefit from remaining compatible with other networks, since they have more customers who benefit from the quality improvement this represents. There is also a small and related literature in telecommunications that addresses the issue of 'inter-connection' (see Shy (2001) for a summary). This literature emphasizes that while smaller telecommunication firms want inter-connection, larger firms do not and instead want to merge.

The setting we study is different, because we do not examine the behavior of vendors

Vogt, 2000).

of EMR technology and their incentives to distort standards to beat their competition. Instead, we study hospital end-users who deploy standards-based technology and get a direct benefit (or not) from inter-connection. We also contribute to a small literature on the health information exchange. Grossman et al. (2006) conducted interviews at 12 major hospitals and found that, while they were planning on developing portals for physicians with admitting privileges, they were not intending to exchange information more broadly.

The paper is organized as follows. Section 2 describes the data we use in the study. Section 3 lays out our conceptual framework and presents initial results. It presents various robustness checks and also presents some suggestive evidence supporting a lock-in interpretation. Section 4 discusses how other hospital data-exchange decisions affect another hospital's decision to exchange information. Section 5 lays out the implications of our findings.

2 Data

2.1 Electronic Exchange of Patient Information

We use the Hospital Electronic Health Record Adoption Database^{TM} from the American Hospital Association (released in May 2009), which reports data from a 2007 survey of 3,404 members of the American Hospital Association. This was a one-off survey which asked whether hospitals exchanged patient and clinical data with other hospitals in their system, outside of their system, and with ambulatory providers. We use each hospital's answers to these questions as dependent variables. The actual survey asked separately about whether a hospital exchanged patient data such as name, background and insurance details and clinical data such as medication lists, discharge summaries, and radiology reports. In the main results in the paper, we present results for whether or not the hospital exchanges any data. In the appendix in section A.2 we show that the results are similar if we analyze the decision to exchange clinical and patient data separately.

The survey did not ask how the electronic exchange of information was achieved. However, it did ask separately whether the hospital was 'actively involved in a Regional Health Information Organization (RHIO).' RHIOs develop databases and software architectures that ease the electronic exchange of patient-level clinical information between health-care providers. Members of RHIOs either deposit all patient information in a central repository every day, or make public patient record locators that allow other members of the RHIO to download them on demand. 9.2 percent of hospitals in our survey described themselves as actively involved.

The concept of RHIOs has been promoted as a means of achieving nation-wide health information exchange. In September 2007, the US Department of Health and Human Services awarded contracts totaling $22.5 million to nine health information exchanges (HIEs) to begin trial implementations of the Nationwide Health Information Network (NHIN). However, only 27 percent of the hospitals that described themselves as active participants in an RHIO exchanged electronic health information externally with other hospitals. 65 percent of hospitals that externally exchanged information did not describe themselves as active in an RHIO. This suggests that most hospital information exchange happens in other ways than via RHIOs. One potential way is for hospitals to use vendor specific software: For example, an Epic EMR system allows a hospital to exchange information with other hospitals through a product module named Epic CareEverywhere. Other alternatives are more ad-hoc systems, where firms use existing Electronic Data Interchange (EDI) software or other software patches to communicate with other hospitals. As an illustration, Appleby (2009) reports on how hospitals within the Seattle area manage to find ways to view each others' records despite purchasing EMR systems from different vendors.

The survey did not ask whom these hospitals exchanged data with. It is necessary to come up with a plausible region over which hospitals are likely to find it useful to exchange patient information in order to define a local network for this patient information. Defining the region allows us to study whether a hospital's decision to exchange patient information internally or externally depends on the number of hospitals within its system, or on the number of hospitals outside its system and within that region. In our study we use a health referral region (HRR) as our definition of a local area within which patients plausibly might transfer between hospitals.[4] There are 306 such regions within the US. We chose this as our underlying measure of other local hospitals because it measures a broad but carefully-defined geographical area from which patients might obtain care. We found similar results when we ran our regressions using the narrower definition of a health service area (HSA), which are smaller and are based on the customary geographical reach of patients. Figure 1 plots histograms for the proportion of hospitals in each HRR who exchange information within their systems and outside of their systems. Exchanging is more common within a system than outside of the system.

2.2 Further Controls

We matched this data on patient data exchange with the most recent round of the AHA hospital survey (2007), which was administered in the same period, to obtain detailed data on hospital characteristics to use as controls in our regressions. This data provides information on a hospital's system's size, which it defines as the number of hospitals owned, leased, sponsored or contract managed by a central organization.[5] Though we use system size as measured by the number of hospitals in our main specifications, we also get similar results if we weight the system size variables by number of beds.[6]

Table 1 provides summary statistics for both our dependent and independent measures.

[4]The Dartmouth Atlas of Health Care defines an HRR as a regional health care market for tertiary medical care, which contains at least one hospital that has performed major cardiovascular procedures and neurosurgery.

[5]We follow the literature such as Ho (2009) that studies networks in healthcare, and focus on hospital systems rather than hospital networks, because a hospital system is the closest to a profit-maximizing unit. As pointed out by Burgess et al. (2005) hospital networks tend to be driven by the behavior of hospital systems in any case.

[6]Since the AHA panel data is sometimes noisy, we cross-checked the *systemid* variable that we base our results on with the *systemid* variable from the 2006 AHA survey as well as the information from the HIMSS Analytics Database.

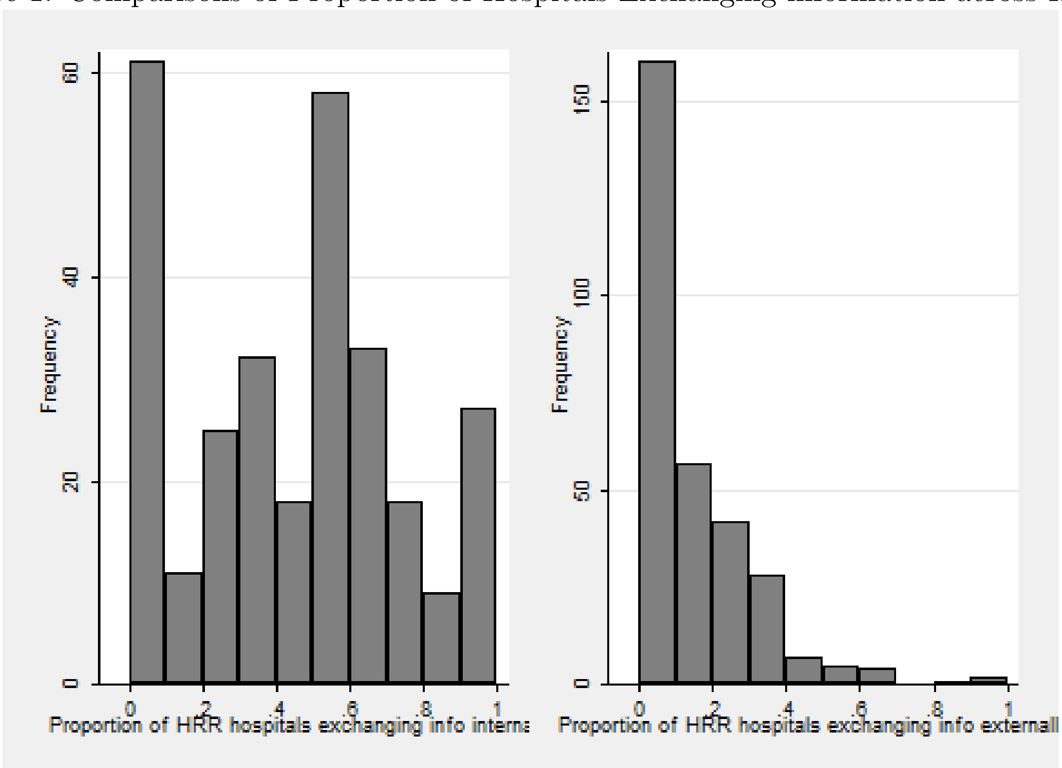
Table 1: Summary Statistics for Hospitals in the EMR Survey

