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Health Information Exchange, System Size and Information Silos

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Abstract

There are many technology platforms that bring benefits only when users share data. In healthcare, this is a key policy issue, because of the potential cost savings and quality improvements from 'big data' in the form of sharing electronic patient data across medical providers. Indeed, one criterion used for federal subsidies for healthcare information technology is whether the software has the capability to share data. We find empirically that larger hospital systems are more likely to exchange electronic patient information internally, but are less likely to exchange patient information externally with other hospitals. This pattern is driven by instances where there may be a commercial cost to sharing data with other hospitals. Our results suggest that the common strategy of using 'marquee' large users to kick-start a platform technology has an important drawback of potentially creating information silos. This suggests that federal subsidies for health data technologies based on 'meaningful use' criteria, that are based simply on the capability to share data rather than actual sharing of data, may be misplaced.

Keywords: Healthcare IT, Technology Policy, Network Externalities

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1 Introduction

The need for information exchange in healthcare is pressing, due to growing evidence that exchanging and sharing patient data can potentially reduce mortality and even reduce costs (Bower, 2005; Walker et al., 2005; Miller and Tucker, 2011a; McCullough et al., 2011). The success of efforts to leverage 'big data' in healthcare, such as the 'learning health' system (Smith et al., 2012), will depend crucially on the willingness of providers to share their data (Goodby et al., 2010). However, it is unclear what the best steps are for policymakers to take to ensure that information exchange happens.

One commonly advocated strategy for kick-starting a platform for data exchange is to secure a large 'marquee' user to help attract other users to the platform. As described by Eisenmann et al. (2006), "the participation of 'marquee users' can be especially important for attracting participants." Gowrisankaran and Stavins (2004) set out a foundational economic framework for understanding this. Due to marquee users' scale, they can internalize some of the network effects inherent in the platform and in turn then attract more users to the platform. To see this, consider a network technology that connects multiple separate firms. Each firm will adopt a network technology based on whether it receives net benefits from being part of the network, but it will not internalize the positive effect that its adoption has for other firms in the network. If a subset of these firms merge, then adoption increases, because the newly merged firm is able to internalize the network benefits from adoption at different locations.

This paper asks how the size of user that adopts an information exchange technology affects subsequent *usage*. We use data on the exchange of electronic health data within a local health area and investigate how the number of hospitals within a hospital's system influences its likelihood of sharing data.

In this setting, larger hospital systems may be better able to internalize the high costs of ensuring compatibility with complex information exchange standards, making it cheaper for them to exchange data both internally and externally. Correspondingly, we find that hospitals with more hospitals in their system are indeed more likely to exchange electronic information internally. However, they are less likely to exchange electronic information externally with other nearby hospitals. This decision to exchange information externally does not seem to be driven by the systems' age or manufacturer, nor by the number of other hospitals they could potentially interact with. We argue that this contrast between a willingness to share data internally and a lack of willingness to share data externally reflects a tendency for larger hospital systems to create 'information silos.' An information silo is a data system that does not exchange data with other similar systems.

A potential explanation for larger hospital systems' propensity to create information silos is that they fear that by facilitating data outflow, they may lose patients. If the hospital allows data outflow, patients may 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 cost-sharing (Melnick and Keeler, 2007). We offer three pieces of evidence, based on estimating heterogeneous effects of system size on data exchange, that suggest that strategic motivations like these at least partially drive our results.

First, we find a stronger negative relationship between hospital system size and external information exchange among hospitals that have insurance arrangements that make it easier for patients to leave their hospital system. Second, hospitals that pay their staff more are less likely to share their data with hospitals outside their system if they are part of a larger system. Third, specialty hospitals are less likely to share data outside their system if they are part of a larger system. The first result suggests that if patients are likely to seek treatment elsewhere, hospitals are less likely to share data. The latter two results suggest that if hospitals invest valuable resources in patient care, they may also be less likely to be willing to share data. While not conclusive, these findings provide some evidence that the creation of information silos that we observe is linked to strategic concerns.

Policymakers and researchers have focused on questions of encouraging compatibility and inter-operability at the IT vendor level, but we show that users who have already adopted may also choose not to exchange information with others. This is important because of recent policy emphasis on the diffusion of Electronic Medical Records (EMRs). The United States federal government has provided $19 billion in financial incentives to healthcare providers under the 2009 HITECH Act to encourage them to adopt EMRs. Part of the motivation for government coordination is the belief that to reduce healthcare spending, it is not enough for healthcare providers to simply adopt the technologies. Providers need to be able to share electronic patient data as well.[1] To help coordinate this sharing of data, EMRs only qualify for aid if they fulfill government criteria for 'meaningful use.'[2]

Much of the policy literature has criticized the 'meaningful use' criteria as setting too a low a standard in terms of adoption of technology (Wolf et al., 2012). This reflects that the focus so far of the 'meaningful use' criteria has been on achieving technical inter-operability rather than actual sharing of data. For example, the pivotal 'Core Measure 13' states that to qualify, a hospital has to have 'Performed at least one test of certified EHR technology's capacity to electronically exchange key clinical information.'[3] This test would qualify even if it used fictional patient data.

However, our results suggest that compatibility or capability alone will not be enough to ensure that electronic information is actually shared. To succeed in ensuring comprehensive

[1]The emphasis on data sharing is shared by industry leaders and consumer advocates (Clark, 2009). Jim Lott, Executive Vice President, Hospital Council of Southern California: "Looking for savings in hospitals that use EMRs is short-sighted. The real payday for use of EMRs will come with interoperability. Measurable savings will be realized as middleware is installed that will allow for the electronic transmission and translation of patient records across different proprietary systems between delivery networks." Johnny Walker, Founder and past CEO of Patient Safety Institute: "EMRs don't save money in standalone situations. However, EMRs will absolutely save significant money (and improve care and safety) when connected and sharing clinical information."

[2]For more historical and policy background on the 'meaningful use' criteria, see Blumenthal and Tavenner (2010), Jha (2010), Buntin et al. (2010) and Adler-Milstein and Jha (2012).

[3]`http://www.cms.gov/EHRIncentivePrograms/Downloads/13_Electronic_Exchange_of_Clinical_Information.pdf`

meaningful use, 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 exchange information. This reluctance to share information may stem from the notion that records are the property of the hospital. As quoted in Knox (2009), Dr. Delbanco, a primary care specialist at Beth Israel Deaconess Medical Center in Boston, states, "You can get it [the patient record] [...] But we do everything in the world to make sure you don't get it." The findings of this paper suggest that this ethos may be echoed in the switch from paper to digital records. This means the digitization of health records may not make patient healthcare provider transitions as seamless as hoped for by policymakers. This is important as policymakers set policy priorities for 'stage 3' of meaningful use, the target date for which is currently 2016.

This adds to a broader literature which has questioned the wisdom and likelihood of achieving a quick transition to digital health given larger general equilibrium issues (Christensen and Remler, 2009; Murray et al., 2011). In particular, they highlight a potential cost of speed, which is that in their haste to give incentives to adopt, policymakers may inadvertently also be giving hospitals incentives to adopt systems that are incompatible with the ultimate aim of widespread sharing of health information.