	Mean	Std Dev	Min	Max	Observations
Adopt EMRs	0.72	0.45	0	1	3430
Any exchanging	0.56	0.50	0	1	3430
External exchange	0.13	0.34	0	1	3430
External exch patient info	0.083	0.28	0	1	3430
External exchange clinical info	0.16	0.37	0	1	3430
Internal exchange only	0.47	0.50	0	1	1884
Internal exch patient info	0.49	0.50	0	1	1884
Internal exch clinical info	0.53	0.50	0	1	1884
No. of hospitals in system in HRR	1.50	3.07	0	20	3430
No of hospitals outside system in HRR	27.3	24.8	0	118	3430
Admissions (000)	7.15	9.52	0.0070	108.6	3430
Proportion Medicare Inpatients	46.1	23.0	0	101.7	3430
Proportion Medicaid Inpatients	18.4	17.5	0	97.4	3430
No. Doctors (000)	0.022	0.082	0	2.07	3430
Births (000)	0.82	1.38	0	16.3	3430
PPO	0.67	0.47	0	1	3430
HMO	0.58	0.49	0	1	3430
Per Capita Payroll	0.049	0.016	0.000045	0.42	3430
Independent Practice Association	0.12	0.33	0	1	3430
Group Practice Association	0.021	0.14	0	1	3430
Closed Phys. Hosp	0.045	0.21	0	1	3430
Open Phys. Hosp	0.12	0.32	0	1	3430
Management Services Org	0.050	0.22	0	1	3430
Integrated Salary Model	0.31	0.46	0	1	3430
Non-Profit Hospital	0.58	0.49	0	1	3430
Speciality Hospital	0.15	0.36	0	1	3430
Age of PhysDoc data system	0.90	2.60	-2	31	3430
Age of EDI data system	1.00	3.22	0	25	3430
Epic System	0.037	0.19	0	1	3430
Meditech System	0.11	0.31	0	1	3430
Cerner System	0.069	0.25	0	1	3430
Mckesson System	0.054	0.23	0	1	3430
Siemens System	0.037	0.19	0	1	3430
Eclipsys System	0.025	0.16	0	1	3430
GE System	0.018	0.13	0	1	3430
Foreign Nurses	0.16	0.37	0	1	3430

Internal exchange dependent variables only applicable to hospitals in systems.

We then matched these data with the 2008 release of the Healthcare Information and Management Systems Society (HIMSS) Analytics^{TM} Database (HADB). This records whether a hospital had adopted an EMR system, and also describes what year the system was contracted to be installed and the vendor from which the hospital purchased the system. We use this information on EMR type as a further control when we check the robustness of our specification. From this survey, we also obtained details of different stand-alone IT systems that the hospital had purchased, such as billing software, physician documentation software and electronic data interchange software. We use the presence and age of such systems to control for differences in hospitals' technological ability to exchange information.

Figure 1: Comparisons of Proportion of Hospitals Exchanging information across HRRs



In all our analysis, the unit of observation is a hospital rather than a hospital system. This is motivated by the lack of uniformity in the information exchange choices of hospitals even within the same system. In 31 percent of systems in our data, no hospitals exchange information internally. In 23.9 percent of systems, all hospitals exchange data internally. Therefore for just under 46 percent of systems in our data, not all hospitals exchange information internally. In 71.23 of systems no hospitals exchange data externally, and in only 4.56 percent of hospital systems do all hospitals exchange data externally. Therefore, in the majority of hospital systems that do exchange data externally at all, there is a disparity in individual hospital exchanging behavior.

3 Analysis and Results

3.1 Conceptual Framework

In traditional theoretical models of network effects (Katz and Shapiro, 1985; Farrell and Saloner, 1985; Economides, 1996), network participants are assumed to be symmetrical in size and and consequently the issue of network user size is not discussed.[7] However, as described by Gowrisankaran and Stavins (2004), if one extends such theoretical models to reflect firm size when firms merge, there should be a positive equilibrium effect on adoption in the presence of network externalities. To see this, consider a network with a number of separate firms. Each firm will adopt a network technology based on whether its profits from adoption are positive, but it will not internalize the positive effect that its adoption has on profits for the other firms in the network. Therefore, if the firms merge into a monopoly holding company with fixed costs at each of its member firms equal to the fixed costs before the merger, then the set of firms that adopts weakly increases. This is due to the monopolist's

[7] More recently Simcoe et al. (2009) find that small technology vendors are more likely to litigate after they disclose patents to a standards-setting organization. They suggest that this is because smaller firms are less likely to earn rents in complementary goods markets, and therefore defend their intellectual property more aggressively.

ability to coordinate adoption across locations and to internalize the network benefits from adoption at different locations.

Such network arguments assume that post-adoption network use of the technology is pre-determined and cannot be influenced by the firm. However, if the decision to exchange information over the network is separate from the decision to adopt a network technology, and firms can opt to exchange information selectively, the effect of firm size on the exchange of information as opposed to adoption of network technologies is less clear. On the one hand, a similar argument suggests that the fixed costs of investing in the additional technological capacity to exchange information should on a per-transaction basis be lower for larger firms. Also, larger firms or hospital systems may have a higher profile in the community which leads them to expect larger patient inflows if patient switching costs are reduced across all hospitals in the local area.

On the other hand, the same argument could suggest that the need to exchange information externally may be less for larger hospitals than for small firms. Large firms may plausibly be able to serve customers' needs within their own firm boundaries and consequently see less network benefit to acquiring customer information from other firms. In other words, large firms may see less value in receiving an inflow of patient records. Alternatively, larger hospital systems may fear that an overall reduction in patient switching costs will lead patients to leave system hospitals and seek follow-up care in community or stand-alone hospitals. Melnick and Keeler (2007) documents that larger hospital systems have seen higher price increases in recent years.[8] Patients may therefore prefer to leave large hospital systems to seek cheaper alternatives if they are are responsive to deductibles and co-pays. This suggests that larger firms may see less value in allowing an outflow of patient records. We present evidence to try and distinguish between these two explanations in section 3.3.

[8]Ho (2009) provides evidence that hospital systems exploit their bargaining power to negotiate better prices with health insurers.

To evaluate the relationship between hospital system size and the decision to exchange data internally or externally, we first use our cross-sectional data to estimate a static model. For a hospital that has completed the survey, the decision to exchange any information electronically is specified as:

$$\text{Prob}(AnyExchange_{ij} = 1 | SystemSize_{ij}, X_{ij}) = \Phi(SystemSize_{ij}, X_{ij}, \gamma) \tag{1}$$

where $AnyExchange_i = 1$ if hospital i in HRR j exchanges information internally or externally and $AnyExchange_i = 0$ otherwise.

Similarly for the decision to exchange information internally, we estimate a separate equation where

$$\text{Prob}(ExchangeInternal_{ij} = 1 | SystemSize_{ij}, X_{ij}) = \Phi(SystemSize_{ij}, X_{ij}, \gamma) \tag{2}$$

and $ExchangeInternal_i = 1$ if hospital i in HRR j exchanges information externally.

Similarly for the decision to exchange information externally, we estimate a separate equation where

$$\text{Prob}(ExchangeExternal_{ij} = 1 | SystemSize_{ij}, X_{ij}) = \Phi(SystemSize_{ij}, X_{ij}, \gamma) \tag{3}$$

and $ExchangeExternal_i = 1$ if hospital i in HRR j exchanges information externally.

$SystemSize_{ij}$, our key variable of interest, captures the number of hospitals within that system in that HRR. X_i is a vector of hospital characteristics as described in table 1 that affect the propensity to exchange information, γ is a vector of unknown parameters, and Φ is the cumulative distribution function of the standard normal distribution. As discussed in Miller and Tucker (2009c,b), state-level regulation of privacy, information security and medical malpractice can affect the adoption of EMR and therefore potentially the use of EMR to exchange information. Therefore we include in our regressions a full set of state fixed effects to abstract from the impact of cross-sectional variation in such state regulations on hospital exchanging decisions.

3.2 Results

Table 2 displays the results of our initial specifications. We include the 3,404 hospitals (of which 1,872 were in a system) that responded to the AHA survey. In the Appendix (Section A.3), we show the results are robust to controlling for potential survey-selection bias. The first column is a probit regression on whether or not that hospital exchanges data in any way. We find here that hospitals which belong to systems with a larger regional presence are more likely to exchange information. However, without knowing the kind of exchanging that the hospital does, it is hard to know whether this reflects exchanging data inside the system and lock-in, or exchanging outside the system, and it is also hard to rule out explanations unrelated to network effects.

The second column is a probit regression for whether the hospital exchanges data *only* within its system. Since only hospitals in a system can answer in the affirmative to this question, we restrict our attention to the 1,872 hospitals who are part of a system. The positive and significant coefficient on the number of local in-system hospitals suggests that the likelihood of exchanging data within the system increases with system size.

The third column is a probit regression for whether the hospital exchanges information outside its system. Here the sign on the size of the local hospital system is strikingly different. Larger hospital systems are less likely to exchange information outside their system.

In these specifications, we include independent variables to control for observable differences in hospital's underlying propensity to exchange information. Many are insignificant.

Generally hospitals that see many Medicaid and Medicare patients are less likely to exchange information within their systems. This could be because the information for such patients is centrally reported to the government and consequently there is less need for a hospital-level information exchanging system.[9]

We also include controls for hospital type. The full results are reported in Table A-1. None of the controls for organization form, such as independent practice association (IPA) or an integrated salary model, were significant.[10] Specialty hospitals were less likely to exchange internal or external data. Non-profit hospitals were more likely to exchange information both internally and externally.

Having an older EDI system negatively affects the likelihood of exchanging information inside a system. Both EDI and Physician Documentation software are built around HL7 standards. This negative relationship between age of the component system and the exchange of information may reflect multiple changes over time to the complexity and usability of HL7 standards over the period we study. HL7 v2.2 was released in 1994; HL7 v2.3.1 in 1999; HL7 v3 in 2005. Each of these releases included new data elements and messages, which despite efforts at backwards compatibility have made exchanging information harder across the different versions. Later, we also use the age of these component systems as instrumental variables when we evaluate how a hospital's decision to exchange depends on the exchanging decisions of other hospitals.

The influence of per-capita payroll is of particular interest, since it affects the decision

[9] The HHS Section 484.20 interim final rule from 1999 requires electronic reporting of data from the Outcome and Assessment Information Set (OASIS) as a condition of participation in the Medicare or Medicaid systems. Hospitals had the option of purchasing data collection software that can be used to support other clinical or operational needs such as the ones that we study in this research, but they could also use a HCFA-sponsored OASIS data entry system (that is, Home Assessment Validation and Entry, or "HAVEN") at no charge. The use of such a system, however, might limit the exchange of data within a system.

[10] Interestingly, hospitals with IPAs have higher response rates to the AHA information technology survey. This relationship is similar to the positive cross-sectional association between IPAs and EMR adoption by 2004 found in Miller and Tucker (2009c), and may reflect the unusual profile of hospitals that retained their IPA arrangements through 2007 (Ciliberto, 2006). Such hospitals likely experienced less internal conflict between physicians and management regarding technology adoption.

to exchange inside a system and outside a system in different ways. Hospitals with high per-capita payrolls are more likely to exchange information within their system. However, hospitals with high per-capita payrolls are less likely to exchange information outside their system. If a general lack of financial resources were driving the decisions to exchange we see in the data, we would expect that hospitals that have the financial ability to offer high salaries would consistently be more likely to exchange information. A possible interpretation of this result is that hospitals who pay their doctors well want to ensure that they capitalize on the positive spillovers of, for example, attracting a famous cardiologist. Therefore, such hospitals are less willing for patients to take their data from a consultation with a famous consultant away from their hospital and to other hospitals. We evaluate the effect of payroll in more detail when we stratify our results by payroll in table 4.

One interpretation of this finding is that larger hospital systems choose to not share data externally because they anticipate that this will result in net outflows of patients from their systems. This would happen if patients saw a specialized consultant in an in-system hospital, but chose to receive follow-up care at a local community hospital. Smaller hospital systems, on the other hand, may anticipate that they will receive net inflows of patients if they make it easier for patients to switch from the 'big players' in the neighborhood. This would suggest that large hospitals, much like many large software vendors, choose to lock in their customers to prevent attrition to competitors. However, since we do not observe information about hospital's intentions when sharing data, and instead only information on the decisions themselves, it is important to consider other alternative explanations of this finding.