2 Conceptual Framework

We study the decisions of hospitals to exchange patient information with other hospitals, inside and outside of their systems. This section presents a conceptual framework for modeling these decisions and then illustrates the various ways in which they can be affected by the hospital's system size. This framework is used to motivate our main empirical analysis and choices of control variables.

Because data exchange is a classic network externality setting, our framework allows for data exchange to generate positive externalities to other local hospitals. This is similar to models of information exchange technology adoption in other settings, such as Gowrisankaran and Stavins (2004), who study the decision of banks to adopt electronic exchange capabilities. We differ from this prior literature along two key dimensions. First, we consider the decision to participate in data exchange separately from the technology adoption decision that enables exchange. This allows us to account for the facts that hospitals can selectively choose to exchange data (only within their system, for example) and that hospitals with IT systems capable of exchange may not participate at all. Second, unlike Gowrisankaran and Stavins (2004) and other papers that assume that consumers are permanently tied to their providers (banks, in their case), our model explicitly considers the potential competitive effects of data exchange that arise when consumers can switch providers. In our setting, this means that we model hospitals as thinking about the impact of data exchange on their their current customer base as well as how participating in data exchange may change their future customer base. These considerations are a crucial motivation for why we might expect system size to have differential effects on the decisions to exchange data internally within the hospital system versus externally outside the system.

2.1 Hospital Decisions to Exchange Data

We formalize the key considerations of hospitals deciding whether or not to exchange patient information with other hospitals in a simple model. We assume that hospitals maximize an objective function that includes net revenues,[4] and patient care quality (converted to dollar terms through the function α, as a proxy for other non-financial mission of the hospital or its leaders, which can include charity care or prestige). Each hospital faces a binary choice and will decide to exchange data only if its utility function increases from doing so, i.e., if:

$$\Delta Utility_i = \Delta \alpha_i(Quality_i) - \Delta Costs_i + \Delta Revenue_i \geq 0 \tag{1}$$

[4] Maintaining non-negative flows of net revenues are still a concern for non-profit hospitals.

In theory, information exchange can affect each of the three terms in the utility function. The direction and magnitude of each effect can in turn vary with hospital characteristics. We discuss the potential effects of data exchange and the key mediating factors in more detail in this section.

First, sharing information can improve the quality of hospital care implying a positive Δ for this component. This is particularly true for patients with chronic conditions who are seeing a new specialist or in emergency situations with patients who are unable to communicate their medical history or allergies (Brailer, 2005). Lowering emergency room admissions due to better access to patient histories can itself improve quality by reducing wait times for other patients when capacity is limited (Delia and Cantor, 2009). Hospitals with objective functions that include quality of care ($\alpha_i > 0$) may invest in data exchange to achieve these quality improvements even if they do not improve net revenues. Quality improvements will produce positive externalities to patients if hospitals are not able to capture (or directly value as much as patients do, possibly because of asymmetric information about quality) the increase in patient welfare. There can also be spillover benefits to other local hospitals if data sharing improves their quality as well.

Second, we consider the effects of data exchange on operating costs. Hospitals that participate in data exchange will incur initial setup and continued support costs associated with health IT systems and network use that enable exchange. Nevertheless, they may still experience a net cost reduction if exchanging patient information with other hospitals in the area allows hospitals to avoid duplicative medical testing. This cost reduction will increase net revenues if the costs of testing are not fully reimbursed by insurance, as is the case for patients whose insurance contract uses a prospective payment scheme that pays a flat amount per diagnosis group, instead of fee-for-service. Hospitals may also have a financial incentive to reduce the frequency and treatment intensity of emergency room visits, which often involve uncompensated care, and where, in addition to Medicare and Medicaid, many private insurers pay a fixed fee.[5] In a case study of Memphis emergency departments, health information exchange was associated with significant decreases in utilization and costs (Frisse et al., 2012). To the extent that some of the costs of duplicative care are borne by insurers, the social value of data sharing will be larger than the private value. Data sharing can also have positive external effects by reducing operating costs for other local hospitals.

Last, we consider the effect of the adoption of external data exchange on revenues. Quality improvements from data exchange that increase demand for hospital care, overall or at particular hospitals engaged in exchange, will imply a positive effect of data exchange on revenues. However, the overall effect of data exchange on revenues is complicated by the possibility that better information flow itself can cause patients to choose different hospitals for their care. If patient records are seen by hospitals as part of their property and containing proprietary business information, then there may be an additional cost from external data exchange that relates to sharing client records with competitors. Detailed patient records that show interventions and health outcomes can also reveal sensitive information about hospital practices and quality that hospitals prefer to keep internal. Without large financial motivations for data sharing, these concerns may limit the willingness of hospitals to freely share their patient data and can lead to data silos in healthcare.

Prestigiacomo (2012) illustrates these concerns when making the case for the Carolina eHealth Alliance (CeHA), a health information exchange established in Charleston, S.C. in 2011. The 'competitive nature' of the area's hospital systems is reflected in the fact that CeHA only covers emergency departments. It is also reflected "in the design of the CeHA interface itself. No data is permanently stored in CeHA, or is able to be saved into an organization's electronic health record (EHR). ... CeHA auto-populates data from patient registration, rather than operating via physician query. When a patient registers and chooses

[5]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 data exchange (Calcanis, 2005).

not to opt-out, CeHA queries the edge servers of the participating organizations to aggregate and consolidate key electronic portions of their medical records. A green checkmark in the interface indicates that CeHA has clinical information on the patient ... from the past 180 days. This information appears in a temporary virtual record that the physician has four hours to view, and afterwards is cleared upon patient discharge." CeHA founder Frank Clark explains the complex structure as accommodating opposition from participating hospitals to any permanent data storage from the exchange, saying "Given their competitive nature they didn't want someone to be mining the data, or trying to lure the patient to another facility."

2.2 System Size and Data Exchange

In this section we consider how alliances between hospitals affect their willingness to exchange patient data and motivate the central question of the paper: how system size affects the sharing of such patient information.[6] Once we expand our framework to consider hospitals being part of systems, it becomes important to distinguish between two types of information exchange, namely, internal exchange, with other hospitals in the same system, and external exchange, outside the boundaries of the system.

The question of how system size affects network technology use is related to more general questions of how user size affects participation in information networks. In traditional theoretical models of network externalities (Katz and Shapiro, 1985; Farrell and Saloner, 1985; Economides, 1996), network participants are assumed to be symmetrical in size and consequently the issue of network user size is not discussed.[7] Later empirical papers, such as

[6]We follow Ho (2009), who studies networks in healthcare, and focus on hospital systems rather than hospital networks, because a hospital system is the closest analog 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.

[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.

Gowrisankaran and Stavins (2004), argue that user size itself can be used to detect the presence of network externalities. Their argument is that because larger customers with more internal sub-units are more able to internalize network externalities, any relative increase in adoption propensity by such larger firms is itself evidence of network externalities.

Although our focus is on technology use rather than technology adoption, that argument from the network effects literature that larger users are more likely to internalize the network benefits from data exchange (in the form of either lower costs or higher quality) applies equally in our setting to internal data exchange among hospitals within a system. This channel implies that larger systems are more likely to exchange data internally but not externally (because they have no advantage in internalizing benefits outside their system). In fact, hospitals in larger systems may find less value from external data exchange (in terms of cost savings or improved quality) than hospitals in smaller systems because they may plausibly be able to serve customers' needs entirely within their own firm boundaries, and consequently see less network benefit to acquiring customer information from other firms. As a general rule, the within system benefits from exchange will be larger and cross-system benefits smaller, if patients tend to get all of their care within the same system (in the extreme case of a health maintenance organization (HMO), for example, or if the system is dominant in that local area).