A possible alternative explanation for the negative relationship between system size and external exchanging that does not represent a strategic desire to lock patients in would be that it simply reflects technological incapacity. It is possible, for example, that hospitals in larger systems adopted Electronic Medical Record technology earlier. This means, however,

Table 2: The size of the hospital system affects the decision to exchange information

	(1) Any exchanging	(2) Internal exchange only	(3) External exchange
No. of hospitals in system in HRR	0.0421***	0.0425***	-0.0239**
	(0.00864)	(0.0103)	(0.0115)
No of hospitals outside system in HRR	0.000336	0.000765	-0.00220
	(0.00112)	(0.00137)	(0.00151)
Admissions (000)	0.0245***	0.0102*	-0.0000479
	(0.00538)	(0.00581)	(0.00565)
Proportion Medicare Inpatients	-0.00718***	-0.0109***	-0.000729
	(0.00129)	(0.00173)	(0.00168)
Proportion Medicaid Inpatients	-0.00546***	-0.00808***	-0.000489
	(0.00159)	(0.00238)	(0.00201)
No. Doctors (000)	0.854*	0.140	0.610*
	(0.470)	(0.385)	(0.328)
Births (000)	-0.00227	0.0122	0.0610*
	(0.0326)	(0.0371)	(0.0343)
PPO	-0.142*	-0.107	-0.263***
	(0.0758)	(0.119)	(0.0952)
HMO	0.0988	0.0784	0.140
	(0.0726)	(0.115)	(0.0928)
Per Capita Payroll	5.251***	6.696***	-5.389**
	(1.532)	(1.750)	(2.489)
Age of PhysDoc data system	-0.00622	-0.0156	-0.0223
	(0.0102)	(0.0135)	(0.0140)
Age of EDI data system	-0.00764	-0.0469***	0.0144
	(0.00760)	(0.0122)	(0.00891)
State Controls	Yes	Yes	Yes
Hospital Type Controls	Yes	Yes	Yes
Contract Year Controls	Yes	Yes	Yes
Observations	3430	1874	3383
Log-Likelihood	-2025.1	-1114.5	-1205.7

Marginal effects; Standard errors in parentheses
(d) for discrete change of dummy variable from 0 to 1
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

that the systems that they chose are less able to exchange information with other hospitals than newer systems which are built around the most current data interchange standards.[11] It could also be that they chose to buy their system from a vendor that makes interoperability less easy. Early Meditech systems, for example, were built around the MAGIC operating system, meaning that they need special auxiliary customized add-ons to be able to exchange data with other non-MAGIC EMR systems. The decision to purchase from a less-interoperable vendor is bound up with the decision to exchange information, but it is possible that the hospital purchased from this vendor before such inter-operability concerns were as important as they are today. To control for such concerns, we repeated the estimation in Table 2 in Table 3 but included vendor fixed effects for the largest EMR vendors and fixed effects for the year that the EMR system was installed. The results remain robust. It is interesting to note, however, that the vendor that the hospital bought the system from seems to be not that significant a factor in whether or not they exchange information. This suggests that the policy needs to focus not just on ensuring interoperability at the vendor level, but also on encouraging hospitals to purchase systems that they actually use to exchange data.

Another concern is that a merger between two nearby hospitals who are already exchanging information will lead to both hospitals belonging to a larger system and to an increase in within-system exchanging and a decrease in exchanging outside of the system, with no change in the real level of information exchange. To examine this, we used previous AHA survey data to identify hospitals that had merged between 1994 and 2007. A t-test on the difference in propensity to exchange revealed both that hospital systems that had mergers were less likely to exchange ($p<0.05$) and that there was no statistically significant difference in the propensity to exchange information outside the hospital between hospitals. This suggests that the pattern we find is not a result of previous merger activity, and instead that merger activity (and perhaps the problems of integrating different IT systems) if anything

[11] These standards were largely only formalized, by bodies like CCHIT, in 2006-2007.

Table 3: The size of the hospital system affects the decision to exchange information: Controlling for EMR system type

	(1) Any exchanging	(2) Internal exchange only	(3) External exchange
No. of hospitals in system in HRR	0.0411***	0.0425***	-0.0243**
	(0.00870)	(0.0103)	(0.0116)
No of hospitals outside system in HRR	0.000658	0.00124	-0.00225
	(0.00113)	(0.00138)	(0.00152)
Admissions (000)	0.0238***	0.00959	0.000545
	(0.00548)	(0.00592)	(0.00577)
Proportion Medicare Inpatients	-0.00725***	-0.0112***	-0.000684
	(0.00129)	(0.00174)	(0.00168)
Proportion Medicaid Inpatients	-0.00536***	-0.00825***	-0.000463
	(0.00160)	(0.00240)	(0.00201)
No. Doctors (000)	0.847*	-0.0355	0.588*
	(0.475)	(0.373)	(0.330)
Births (000)	-0.00526	0.00435	0.0607*
	(0.0326)	(0.0375)	(0.0345)
PPO	-0.137*	-0.135	-0.266***
	(0.0760)	(0.121)	(0.0954)
HMO	0.0915	0.106	0.139
	(0.0728)	(0.117)	(0.0930)
Per Capita Payroll	5.136***	6.822***	-5.377**
	(1.535)	(1.760)	(2.499)
Age of PhysDoc data system	-0.00555	-0.0144	-0.0240*
	(0.0104)	(0.0140)	(0.0143)
Age of EDI data system	-0.00684	-0.0443***	0.0141
	(0.00766)	(0.0123)	(0.00897)
Epic System	0.161	0.192	0.133
	(0.143)	(0.162)	(0.164)
Meditech System	0.198**	0.286**	-0.0407
	(0.0909)	(0.132)	(0.111)
Cerner System	0.320***	0.638***	-0.113
	(0.124)	(0.155)	(0.142)
Mckesson System	0.432***	0.560***	-0.107
	(0.122)	(0.159)	(0.145)
Siemens System	0.227	1.132***	-0.199
	(0.145)	(0.223)	(0.171)
Eclipsys System	0.00661	0.366	-0.0650
	(0.174)	(0.241)	(0.204)
GE System	-0.144	0.00531	-0.0237
	(0.199)	(0.226)	(0.230)
State Controls	Yes	Yes	Yes
Contract Year Controls	Yes	Yes	Yes
Hospital Type Controls	Yes	Yes	Yes
Observations	3430	1874	3383
Log-Likelihood	-2014.3	-1092.5	-1204.0

Marginal effects; Standard errors in parentheses
(d) for discrete change of dummy variable from 0 to 1
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

results in less internal information exchange rather than more.

3.3 Further Exploring the Potential for Lock-In

As we discussed in section 3.1, the finding that larger hospital systems are less likely to exchange information externally could be a result of domination of an HRR by one large system. That system would expect to receive little net inflow of patients from exchanging patient information outside their system. However, if concerns over the potential of the local HRR to produce patient inflows were dominant, then we would expect hospitals to be more likely to exchange with outside hospitals when there are more of outside hospitals within the same HRR from whom they could potentially gain patients from. This is not what we find in Tables 2 and 3.

An alternative interpretation is that hospitals, instead of responding to a decrease in the value of potential inflows of patient data, are primarily concerned with preventing an outflow of patient data. That is, they want to maintain switching costs for patients at that hospital who might try and leave the system. In this section, we explore whether there is evidence in favor of such strategic behavior. We look in turn at the decisions of hospitals who have an asymmetrical benefit from keeping their patient records within the system, and then at hospitals for whom it is more likely that patients will try and switch.

One of the many motivations that hospitals may have to lock in their patients's records is to avoid competitors benefiting from the opinions of highly paid clinical staff. Such hospitals have more to gain from losing patients, and less to gain from patients transferring into their hospital. This asymmetry should augment incentives to lock-in patients or create proprietary network effects. We present estimates for the importance of hospital system size that vary by average salary paid to hospital staff. Table 4 shows that hospitals with higher paid employees have larger coefficient estimates for the responsiveness of exchanging to system size. High-pay hospitals are defined as hospitals with above-median per-capita payrolls. They also show that larger systems that also have higher pay scales are less likely to exchange information outside the system.