Still, it is also possible that the costs of supporting data exchange are lower, on a per-transaction basis, for larger systems. That would lead larger systems to invest more in the IT capacity for exchange and, conditional on capacity, to engage in more network use overall, both internal and external.

These first two channels, through costs and quality, suggest a positive relationship between system size and internal data exchange but a weaker or negative relationship for external data exchange. When strategic considerations about patient hospital choice are included in the calculation, then larger systems are expected to be less likely to engage in external data exchange. Larger systems may be especially fearful that facilitating data outflow will lead their customers to leave their firm and seek service from smaller and potentially cheaper alternative firms. In the healthcare setting that we study, Melnick and Keeler (2007) documents that larger hospital systems have seen higher price increases in recent years. Ho (2009) provides evidence that larger hospital systems exploit their bargaining power to negotiate better prices with health insurers. This was confirmed in a recent study performed in Massachusetts by the state attorney general, which documented that larger hospital networks charge more even after controlling for differences in difficulty of care provided (Coakley, 2010). Patients may therefore prefer to leave large hospital systems to seek cheaper alternatives if they are responsive to deductibles and co-pays. This suggests that larger firms may see less value in allowing an outflow of patient records.

The question of how system size affects the decision to share information is new. Nevertheless, our results do relate to a literature that asks whether competition encourages or deters technology firms from adopting compatible standards for their technology (Farrell and Klemperer, 2007). Work on standards deployment, such as Augereau et al. (2006)'s 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. (2009) built 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. There is also a small and related literature in ICT that addresses the issue of 'inter-connection' (Shy, 2001). This literature emphasizes that while smaller telecommunication firms want inter-connection, larger firms do not and instead prefer to merge. Mata et al. (1995), by contrast, argues that switching costs are not a sustainable source of competitive advantage for any firm regardless of size. The setting we study is different, because we do not examine the behavior of vendors of EMR technology and their incentives to distort standards to gain market power. Instead, we study hospital end-users who deploy standards-based technology and get a direct benefit (or not) from inter-connection.

3 Data

3.1 Electronic Exchange of Patient Information

We use the Hospital Electronic Health Record Adoption Database^{TM} from the American Hospital Association (AHA, released in May 2009), which reports data from a 2007 survey of members of the American Hospital Association.[8] This survey is funded by the Office of the National Coordinator for Health Information Technology (ONC) and is intended to be the most comprehensive and representative survey of the state of healthcare IT.

This survey asked whether hospitals exchanged patient and clinical data with other hospitals in their system and externally outside of their system. Having data on actual sharing of health data rather than technology adoption allows us to advance on previous research in this area, which has only had data on health care information technology adoption.[9]

Because the original 2007 survey was not sufficiently comprehensive, the American Hospital Association repeated the survey with different supplementary questions in 2008 and 2009. We use these additional survey waves to augment our dataset where there are missing observations (around 600 cases). However, our results are similar if we restrict our analysis to 2007. We are not able to exploit these supplementary questions as a panel because three years of data is too short to measure effects. This is because of the two-year lead time for IT implementations (Miller and Tucker, 2011a), and the antitrust scrutiny attendant on hospital system mergers and acquisitions, meaning that system size does not change rapidly.

[8] In earlier versions of this paper, we show the results are robust to controlling for potential survey-response bias. We have also checked that consistency in the answers to the questions over time did not vary with any of our key explanatory variables, including system size. This helps rule out distortions in responses based on strategic considerations and attempts to influence the development of the meaningful use criteria.

[9] Tucker (2008) exploits network usage data to identify network externalities, but does not measure strategic decisions to interact or not over a network after adoption.

The survey did not ask hospitals to report with whom they exchanged their data. We use hospital referral regions (HRRs) as our definition of a local area within which patients plausibly might transfer between hospitals.[10] 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 hospital service area (HSA), which are smaller and are based on the customary geographical reach of patients.

3.2 Further Controls

We matched the information on patient data exchange with the most recent rounds of the AHA hospital survey to obtain detailed data on hospital characteristics for controls in our regressions. The data provide information on a hospital's system's size, defined as the number of hospitals owned, leased, sponsored or contract-managed by a central organization. Though we use system size as measured by the number of hospitals in our main specifications, we also obtain similar results if we weight the system size variables by number of beds.[11] We observe 430 hospital systems in our data. The average system contains six hospitals and operates in just under four regional markets. Among hospitals in our data that belong to multi-hospital systems, the average system size is 36 hospitals. In our full sample, hospitals have an average of 1.5 other hospitals from their system in the same HRR and 19.7 hospitals in their system located outside of the HRR. Table 1 and Table 2 provide summary statistics for our dependent and explanatory measures.

In addition to our main explanatory variables for system size and local hospital competition, our empirical models also include variables that could affect the propensity of hospitals

[10] 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.

[11] Because the AHA panel data on system membership is sometimes noisy from year to year (Madison, 2004), we also cross-checked the *systemid* variable that we base our results on with the *systemid* variable from the 1996-2006 AHA surveys to weed out any inconsistencies.

to exchange information, either internally or externally. Most of these variables are from the AHA. Hospital size could predict data exchange because it is related to patient flows and larger hospitals are more willing to absorb the fixed costs associated with establishing data exchanges. The insurance status of patients can also affect data exchange among providers by affecting the mobility of patients, within or across systems, or by affecting the financial status of hospitals (through differences in reimbursement rates). We separately control for the proportions of inpatient days covered by Medicare and Medicaid because of differences in reimbursement levels and patient populations in the two public programs. We also control for hospital per-capita payroll costs, as these may be related to greater quality and investment overall at the hospital, including IT. Furthermore, we account for the fact that hospitals vary not only in their average payroll costs but also in their relationships with physicians (affecting both compensation and governance structure) by controlling for independent practice association, group practice association, and integrated salary model. These variables can affect the degree of control that physicians exercise over hospitals' investments and data use. Finally, we control for hospital type, to allow for the possibility that nonprofit hospitals have different objective functions than for-profits and that specialty hospitals may have different motivations for sharing data than general hospitals. This was something that was documented by Adler-Milstein et al. (2011) in other research that used this dataset. In addition to these key AHA controls, we also add information from HIMSS about the IT vendor used by each hospitals. This allows us to distinguish between variation in data exchange outcomes driven by differences in hospitals' *ability* to exchange data and by differences in hospitals' *willingness* to exchange data, conditional on capacity.

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 systems in our data - some hospitals share information externally and some do not. This may stem from organizational structures

Table 1: Rates of Data Exchange by Hospitals in the AHA Technology Survey

	Mean
External exchange	0.17
External patient	0.11
External clinical	0.16
Exchange Insurance	0.54
Not member RHIO	0.19
Internal exchange	0.68
Internal patient	0.66
Internal clinical	0.64
Observations	4060

Internal exchange dependent variables only applicable to 2573 hospitals that are part of a system.

Table 2: Summary Statistics for Characteristics of Hospitals in the AHA Technology Survey

	Mean	Std Dev
# hospitals in system in HRR	1.48	2.87
# hospitals outside system in HRR	28.4	21.6
Admissions (000)	7.53	9.47
Proportion Medicare Inpatients	45.7	22.2
Proportion Medicaid Inpatients	18.1	16.4
No. Doctors (000)	0.023	0.085
PPO	0.64	0.48
HMO	0.56	0.50
Per Capita Payroll	0.050	0.016
Independent Practice Association	0.11	0.31
Group Practice Association	0.020	0.14
Integrated Salary Model	0.30	0.46
Non-Profit Hospital	0.43	0.50
Speciality Hospital	0.39	0.49
Cerner System	0.077	0.27
Eclipsys System	0.028	0.17
Epic System	0.044	0.20
GE System	0.018	0.13
Mckesson System	0.071	0.26
Meditech System	0.17	0.37
Siemens System	0.045	0.21
Other System	0.0049	0.070
# hospitals outside HRR in system	19.7	42.7
StandAlone	0.37	0.48
Observations	4060	

surrounding IT purchases that predate the idea of a networked IT system.[12] Therefore, if hospital systems do exchange data externally at all, there is diversity in individual hospital exchanging behavior.

4 Analysis and Results

4.1 Exchange within a system

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

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

and $ExchangeInternal_{ij} = 1$ if hospital i in HRR j exchanges information internally.

$SystemSize_{ij}$, our key variable of interest, captures the number of hospitals within that system in that HRR. X_{ij} is a vector of hospital characteristics 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.

Table 3 displays the results of our initial specification. Since only hospitals in a system can answer in the affirmative to this question, we restrict our attention to the 2,571 hospitals who are part of a system in our data.

Column (1) is a Probit regression for whether or not that hospital exchanges data with other hospitals in its system. The positive and significant marginal effect of the number of local in-system hospitals suggests that the likelihood of exchanging data within the system

[12] This is consistent with data from HIMSS surveys of both hospital and hospital systems about the nature of the approval process for IT purchases. In only about 11% of hospital systems and 20% of hospitals were purchasing decisions taken at the Board level. In the remainder of cases, the decision was taken at a far lower level, most frequently that of the hospital's chief information technology officer.

Table 3: Larger Hospital Systems are More Likely to Exchange Information Internally

	(1) Mrg Eff./S.E.	(2) Mrg Eff./S.E.	(3) Mrg Eff./S.E.	(4) Mrg Eff./S.E.	(5) Mrg Eff./S.E.	(6) Mrg Eff./S.E.
# hospitals in system in HRR	0.017***	0.020***	0.021***	0.022***	0.021***	0.019***
	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)	(0.010)
# hospitals outside system in HRR	-0.001***	-0.001	-0.001**	-0.001**	-0.001**	-0.001***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Admissions (000)			0.009***	0.009***	0.007***	0.007***
			(0.004)	(0.004)	(0.004)	(0.004)
Proportion Medicare Inpatients			-0.003***	-0.003***	-0.003***	-0.003***
			(0.001)	(0.002)	(0.002)	(0.002)
Proportion Medicaid Inpatients			-0.005***	-0.005***	-0.004***	-0.004***
			(0.002)	(0.002)	(0.002)	(0.002)
No. Doctors (000)			0.301	0.302	0.283	0.250
			(0.633)	(0.613)	(0.600)	(0.561)
PPO			-0.080**	-0.088**	-0.084**	-0.110***
			(0.102)	(0.102)	(0.102)	(0.098)
HMO			0.112***	0.121***	0.113***	0.139***
			(0.099)	(0.099)	(0.099)	(0.094)
Per Capita Payroll			1.622*	1.588*	1.518*	1.786*
			(2.704)	(2.698)	(2.579)	(2.687)
Independent Practice Association			-0.018	-0.026	-0.019	-0.027
			(0.099)	(0.100)	(0.101)	(0.099)
Group Practice Association			0.023	0.023	0.028	0.050
			(0.229)	(0.232)	(0.236)	(0.229)
Integrated Salary Model			-0.015	-0.014	-0.015	-0.020
			(0.066)	(0.067)	(0.067)	(0.064)
Non-Profit Hospital			0.086***	0.084***	0.066***	0.062***
			(0.072)	(0.073)	(0.073)	(0.069)
Speciality Hospital			0.057**	0.056**	0.044*	0.041*
			(0.068)	(0.068)	(0.069)	(0.066)
Cerner System					0.167***	0.160***
					(0.124)	(0.122)
Eclipsys System					-0.017	-0.002
					(0.193)	(0.193)
Epic System					0.229***	0.228***
					(0.177)	(0.175)
GE System					0.068	0.086
					(0.219)	(0.217)
Mckesson System					0.066	0.074*
					(0.127)	(0.126)
Meditech System					-0.037	-0.032
					(0.092)	(0.090)
Siemens System					0.149**	0.149***
					(0.170)	(0.163)
Other System					0.280**	0.306**
					(0.413)	(0.409)
State Fixed Effects	No	Yes	Yes	Yes	Yes	No
Installation Year Controls	No	No	No	Yes	Yes	Yes
Observations	2573	2571	2571	2571	2571	2573
Log-Likelihood	-1589.61	-1539.01	-1440.10	-1426.39	-1403.49	-1435.67

Probit estimates. Dependent variable is whether the hospital exchanges electronic data internally within its system. Robust Standard Errors. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

increases with system size. The decision does not appear to be positively related to the presence of other hospitals in the local area. This finding is in alignment with a traditional approach to network effects which suggests that larger coordinated firms are better able to internalize network externalities and consequently more likely to share information.[13]

In Columns (2)-(5) we show that the results remain robust when we add controls for the state the hospital is located in, hospital characteristics, the age of the technology, and the manufacturer of the system. We add these controls to address concerns that the explanatory variable of system size is driven by external factors that also determine whether the hospital shares data with others.

The state fixed effects in columns (2) to (5) account for cross-state differences in system size and the propensity to exchange data. In particular, as discussed in Miller and Tucker (2009, 2011b, 2012), state-level regulation of privacy, information security, and medical malpractice can affect the adoption of EMRs and therefore potentially the use of EMRs to exchange information. They might also at the same time lead hospital systems to grow or shrink. By including the full set of state fixed effects in these models, we can abstract away from the impact of cross-sectional variation in such state regulations on hospital exchanging decisions.

There is also the possibility that our estimates are capturing something else about the hospital that determines its decision to share data – for example its organizational or financial structure. In Column (3), we add additional controls for such hospital characteristics. Many of these controls are insignificant. Generally, hospitals that see many Medicaid and Medicare patients are less likely to exchange information within their systems. This could

[13]To explore the possibility that this positive relationship between system size and internal exchange is driven from a mechanical effect coming from hospitals in larger systems having more potential opportunities for exchange, we also estimated the models in Table 3 using 'any exchange' (including either internal or external) as the dependent variables. The effects of system size is positive and significant in those models as well, where all hospitals in the same HRR have the same number of potential exchange partners, which provides some additional support for the interpretation that larger systems are better able to internalize network benefits from data exchange.