The ease with which a patient can leave a hospital system may depend on their insurance plan. Generally, while a patient with a PPO can seek a new provider at will, a patient with an HMO insurance plan must make a request for an new referral to their primary care provider. This means that patients with PPOs have lower switching costs than HMO patients. Therefore the kind of insurance plans that a hospital accepts will influence the likelihood of patients transferring from that hospital to another. Table 5 presents estimates by whether or not that hospital has a non-zero number of PPO contracts. Table 5 suggests that PPO hospitals in larger systems are far less likely to exchange with outside hospitals compared to hospitals that do not have PPO contracts.

PPO status and high payroll are positively related in our data, but they only show a 0.11 correlation, suggesting that each of these stratifications reflect the choices of different sets of hospitals.

4 Responses to the Installed Base

The findings in section 3.2 suggest that larger hospital systems are more likely to lock customers in and only exchange patient records internally. However, the policy implications of this finding for the national policy of establishing a National Health Information Network and maximizing the exchange of patient data is not clear. When hospitals exchange information purely within their network, they are still exchanging information. However, if there are negative spillovers to other hospitals and patients at other hospitals from this strategic behavior, then there will be un-internalized negative consequences on the level of exchange of patient data. Such externalities may warrant policy intervention. To evaluate this, we assess whether there is evidence in our data of spillovers from one hospital's electronic patient information exchange choices to other hospitals.

Table 4: How Decision to Exchange Data by Hospitals depends on their size: By per capita pay

	Low Pay		High Pay	
	(1)	(2)	(3)	(4)
	Internal exchange only	External exchange	Internal exchange only	External exchange
No. of hospitals in system in HRR	0.0361**	-0.00295	0.0637***	-0.0548***
	(0.0158)	(0.0167)	(0.0161)	(0.0185)
No of hospitals outside system in HRR	-0.00123	-0.00504**	-0.0000776	-0.000148
	(0.00251)	(0.00255)	(0.00186)	(0.00212)
Admissions (000)	0.0237	0.0123	0.00719	-0.00144
	(0.0147)	(0.0145)	(0.00684)	(0.00672)
Proportion Medicare Inpatients	-0.00446	-0.00381	-0.0179***	0.00418
	(0.00287)	(0.00242)	(0.00255)	(0.00274)
Proportion Medicaid Inpatients	-0.00266	-0.00325	-0.0138***	0.00588*
	(0.00390)	(0.00292)	(0.00358)	(0.00319)
No. Doctors (000)	-0.471	2.562***	0.0450	0.371
	(0.841)	(0.823)	(0.454)	(0.399)
Births (000)	-0.00135	0.00685	-0.00177	0.0589
	(0.0970)	(0.0941)	(0.0433)	(0.0384)
PPO	-0.0543	-0.469***	-0.112	-0.0650
	(0.186)	(0.135)	(0.190)	(0.156)
HMO	0.00206	0.143	0.0364	0.0463
	(0.175)	(0.134)	(0.185)	(0.149)
Per Capita Payroll	16.16*	-6.430	-0.379	-7.397*
	(9.179)	(6.964)	(2.482)	(4.375)
Age of PhysDoc data system	-0.0245	-0.0202	-0.0343*	-0.0198
	(0.0263)	(0.0255)	(0.0188)	(0.0189)
Age of EDI data system	-0.0196	0.0225	-0.0476***	0.0101
	(0.0210)	(0.0156)	(0.0164)	(0.0121)
Vendor Controls	Yes	Yes	Yes	Yes
Contract Year Controls	Yes	Yes	Yes	Yes
State Controls	Yes	Yes	Yes	Yes
Hospital Type Controls	Yes	Yes	Yes	Yes
Observations	693	1545	1161	1764
Log-Likelihood	-362.8	-490.6	-653.9	-640.3

Marginal effects; Standard errors in parentheses
(d) for discrete change of dummy variable from 0 to 1
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: How Decision to Exchange Data by Hospitals depends on their size: By PPO status

	Not PPO		PPO	
	(1)	(2)	(3)	(4)
	Internal exchange only	External exchange	Internal exchange only	External exchange
No. of hospitals in system in HRR	0.0371*	0.0123	0.0492***	-0.0357**
	(0.0210)	(0.0209)	(0.0131)	(0.0149)
No of hospitals outside system in HRR	0.000818	-0.00755**	0.00154	-0.000512
	(0.00284)	(0.00321)	(0.00170)	(0.00184)
Admissions (000)	0.0267*	-0.0321**	0.00813	0.00301
	(0.0149)	(0.0159)	(0.00699)	(0.00660)
Proportion Medicare Inpatients	-0.0130***	0.00206	-0.00626**	0.000206
	(0.00294)	(0.00275)	(0.00299)	(0.00268)
Proportion Medicaid Inpatients	-0.0128***	-0.000691	-0.00242	0.00151
	(0.00472)	(0.00348)	(0.00364)	(0.00302)
No. Doctors (000)	-0.666	5.048***	0.0408	0.0976
	(1.189)	(1.207)	(0.425)	(0.380)
Births (000)	-0.114	0.108	0.0329	0.0511
	(0.0890)	(0.0930)	(0.0450)	(0.0393)
HMO	0.212	0.0510	0.0517	0.220*
	(0.279)	(0.234)	(0.139)	(0.113)
Per Capita Payroll	4.526*	-6.066	13.22***	-3.282
	(2.553)	(3.885)	(3.303)	(3.618)
Age of PhysDoc data system	0.0104	-0.0216	-0.0352*	-0.0238
	(0.0236)	(0.0288)	(0.0202)	(0.0181)
Age of EDI data system	-0.0415	0.0339	-0.0391***	0.00978
	(0.0300)	(0.0210)	(0.0144)	(0.0106)
Constant	0.705	0.793	-0.845	-0.383
	(205.9)	(0.915)	(0.880)	(0.661)
Vendor Controls	Yes	Yes	Yes	Yes
Contract Year Controls	Yes	Yes	Yes	Yes
State Controls	Yes	Yes	Yes	Yes
Hospital Type Controls	Yes	Yes	Yes	Yes
Observations	583	1070	1261	2265
Log-Likelihood	-317.1	-361.9	-713.0	-782.7

Marginal effects; Standard errors in parentheses
(d) for discrete change of dummy variable from 0 to 1
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In Table 6, we study how one hospital's decision to exchange data externally affects the decisions of other local hospitals who are not members of the same system. In the first column, we estimate the a simple probit model, treating the exchanging decisions of other hospitals as exogenous and ignoring the potential reflection problem or correlated local unobservable factors that affect external exchange decisions for all hospitals (Manski, 1993). The main explanatory variable is a count of the number of other hospitals in the HRR who are exchanging information externally. The positive and significant relationship indicates that external sharing decisions are correlated between hospitals within HRRs, even after conditioning on the key observable factors.

The second column presents results from joint estimation of the decision of each individual hospital to exchange information externally and the number of other hospitals in their HRR who are exchanging information externally, using Roodman (2007)'s conditional recursive mixed-process estimator. We impose the exclusion restriction that the mean number of other hospitals in the local area with EDI and Physician Documentation systems that were old enough to have been made outdated by changes in various HL7 Standards shifts the number of other hospitals who exchange information, but does not otherwise affect the value of information exchange. The excluded variables reflect past choices made by neighboring hospital systems that have unintentionally rendered them less interoperable. The exogenous changes to the HL7 standards of data exchange had the effect of shifting their ability to exchange information. We make the identification argument that hospitals who wish to exchange information externally must themselves bear the costs of making their systems comply with existing standards. This cost may deter hospitals with less interoperable systems from entering regional exchanges, but it should not affect the value of information exchange to hospitals who already engage in exchange. Hence, the state of a neighboring hospital system's IT system should only affect a hospital's willingness to share information by shifting the number of neighboring hospitals with whom it is possible to exchange information.

This second column suggests that when other external hospitals are willing to exchange information for exogenous reasons, then this increases the propensity of a hospital in the local area to also exchange externally. This implies that when larger hospital systems choose to not exchange information externally, they reduce the likelihood other hospitals also exchanging information externally. Since it is unlikely that the large hospital system internalizes the negative welfare effects for these external hospitals or their patients, this means such strategic behavior reduces welfare for these external hospitals and their patients. In the third column of the table, we confirm the robustness of the IV estimates to the inclusion of state fixed effects.

In columns 2 and 3, we report the F-test statistic for the first stage of an identically specified two-stage least squares linear probability model. The high value for this F-test suggests that our instruments are strong predictors of the installed base. We also report the Sargan test statistics for over-identification, and this test suggests that we cannot reject the null hypothesis that the equation is over-identified.

Though there exist formal tests to allow us to evaluate how strongly the instruments predict the endogenous variable, there are no such formal tests for the exclusion restriction. This exclusion restriction requires that the instrument affects the outcome variable only through a single known causal channel. It would be problematic for the interpretation of our results, for example, if the age of neighboring hospital's EDI system were related in unobserved ways to the underlying health of the patient population that in turn affected the propensity of hospitals to exchange information. To provide evidence to support that the age of neighboring hospital system's EDI and physician documentation systems affects only their propensity to exchange information, we also conducted a falsification test using a placebo installed base. As a placebo installed base, we used the decision to exchange information externally by hospitals in the same system. If the instruments that measure the age of external hospitals' IT components are picking up unobserved heterogeneity about patient characteristics, then they should also affect the decision of hospitals in the same system. In fact, these variables are not significant predictors of placebo installed base. The F-statistic for the first stage is 0.64 with a p-value of 0.59. This lack of significance in the falsification test suggests that the instruments only operate through the expected causal channel.

5 Implications

This research investigates the relationship between the size of firm that uses a network and the kind of network effects they both respond to and create. We find that larger firms are less likely to exchange information across a network and more likely to exchange information within their own network.

Policy makers and researchers have focused on questions of encouraging compatibility and inter-operability at the vendor level, but our findings suggest that customers can also engage in strategic behavior when using network goods and choose not to exchange information over a network. This suggests that policies designed to encourage inter-connection may need to be broadened to include customers as well as vendors of technologies. This is of crucial significance for current Department of Health and Human Services policy to create a national health information network which would enable all patients and health providers to exchange information across the nation. So far, most policy has been directed towards establishing IT systems that are interoperable. However, our results suggest that it is just as important to design policy that encourages hospitals to actually exchange data, as well as buying IT systems that theoretically could do so. Our findings also suggest, that while larger hospital systems may indeed be more likely to adopt healthcare IT, the welfare effects of their doing so are not necessarily positive. Larger firms are indeed more likely to exchange information internally, but they are less likely to exchange information externally. This lack of external data exchange is also making other local hospitals less likely to exchange patient information externally.

Table 6: How exchanging data outside the hospital system depends on other hospitals also exchanging outside their systems.

	Probit (1) External exchange	Probit:IV (2) External exchange	Probit:IV (3) External exchange
No. hosps exchanging out-system externally in HRR	0.0746*** (0.0124)	0.234*** (0.0726)	0.284*** (0.106)
No. of hospitals in system in HRR	-0.0171* (0.0104)	-0.0166* (0.00971)	-0.0213** (0.0105)
No of hospitals outside system in HRR	-0.00694*** (0.00151)	-0.0119*** (0.00251)	-0.0132*** (0.00417)
Admissions (000)	-0.00274 (0.00547)	-0.00255 (0.00510)	0.000772 (0.00507)
Proportion Medicare Inpatients	-0.00150 (0.00161)	-0.00128 (0.00150)	-0.000545 (0.00149)
Proportion Medicaid Inpatients	-0.000747 (0.00192)	-0.000490 (0.00180)	-0.000190 (0.00178)
No. Doctors (000)	0.648** (0.322)	0.627** (0.301)	0.531* (0.294)
Births (000)	0.0629* (0.0333)	0.0592* (0.0313)	0.0534* (0.0309)
PPO	-0.252*** (0.0895)	-0.241*** (0.0847)	-0.246*** (0.0870)
HMO	0.130 (0.0869)	0.124 (0.0814)	0.129 (0.0828)
Per Capita Payroll	-2.974 (2.139)	-2.796 (2.004)	-4.667** (2.259)
Age of PhysDoc data system	-0.0231* (0.0137)	-0.0193 (0.0131)	-0.0189 (0.0129)
Age of EDI data system	0.0148* (0.00858)	0.00951 (0.00854)	0.00781 (0.00848)
No. hosps exchanging out-system externally in HRR No of hospitals outside system in HRR		0.0348*** (0.00150)	0.0400*** (0.00135)
HRR_4yrPhysDoc		-1.321*** (0.454)	-1.072*** (0.396)
HRR_4yrEDI		2.973*** (0.389)	2.240*** (0.339)
HRR_8yrPhysDoc		0.854 (1.082)	0.799 (0.932)
HRR_12yrPhysDoc		-4.634*** (1.537)	-2.144 (1.319)
Vendor Controls	Yes	Yes	Yes
Contract Year Controls	Yes	Yes	Yes
State Controls	No	No	Yes
Hospital Type Controls	Yes	Yes	Yes
Observations	3418	3430	3430
Log-Likelihood	-1245.6	-8753.4	-7913.0
Sargan Test of over-identification		0.38	1.43
Sargan Test of over-identification P-value		0.94	0.70
First Stage R2		0.18	0.48
First Stage F-Test		16.80	11.90
First Stage F-test p-value		0.00	0.00

Marginal effects; Standard errors in parentheses
(d) for discrete change of dummy variable from 0 to 1
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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A.1 Full Table with all controls reported

A.2 Distinguishing Between Clinical and Patient Data

In Table A-2, we report estimates from separate models for decisions to exchange different types of data: patient information (such as billing information, address, patient history) and medical data (such as clinical data, radiology reports, lab reports, discharge summaries, medication lists). We previously observed a pattern that hospital systems are more likely to exchange information only within their system and less likely to exchange information outside their system, and that pattern holds here across these two information types.