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.[14] Non-profit hospitals and specialty hospitals are more likely exchange data internally. Controlling for the technology installation year in Column (4) and vendor in Column (5) leaves the main estimates unchanged. Finally, Column (6) reports estimates from the model with the full set of controls but omits the state fixed effects.

Across all specifications, the estimated marginal effects imply that each additional hospital in a system increases the chances that individual hospitals in that system exchange data internally by about 2 percentage points. This is a moderate effect size in relation to the mean rate of internal exchange in our sample of 68% (Table 1). A standard deviation increase in system size (of about 3 hospitals; Table 2) would increase internal exchange by 6 percentage points or about 8.8 percent.

4.2 External Exchange of Data

However, of crucial importance for firms that own information-sharing platforms and policy-makers who are relying on large hospital system users to kick-start the network (or to provide a foundation for 'big data' application in healthcare) is whether a network user exchanges information *externally*.

For this decision, we similarly estimate a separate equation where:

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

and $ExchangeExternal_{ij} = 1$ if hospital i in HRR j exchanges information externally. The

[14]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.

controls remain the same as before.

Table 4 reports the incremental results as we build up to our final specification. Column (1) of Table 4 is a Probit regression for whether the hospital exchanges information externally. Here, the sign on the size of the local hospital system is strikingly different from the sign in Table 3. Larger hospital systems are less likely to exchange information externally.

Importantly, the decision to exchange information externally does not appear to be positively affected by the number of potential external partners. The coefficient for this is negative, small, and generally insignificant. As we discussed in Section 2, the finding that larger hospital systems are less likely to exchange information externally could be the result of some HRRs being dominated by a single large system. That system would expect to receive little net inflow of patients from exchanging patient information externally. 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 data externally when there are more external hospitals. However, this is not what we find.

Column (2) of Table 4 adds state fixed effects and Column (3) add hospital characteristics to control for observable differences in hospitals' underlying propensity to exchange information. Generally, the ability to share data externally appears to increase in proxies for hospital size such as beds or number of doctors. It also rises in the proportion of Medicare inpatients, which very speculatively may reflect the benefits to sharing data under fixed-fee payment systems. The indicator for having an integrated salary model with physicians has a positive effect on external exchange, but the controls for other organizational forms, such as independent practice association (IPA), are not significant.[15]

[15] This may reflect the unusual profile of hospitals that retained their IPA arrangements through 2007 (Ciliberto, 2006).

Table 4: Larger Hospital Systems are Less Likely to Exchange Information Externally

	All Hospitals						System Hospital
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Mrg Eff./S.E.	Mrg Eff./S.E.	Mrg Eff./S.E.	Mrg Eff./S.E.	Mrg Eff./S.E.	Mrg Eff./S.E.	Mrg Eff./S.E.
# hospitals in system in HRR	-0.005**	-0.007***	-0.007***	-0.007***	-0.007***	-0.005*	-0.007***
	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)	(0.009)	(0.011)
# hospitals outside system in HRR	-0.001*	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Admissions (000)			0.002**	0.002**	0.002**	0.000	0.002**
			(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Proportion Medicare Inpatients			0.001**	0.001**	0.001**	0.001**	0.000
			(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Proportion Medicaid Inpatients			0.001	0.001	0.001*	0.001**	0.000
			(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
No. Doctors (000)			0.165**	0.157**	0.144*	0.177**	0.150*
			(0.296)	(0.313)	(0.316)	(0.310)	(0.351)
PPO			-0.037*	-0.042**	-0.041**	-0.029	-0.025
			(0.080)	(0.081)	(0.081)	(0.077)	(0.115)
HMO			0.012	0.014	0.015	-0.004	0.013
			(0.078)	(0.079)	(0.079)	(0.075)	(0.112)
Per Capita Payroll			-1.252***	-1.329***	-1.267***	-0.916**	-1.431***
			(1.915)	(1.907)	(1.904)	(1.647)	(2.340)
Independent Practice Association			-0.010	-0.008	-0.007	-0.010	-0.008
			(0.088)	(0.089)	(0.089)	(0.086)	(0.118)
Group Practice Association			-0.012	-0.014	-0.016	-0.015	-0.018
			(0.198)	(0.195)	(0.194)	(0.188)	(0.245)
Integrated Salary Model			0.026*	0.024*	0.024*	0.044***	0.013
			(0.055)	(0.055)	(0.056)	(0.053)	(0.074)
Non-Profit Hospital			-0.000	-0.001	-0.000	0.008	0.009
			(0.062)	(0.063)	(0.063)	(0.058)	(0.083)
Speciality Hospital			-0.004	-0.002	-0.002	-0.004	0.002
			(0.061)	(0.061)	(0.062)	(0.058)	(0.081)
Cerner System					-0.040	-0.046*	-0.045
					(0.106)	(0.103)	(0.133)
Eclipsys System					-0.006	-0.012	0.020
					(0.156)	(0.155)	(0.207)
Epic System					0.033	0.038	0.042
					(0.125)	(0.120)	(0.153)
GE System					-0.092**	-0.085*	-0.079*
					(0.189)	(0.193)	(0.200)
Mckesson System					-0.020	-0.011	0.004
					(0.100)	(0.100)	(0.135)
Meditech System					-0.035*	-0.032*	0.001
					(0.079)	(0.077)	(0.109)
Siemens System					-0.015	-0.029	-0.020
					(0.129)	(0.122)	(0.179)
Other System					-0.075	-0.098	0.037
					(0.383)	(0.388)	(0.418)
State Fixed Effects	No	Yes	Yes	Yes	Yes	No	Yes
Installation Year Controls	No	No	No	Yes	Yes	Yes	Yes
Observations	4060	4060	4060	4060	4060	4060	2561
Log-Likelihood	-1860.19	-1781.43	-1764.15	-1746.78	-1741.23	-1813.83	-1034.11

Probit estimates. Dependent variable is whether the hospital exchanges electronic data externally outside its system. Robust Standard Errors. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The influence of per-capita payroll is of particular interest, since it affects the decision to exchange inside a system and outside a system in different ways. Table 3 shows that 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 that pay their staff well want to ensure that they capitalize on the positive spillovers of, for example, attracting more competent technicians to operate expensive diagnostic testing technologies. Therefore, such hospitals are less willing for patients to take their data from such tests that require expensive manpower away from their hospital and to other hospitals. We explore this in more detail in later regressions.

A possible explanation for the negative relationship between system size and external data exchange is that it simply reflects technological incapacity. It is possible, for example, that hospitals in larger systems adopted Electronic Medical Record technology earlier. This means 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.[16] It could also be that they chose to buy their system from a vendor that makes interoperability harder. 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, in Column (4) of Table 4 we include fixed effects for the year the EMR system was installed. In Column (5), we also

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

report vendor fixed effects for the largest EMR vendors. In both cases, the results remain robust. Often 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.

Column (6) shows the robustness of the estimates with the full set of controls to omitting the state fixed effects.

Finally, in Column (7) of Table 4, we show that the result holds when we restrict attention to hospitals that are part of hospitals systems. This is precisely the same sample as we used for the analysis in Table 3.

The magnitude of the marginal effects indicates that each additional hospital in a system lowers the chance of external data exchange from hospitals in that system by 0.7 percentage points. This implies that a standard deviation increase in system size of about 3 hospitals (Table 2) would decrease external exchange by 2.1 percentage points, or by about 12 percent of the sample mean (of 17 percent; Table 1).

4.3 Robustness

We conduct multiple robustness checks for the novel finding in Table 4 that hospitals in larger systems are less likely to exchange data externally.

We first show the robustness of our result to alternative dependent variables. Table 5 displays the results. The 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. Columns (1) and (2) distinguish between decisions to exchange different types of data. The pattern that hospitals are less likely to share externally if they are part of a large local system is replicated across these two types of data.

Table 5: Checking the Robustness of Our Results to Different Dependent Variables

	(1) External patient Mrg Eff./S.E.	(2) External clinical Mrg Eff./S.E.	(3) Not member RHIO Mrg Eff./S.E.
# hospitals in system in HRR	-0.006***	-0.005**	0.004*
	(0.011)	(0.010)	(0.009)
# hospitals outside system in HRR	0.000	-0.001*	-0.000
	(0.001)	(0.001)	(0.001)
Admissions (000)	0.002***	0.002**	0.004***
	(0.003)	(0.003)	(0.003)
Proportion Medicare Inpatients	0.000	0.001**	0.001*
	(0.002)	(0.001)	(0.001)
Proportion Medicaid Inpatients	0.000	0.001*	0.001***
	(0.002)	(0.002)	(0.002)
No. Doctors (000)	0.063	0.152**	-0.099
	(0.300)	(0.325)	(0.339)
PPO	-0.042***	-0.031*	-0.041**
	(0.091)	(0.083)	(0.078)
HMO	0.011	0.010	0.042**
	(0.089)	(0.081)	(0.076)
Per Capita Payroll	-0.755**	-0.909**	0.487
	(2.168)	(1.891)	(1.465)
State Fixed Effects	Yes	Yes	Yes
Hospital Type Controls	Yes	Yes	Yes
Vendor Controls	Yes	Yes	Yes
Installation Year Controls	Yes	Yes	Yes
Observations	4016	4060	4060
Log-Likelihood	-1296.40	-1632.28	-1807.81

Probit estimates. Robust Standard Errors. Dependent variable as described in column headers. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In Column (3), we check whether our result holds for a different potential measure of external sharing of information, which is whether or not the hospital actively participates 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. It appears that indeed hospitals with a larger regional system presence are more likely to *not* actively participate in an RHIO.

We then go on to check our results using alternative subsamples and conduct falsification tests in Table 6.

The first columns of Table 6 address the concern that, because HRRs vary in size, the number of hospitals in and out of a system in an HRR may not adequately capture market share or position. To address this, we split our sample into HRRs that have above and below the mean number of hospitals. Columns (1) and (2) show the results. We find that the decision to share information is negatively related to system size in both instances. This suggests that non-linearities introduced by differing HRR size are not driving our results.

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 external data exchanging, with no change in the real level of information exchange. As pointed out by Town et al. (2007), there has been considerable consolidation in the US over the past two decades. To check for this, we exclude observations of hospitals that had experienced mergers in the past 10 years in Column (3) of Table 6. Column (4) also excludes hospitals that are not part of systems. The results remain similar. This suggests that the pattern we find is not a result of previous merger activity.

Table 6: Robustness and Falsification Checks

	Big HHR (1) Mrg Eff./S.E.	Small HRR (2) Mrg Eff./S.E.	No Merger (3) Mrg Eff./S.E.	No Merger: Systems Only (4) Mrg Eff./S.E.	Out of Network (5) Mrg Eff./S.E.	Insurance (6) Mrg Eff./S.E.
# hospitals in system in HRR	-0.009***	-0.016***	-0.007**	-0.007**		-0.003
	(0.015)	(0.024)	(0.013)	(0.013)		(0.008)
# hospitals outside HRR in system					-0.000	
					(0.001)	
# hospitals outside system in HRR	-0.001	-0.001	-0.001*	-0.001*	-0.001*	0.001
	(0.004)	(0.008)	(0.002)	(0.002)	(0.002)	(0.001)
Admissions (000)	0.000	0.003***	0.002***	0.002***	0.002**	0.011***
	(0.006)	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)
Proportion Medicare Inpatients	0.000	0.000	0.000	0.000	-0.000	0.000
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Proportion Medicaid Inpatients	0.001	-0.000	0.000	0.000	-0.000	0.001
	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)	(0.001)
No. Doctors (000)	0.107	0.324**	0.124	0.124	0.143*	-0.262**
	(0.457)	(0.569)	(0.375)	(0.375)	(0.361)	(0.292)
PPO	0.038	-0.077**	-0.016	-0.016	-0.027	0.064**
	(0.194)	(0.156)	(0.136)	(0.136)	(0.115)	(0.069)
HMO	-0.029	0.057	-0.005	-0.005	0.013	0.023
	(0.190)	(0.153)	(0.131)	(0.131)	(0.112)	(0.067)
Per Capita Payroll	-2.065**	-0.777	-1.606***	-1.606***	-1.366***	0.892
	(4.149)	(3.095)	(2.670)	(2.670)	(2.333)	(1.753)
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Hospital Type Controls	Yes	Yes	Yes	Yes	Yes	Yes
Vendor Controls	Yes	Yes	Yes	Yes	Yes	No
Installation Year Controls	Yes	Yes	Yes	Yes	Yes	No
Observations	1036	1450	1908	1908	2561	4060
Log-Likelihood	-378.00	-596.95	-771.17	-771.17	-1036.89	-2596.01

Probit estimates. Dependent variable is whether the hospital exchanges electronic data externally outside its system. Robust Standard Errors. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This robustness check is independently interesting because it 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.[17] For example, in the Evanston Northwestern-Highland Park case, one of the claims 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 externalities for a technology in the specific sense of promoting information exchange.

In Columns (5) and (6), we move on to two falsification checks. In Column (5), we add a new variable that captures the number of hospitals outside the local HRR but within the same system. If we were capturing something about organizational capacity, for example that larger systems have organizational structures which means they adopt technological innovations more slowly, we would expect this to have a similar negative and significant effect. However, Column (5) shows that we do not find such an effect.

In Column (6), we report results for a falsification check in which we estimate the effects of system size on the decision to exchange information with an insurance provider. If, again, there were unobserved technological capacity issues to do with having a large system size that were leading firms to not be able to exchange information externally, we would expect to see a similar result for this metric because it also captures external exchange of data. We do not know about the details of the insurance system implementation from the AHA

[17] This is an example of the "efficiencies defense" commonly used in hospital merger cases (Gaynor and Vogt, 2000).

survey so cannot include system age or manufacturer as controls. However, the results in Column (6) suggest that indeed there is no negative relationship between system size and the decision to exchange information with insurers.

4.4 Instrumenting for System Size

Our estimates so far assume that system size is unrelated to other unobserved factors that also determines a hospital's decision to share information externally or internally. This may be reasonable if system size was largely determined prior to the advent of electronic health information exchange. However, though there we employ a battery of controls in case the decision to exchange data and system size are jointly determined by observed factors, there is still the potential for there being an unobserved source of bias or for system size itself to be endogenous. For example, it may be the case that like-minded hospitals formed a system specifically because it facilitated their efforts to to exchange data with one another.