A.3 Controlling for Survey Response Bias

One problem that we faced with using this survey data is that out of 6,312 hospitals that were reported as AHA members in 2007, only 3,451 responded to the survey. It appeared that there was selection bias, since 72 percent of hospitals reported using Electronic Medical Records compared to estimates of 40 percent for the most basic forms of EMR that have been reported in other studies (Jha et al., 2009). To address this selection issue, we redid our regressions by augmenting our data with data on the 6,200 hospitals that took part in the general 2007 AHA survey. 2,784 did not take part in the EMR adoption survey. Table A-3 reports summary statistics for this extended dataset. The proportion of hospitals that have adopted a basic EMR system for this dataset is just over 40 percent, which is in line for previous reports. This suggests that hospitals that did complete the survey had a larger propensity towards EMR adoption that those that did not. The hospitals that did respond are also larger than those that did not respond. To control for survey bias, we performed a new regression which estimated a two-step model for whether or not the hospital completed the survey.

Table A-4 reports the results of these regressions. The results are similar to those reported in Table 2, suggesting that survey response bias did not drive our results.

Table A-1: The size of the hospital system affects the decision to exchange information: Displaying full hospital controls

	(1) Any exchanging	(2) Internal exchange only	(3) External exchange
No. of hospitals in system in HRR	0.0421***	0.0425***	-0.0239**
	(0.00864)	(0.0103)	(0.0115)
No of hospitals outside system in HRR	0.000336	0.000765	-0.00220
	(0.00112)	(0.00137)	(0.00151)
Admissions (000)	0.0245***	0.0102*	-0.0000479
	(0.00538)	(0.00581)	(0.00565)
Proportion Medicare Inpatients	-0.00718***	-0.0109***	-0.000729
	(0.00129)	(0.00173)	(0.00168)
Proportion Medicaid Inpatients	-0.00546***	-0.00808***	-0.000489
	(0.00159)	(0.00238)	(0.00201)
No. Doctors (000)	0.854*	0.140	0.610*
	(0.470)	(0.385)	(0.328)
Births (000)	-0.00227	0.0122	0.0610*
	(0.0326)	(0.0371)	(0.0343)
PPO	-0.142*	-0.107	-0.263***
	(0.0758)	(0.119)	(0.0952)
HMO	0.0988	0.0784	0.140
	(0.0726)	(0.115)	(0.0928)
Per Capita Payroll	5.251***	6.696***	-5.389**
	(1.532)	(1.750)	(2.489)
Independent Practice Association	-0.0401	0.0235	0.00792
	(0.0787)	(0.109)	(0.0991)
Group Practice Association	-0.0446	0.0451	-0.108
	(0.176)	(0.245)	(0.232)
Closed Phys. Hosp	-0.0440	0.101	0.0265
	(0.113)	(0.166)	(0.138)
Open Phys. Hosp	0.0785	0.0268	0.0212
	(0.0766)	(0.106)	(0.0919)
Management Services Org	0.174	0.149	0.00902
	(0.111)	(0.148)	(0.130)
Integrated Salary Model	-0.0115	-0.0623	0.0770
	(0.0540)	(0.0754)	(0.0655)
Non-Profit Hospital	0.257***	0.261***	0.142**
	(0.0553)	(0.0792)	(0.0714)
Speciality Hospital	-0.530***	-0.420***	-0.344***
	(0.0734)	(0.0983)	(0.105)
Age of PhysDoc data system	-0.00622	-0.0156	-0.0223
	(0.0102)	(0.0135)	(0.0140)
Age of EDI data system	-0.00764	-0.0469***	0.0144
	(0.00760)	(0.0122)	(0.00891)
State Controls	Yes	Yes	Yes
Contract Year Controls	Yes	Yes	Yes
Observations	3430	1874	3383
Log-Likelihood	-2025.1	-1114.5	-1205.7

Marginal effects; Standard errors in parentheses
(d) for discrete change of dummy variable from 0 to 1
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A-2: The size of the hospital system affects the decision to exchange both medical and patient information

	(1) Internal exch clinical info	(2) External exchange clinical info	(3) Internal exch patient info	(4) External exch patient info
No. of hospitals in system in HRR	0.0423***	-0.0189*	0.0459***	-0.0351**
	(0.0103)	(0.0107)	(0.0103)	(0.0142)
No of hospitals outside system in HRR	0.00120	-0.00300**	0.000696	-0.000499
	(0.00135)	(0.00142)	(0.00138)	(0.00173)
Admissions (000)	0.00335	-0.00171	0.00784	0.00598
	(0.00585)	(0.00567)	(0.00598)	(0.00607)
Proportion Medicare Inpatients	-0.00669***	0.00164	-0.0115***	-0.00298
	(0.00170)	(0.00152)	(0.00174)	(0.00195)
Proportion Medicaid Inpatients	-0.00741***	0.000341	-0.00982***	-0.00268
	(0.00237)	(0.00188)	(0.00240)	(0.00234)
No. Doctors (000)	0.0464	0.603*	0.361	0.135
	(0.386)	(0.326)	(0.417)	(0.386)
Births (000)	0.0251	0.0598*	0.0243	0.0466
	(0.0379)	(0.0339)	(0.0382)	(0.0362)
PPO	-0.150	-0.247***	-0.237**	-0.282**
	(0.118)	(0.0884)	(0.120)	(0.114)
HMO	0.189*	0.0767	0.202*	0.159
	(0.113)	(0.0862)	(0.116)	(0.113)
Per Capita Payroll	7.916***	-5.195**	5.352***	-7.306**
	(1.787)	(2.291)	(1.751)	(3.006)
Age of PhysDoc data system	-0.00604	-0.0288**	-0.0106	-0.0187
	(0.0134)	(0.0137)	(0.0138)	(0.0157)
Age of EDI data system	-0.0291**	0.0192**	-0.0433***	0.0193**
	(0.0115)	(0.00844)	(0.0122)	(0.00975)
Vendor Controls	Yes	Yes	Yes	Yes
Contract Year Controls	Yes	Yes	Yes	Yes
State Controls	Yes	Yes	Yes	Yes
Hospital Type Controls	Yes	Yes	Yes	Yes
Observations	1883	3418	1874	3291
Log-Likelihood	-1117.0	-1399.5	-1098.0	-876.0

Marginal effects; Standard errors in parentheses
(d) for discrete change of dummy variable from 0 to 1
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A-3: Summary Statistics for all AHA hospitals