We address this concern by using system size for the hospital in 1994 as an instrumental variable for current system size. By using pre-internet era system size as our source of exogenous variation, our idea is that this strips out system amalgamation decisions which occurred in response to similar goals or technical abilities related to health IT or data exchange. This is similar to the identification strategy used in Miller and Tucker (2013), who use pre-internet capital-staff ratios to identify post-internet online sharing behavior.

The IV-Probit estimate in Column (1) confirms the finding of a positive effects of system size on internal exchange. The IV-Probit estimates in Column (2) confirm the negative effect of system size on external exchange using the full sample of hospitals, while the estimate in Column (3) does the same for the sample restricted to hospitals that are members of systems. The marginal effect estimates share the same signs in the basic Probit and IV-Probit models, but the IV-Probit estimates are larger. The effect of an additional hospital in the system is estimated to increase internal exchange by 4.3% in the IV model (rather than 2.1% from the

Table 7: Instrumenting for System Size

	System Only (1) Internal exchange	All (2) External exchange	System Only (3) External exchange
# hospitals in system in HRR	0.0432**	-0.0413**	-0.0446*
	(0.0208)	(0.0176)	(0.0253)
# hospitals outside system in HRR	-0.00182	-0.00148	-0.00340
	(0.00221)	(0.00163)	(0.00281)
# hospitals in system in HRR			
# hospitals in system in 1994	0.932***	1.051***	0.932***
	(0.0258)	(0.0165)	(0.0258)
# hospitals outside system in HRR	0.00316	-0.000963	0.00315
	(0.00303)	(0.00153)	(0.00303)
State Fixed Effects	Yes	Yes	Yes
Hospital Controls	Yes	Yes	Yes
Vendor Controls	Yes	Yes	Yes
Installation Year Controls	Yes	Yes	Yes
Observations	1471	2960	1471
Log-Likelihood	-3820.10	-6652.19	-3610.11

Marginal effects from IV-Probit models. Dependent variable in the top panel is internal exchange in Column (1) and external exchange in Columns (2) and (3). Dependent variable in the bottom panel is the number of hospitals in the system in the HRR. Dependent variables as shown. Robust Standard Errors. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

comparable Probit model in Column (5) of Table 3) and to decrease external exchange by 4.2% (rather than 0.7% in the Probit model in Column (5) of Table 4). These effect sizes are nontrivial relative to the mean rates of data exchange in our sample of 68% for internal and 17% for external exchange (see Table 1).

4.5 Are Large Hospital Systems' Decisions Not to Share Data Strategic?

Given that the results of Table 6 appear to rule out an explanation based on technological capacity, we turn to exploring whether the decisions by large hospital systems to not share patient data reflect a strategic decision to prevent an outflow of patient data and, with it, patients.

The ease with which a patient can leave a hospital system may depend on their insurance plan. Generally, a patient with a Preferred Provider Organization (PPO) insurance plan can seek a new provider at will. However, a patient with an HMO insurance plan must make a request for a new referral to their primary care provider. This means that patients with PPOs have more risk of leaving the system 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. Columns (1) and (2) of Table 8 presents estimates by whether or not that hospital has a non-zero number of PPO contracts.[18] The results suggest that PPO hospitals in larger systems are less likely to exchange data with outside hospitals than are hospitals that do not have PPO contracts. We caution that though the difference in size of point estimates is suggestive, the large standard error in Column (2) means that these coefficients are not statistically different. It is also striking that we do not see this pattern for HMO providers since they are examples of healthcare systems where there is far less need for patient data portability, as patients have limited choice in providers. We repeat this estimation for the decision to share data internally within a system in Table A1 and find no such relationship.

[18]We employ a binary indicator (as in Song (1995), for example) because the data do not contain information on the share of patients or revenues from PPO contracts.

Table 8: External Data Exchange Is More Responsive to System Size at PPO, High-Wage, and Specialty Hospitals

	(1) PPO Mrg Eff./S.E.	(2) No PPO Mrg Eff./S.E.	(3) Above Average Wage Mrg Eff./S.E.	(4) Below Average Wage Mrg Eff./S.E.	(5) Speciality Mrg Eff./S.E.	(6) Not Speciality Mrg Eff./S.E.
# hospitals in system in HRR	-0.007**	-0.005	-0.013***	-0.004	-0.011**	-0.005*
	(0.013)	(0.017)	(0.018)	(0.013)	(0.021)	(0.012)
# hospitals outside system in HRR	-0.000	-0.000	-0.001	-0.000	-0.000	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Admissions (000)	0.002**	-0.002	0.001	0.002*	0.004**	0.001
	(0.004)	(0.008)	(0.007)	(0.004)	(0.006)	(0.004)
Proportion Medicare Inpatients	0.000	0.002***	0.000	0.001**	0.001*	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Proportion Medicaid Inpatients	0.001	0.000	0.000	0.001**	0.001	0.001
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)
No. Doctors (000)	0.014	0.856***	0.131	0.176*	0.106	0.120
	(0.316)	(0.828)	(0.414)	(0.420)	(0.547)	(0.340)
Per Capita Payroll	-0.796	-1.580**	-1.548	-1.231*	-0.686	-1.966***
	(2.774)	(2.846)	(4.708)	(3.017)	(2.723)	(2.835)
PPO			-0.048*	-0.026	-0.027	-0.059**
			(0.118)	(0.124)	(0.147)	(0.103)
HMO			0.008	0.017	0.019	0.019
			(0.115)	(0.120)	(0.148)	(0.098)
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Hospital Type Controls	Yes	Yes	Yes	Yes	Yes	Yes
Installation Year Controls	Yes	Yes	Yes	Yes	Yes	Yes
Vendor Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2591	1444	1826	2221	1564	2478
Log-Likelihood	-1071.50	-620.61	-794.63	-893.77	-634.19	-1061.89

Marginal effects from Probit models. Dependent variable is whether the hospital exchanges electronic data externally outside its system. Robust Standard Errors. * $p < 0.10$, ** $p < 0.05$,*** $p < 0.01$

One of the many motivations that hospitals may have to silo their patients' records is to avoid competitors benefiting from the opinions of highly-paid clinical or technical staff. Columns (3) and (4) of Table 8 explore this by presenting estimates where we allow the importance of hospital system size to vary by average salary paid to hospital staff. The results suggest that hospitals with highly-paid employees have larger coefficient estimates for the responsiveness of sharing to system size. We repeat this estimation for the decision to share data internally within a system in Table A1 and find no such relationship. This suggests that the decision to create information silos is related to the value of the inputs that a firm is paying for the creation of that data. The more valuable the inputs, the more reluctant firms are to share such data externally.

Along similar lines, we also stratified by whether or not a hospital had a 'specialty' such as cardiology or oncology. Columns (5) and (6) present the result. The point estimates suggest that specialty hospitals were more likely than non-specialty hospitals to not share information externally, if they were part of a larger system. Like the results in Columns (3) and (4), an explanation of this may be that hospitals find it commercially more important to stop the outflow of data outside their hospital system from specialty hospitals (where there are often expensive inputs) than from regular hospitals. This may be so that the hospital system can make sure that they are responsible for potentially profitable care such as routine follow-up CT scans for cancer patients.