	Mean	Std Dev	Min	Max	Observations
Adopt EMRs	0.39	0.49	0	1	6230
Any exchanging	0.31	0.46	0	1	6230
External exchange	0.072	0.26	0	1	6230
External exch patient info	0.046	0.21	0	1	6230
External exchange clinical info	0.088	0.28	0	1	6230
Internal exchange only	0.26	0.44	0	1	3454
Internal exch patient info	0.27	0.44	0	1	3454
Internal exch clinical info	0.29	0.45	0	1	3454
No. of hospitals in system in HRR	1.31	2.69	0	20	6230
No of hospitals outside system in HRR	27.8	25.0	0	118	6230
Admissions (000)	6.05	8.61	0.0030	108.6	6230
Proportion Medicare Inpatients	45.4	23.5	0	101.7	6230
Proportion Medicaid Inpatients	17.7	17.0	0	99.5	6230
No. Doctors (000)	0.019	0.074	0	2.07	6230
Births (000)	0.67	1.26	0	18.0	6230
PPO	0.55	0.50	0	1	6230
HMO	0.47	0.50	0	1	6230
Per Capita Payroll	0.048	0.018	0.000045	0.42	6230
Independent Practice Association	0.10	0.30	0	1	6230
Group Practice Association	0.018	0.13	0	1	6230
Closed Phys. Hosp	0.031	0.17	0	1	6230
Open Phys. Hosp	0.093	0.29	0	1	6230
Management Services Org	0.041	0.20	0	1	6230
Integrated Salary Model	0.24	0.43	0	1	6230
Non-Profit Hospital	0.32	0.47	0	1	6230
Speciality Hospital	0.53	0.50	0	1	6230
Age of PhysDoc data system	0.85	2.71	-2	31	6230
Age of EDI data system	0.86	2.94	0	25	6230
Epic System	0.032	0.18	0	1	6230
Meditech System	0.091	0.29	0	1	6230
Cerner System	0.054	0.23	0	1	6230
Mckesson System	0.045	0.21	0	1	6230
Siemens System	0.031	0.17	0	1	6230
Eclipsys System	0.018	0.13	0	1	6230
GE System	0.015	0.12	0	1	6230
Foreign Nurses	0.13	0.34	0	1	6230

Using our cross-sectional data on hospitals, we estimate a static model of the decisions to complete the survey and to exchange health information electronically. The decision to complete the survey is summarized by:

$$\text{Prob}(survey_i = 1|Z_i) = \Phi(Z_i\beta), \tag{A-1}$$

where $survey_i = 1$ if hospital i completes the survey and $survey_i = 0$ otherwise, Z_i is a vector of explanatory variables that influence adoption, β is a vector of unknown parameters, and Φ is the cumulative distribution function of the standard normal distribution.

For a hospital that has completed the survey, the decision to exchange information electronically is specified as:

$$\text{Prob}(Exchange_i = 1|X_i) = \Phi(X_i\gamma), \tag{A-2}$$

where $Exchange_i$ denotes the decision to exchange information, X_i describes a vector of explanatory variables that affect the propensity to exchange information, and γ is a vector of unknown parameters.

In order to account for the fact that we observe a hospital's decision to exchange information only if the hospital was interested enough in IT to complete the survey, we estimate these two equations simultaneously using a bi-variate probit. This approach is similar to a full information maximum likelihood Heckman correction, adjusted for the fact that both our dependent variables are binary. Estimating a Heckman-style model requires imposing an exclusion restriction on the initial adoption equation. That is, we need to identify a variable that belongs in Z_i but not in X_i. This variable will affect the hospital's decision to be interested enough in EMR technology to complete the survey but will not affect its decision to exchange information with other hospitals or health providers. One reason that hospitals are interested in EMR systems independent of their ability to exchange records is to prevent medical errors from internal staff. Transcribing and recording errors may be larger when employees are not native speakers of English or well versed in American hospital practice. Therefore we use as our excluded variable whether or not the hospital had employed 'foreign nurses' according to the 2007 AHA survey.

Table A-4 displays the results from an initial specification that estimated a Heckman-style two stage model with a bivariate probit distribution. The results are similar to those reported in Table 2, suggesting that survey response bias did not drive our results.

Table A-4: The size of the hospital system affects the decision to exchange patient information after controlling for survey selection

	(1) Any exchanging	(2) Internal exchange only	(3) External exchange
No. of hospitals in system in HRR	0.0414***	0.0416***	-0.0242**
	(0.00870)	(0.0103)	(0.0116)
No of hospitals outside system in HRR	0.000575	0.00108	-0.00232
	(0.00113)	(0.00138)	(0.00152)
Admissions (000)	0.0239***	0.0101*	0.000879
	(0.00548)	(0.00594)	(0.00577)
Proportion Medicare Inpatients	-0.00705***	-0.0110***	-0.000500
	(0.00130)	(0.00175)	(0.00169)
Proportion Medicaid Inpatients	-0.00545***	-0.00818***	-0.000631
	(0.00160)	(0.00240)	(0.00202)
No. Doctors (000)	0.815*	-0.0592	0.584*
	(0.472)	(0.371)	(0.330)
Births (000)	-0.00204	0.00432	0.0609*
	(0.0327)	(0.0375)	(0.0344)
PPO	-0.142*	-0.136	-0.271***
	(0.0760)	(0.121)	(0.0955)
HMO	0.0875	0.0965	0.136
	(0.0729)	(0.117)	(0.0930)
Per Capita Payroll	5.040***	6.579***	-5.540**
	(1.539)	(1.770)	(2.501)
Age of PhysDoc data system	-0.00598	-0.0149	-0.0244*
	(0.0104)	(0.0139)	(0.0143)
Age of EDI data system	-0.00685	-0.0450***	0.0141
	(0.00766)	(0.0123)	(0.00897)
Took Survey			
Foreign Nurses	0.397***	0.340**	0.403***
	(0.120)	(0.133)	(0.120)
No. of hospitals in system in HRR	-0.0361*	-0.00377	-0.0400**
	(0.0186)	(0.0184)	(0.0187)
No of hospitals outside system in HRR	0.00600***	0.00876***	0.00600***
	(0.00128)	(0.00136)	(0.00129)
Admissions (000)	-0.136***	-0.134***	-0.135***
	(0.0210)	(0.0233)	(0.0210)
Proportion Medicare Inpatients	-0.00763***	-0.00413***	-0.00762***
	(0.00129)	(0.00149)	(0.00130)
Proportion Medicaid Inpatients	-0.00712***	-0.00608***	-0.00706***
	(0.00193)	(0.00232)	(0.00193)
No. Doctors (000)	2.032**	2.946***	1.936*
	(0.986)	(0.992)	(0.991)
Births (000)	-0.0926	-0.0232	-0.103
	(0.0919)	(0.0948)	(0.0925)
PPO	-0.0502	0.0255	-0.0391
	(0.119)	(0.135)	(0.118)
HMO	0.298**	0.285**	0.288**
	(0.122)	(0.137)	(0.122)
Per Capita Payroll	-0.806	1.591	-0.739
	(1.652)	(1.678)	(1.645)
Age of PhysDoc data system	-0.00618	0.00525	-0.00745
	(0.0139)	(0.0140)	(0.0140)
Age of EDI data system	-0.0267	-0.0322	-0.0256
	(0.0195)	(0.0227)	(0.0194)
Vendor Controls	Yes	Yes	Yes
Contract Year Controls	Yes	Yes	Yes
State Controls	Yes	Yes	Yes
Hospital Type Controls	Yes	Yes	Yes
Observations	6230	4684	6230
Log-Likelihood	-2916.6	-1765.9	-2106.5

Marginal effects; Standard errors in parentheses
(d) for discrete change of dummy variable from 0 to 1
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$