5 Responses to the Installed Base

The findings in Section 4 suggest that larger hospital systems are more likely to exchange patient records internally with other hospitals in their same systems but less likely to share data with hospitals outside of their systems. The policy implications of these findings for maximizing the exchange of patient data are not clear. On the one hand, when hospitals exchange information purely within their network, they are still exchanging information, which can improve care within the system. On the other hand, the decision not to exchange data externally can reduce the opportunities for external data exchange for hospitals outside of the large hospital system. While the benefits from greater internal exchange may be captured within the system, the harm from less external exchange can produce negative spillovers for hospitals outside of the system and their patients. Such negative externalities may warrant policy intervention. To evaluate the empirical importance of this concern, we assess whether there is in fact evidence in our data of positive spillovers from one hospital's electronic patient information exchange with external hospitals on the external exchange decisions of other local hospitals.[19]

In Table 9, 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 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 but outside of the system 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 IV-Probit estimates of the individual hospital decision to exchange information externally, treating the number of out-system hospitals in their HRR who are exchanging information externally as endogenous. We instrument for external exchange by other out-system hospitals using the mean number of other hospitals in the local area with Electronic Data Interchange (EDI) and Physician Documentation systems

[19] These estimates may understate the positive externalities associated with external data exchange, as they will not capture the potential externalities from data sharing that involve researchers or healthcare providers outside of the local area, as would occur, for example, in a national 'learning health' system (Smith et al., 2012).

Table 9: Hospitals Are More Likely to Exchange Data Externally When More External Hospitals Do the Same

	Probit	IV-Probit	IV-Probit (System)
	(1)	(2)	(3)
	External exchange	External exchange	External exchange
# out-system hospitals exchanging externally in HRR	0.0316***	0.141*	0.233**
	(0.00901)	(0.0779)	(0.0957)
# hospitals in system in HRR	-0.0293***	-0.0318***	-0.0430***
	(0.00989)	(0.00968)	(0.0110)
# hospitals outside system in HRR	-0.00545***	-0.0181**	-0.0282***
	(0.00182)	(0.00908)	(0.0105)
# out-system hospitals exchanging externally in HRR			
# hospitals in system in HRR		0.0326**	0.0633***
		(0.0154)	(0.0169)
# hospitals outside system in HRR		0.118***	0.113***
		(0.00218)	(0.00263)
HRR_4yrEDI		2.841***	1.950***
		(0.529)	(0.612)
HRR_4yrPhysDoc		-2.702***	-1.944***
		(0.630)	(0.699)
HRR_8yrPhysDoc		1.622	-0.461
		(1.514)	(1.717)
HRR_12yrPhysDoc		-3.860*	-2.763
		(2.151)	(2.494)
Vendor Controls	Yes	Yes	Yes
Deploy Year Controls	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes
Hospital Controls	Yes	Yes	Yes
Observations	4060	4060	2561
Log-Likelihood	-1735.03	-11235.49	-6854.27
Sargan Test of over-identification		0.40	1.54
Sargan Test of over-identification P-value		0.94	0.67
First Stage R2		0.40	0.44
First Stage F-Test		15.53	15.04
First Stage F-test p-value		0.00	0.00

Marginal effects from Probit and IV-Probit models. Dependent variable in the top panel is external exchange. Dependent variable in the bottom panel is the number of hospitals in the HRR outside of the focal hospital's system that are exchanging data externally. Instrumental variables are HRR-level measures of technology adoption type and timing. Standard errors in parentheses

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

that were old enough to have been made outdated by changes in various HL7 standards (more than 4 years old for EDI and more than 4, 8 or 12 years old for Physician Documentation).

Our assumption is that technology adoption decisions were made before the standards changed, and that the updated standards affect the number of other hospitals who exchange information, but do 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. Hospitals with older systems must bear an additional cost to make their systems comply with existing standards in order to be able to exchange data with other data systems and to participate in regional exchanges. Once they bear this cost, however, the value of the data they share should not directly be affected by the timing of their technology adoption.

This second column suggests that when other external hospitals are more willing to exchange information for exogenous reasons, then this increases the propensity of a hospital in the same local area but in a different hospital system to also exchange externally. This implies that when larger hospital systems choose to not exchange information externally, they reduce the likelihood that other hospitals also exchange information externally. Since it is unlikely that the large hospital system internalizes the negative welfare externalities 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 repeat the instrumental variables estimation but only look at the subsample of hospitals that are part of systems. The estimated effects are even larger in this sample.

For both 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. The estimated effects of older Physician Documentation systems are negative and significant for systems older than 4 or 12 years. However, conditional on the age of the Physician Documentation system, the presence of an older EDI system is positively related to data exchange, possibly because the costs of updating an older EDI system to comply with new standards were still lower than the costs of new adoption. We also report the Sargan test statistics for over-identification (which assumes the validity of at least one of our instruments), and this test suggests that we cannot reject the null hypothesis that the equation is over-identified.

6 Implications

This research investigates motivations for the sharing of electronic health information by hospitals. We find that larger hospital systems are less likely to exchange information across a network and more likely to exchange information within their own network. Our findings suggest that commonly-advocated strategies for vendors who sell network products to kick-start their company may need modifying. Often, software and hardware firms are advised to secure initial marquee users to help firms overcome the chicken-and-egg problem inherent in network technology markets. However, our research suggests that when firms need to rely on the marquee user to establish system-wide network effects, the success of their strategies in later stages of the network's development depend on whether marquee users are willing to use the network broadly. Therefore firms need to make sure, either contractually or technologically, that marquee users are obliged to share information across a network technology and not silo their data.[20]

The anticipated benefits from widespread health IT diffusion, in terms of costs savings and improved health outcomes, depend in large part on the electronic exchange of patient information. The results of this research suggest that adoption of EMR systems alone, even of systems with the capacity for data sharing, may not be sufficient to ensure that the

[20]Though we our study is based on the healthcare industry, our results also appear to apply to other industries such as the construction of platforms that enable customers to share reward points. Here, despite the benefits of such schemes for consumers, larger vendors (such as major airlines) refuse to allow consumers to transfer their reward points outside of their system.

full value from health IT is realized. This provides a potential rationale for public policy specifically aimed at promoting the electronic exchange of clinical information across firms and hospital system boundaries.

Currently the 'Eligible Hospital and Critical Access Hospital Meaningful Use Core Measure 13' states that to qualify, a hospital has to have 'Performed at least one test of certified EHR technology's capacity to electronically exchange key clinical information.'[21] To qualify, hospitals can simply use information of a fictional patient. This measure reflects the current policy focus on technological inter-operability as being the most important barrier to the exchange of healthcare information. However, our results suggest that policymakers should also consider how to improve incentives so that hospitals actually share commercially valuable patient data with each other. This is important as policymakers set policy priorities for 'stage 3' of meaningful use, the target date for which is currently 2016.

[21] http://www.cms.gov/EHRIncentivePrograms/Downloads/13_Electronic_Exchange_of_Clinical_Information.pdf

References

Adler-Milstein, J., C. M. DesRoches, and A. K. Jha (2011). Health information exchange among us hospitals. *Am J Manag Care.* (11), 761–768.

Adler-Milstein, J. and A. Jha (2012). Sharing clinical data electronically: A critical challenge for fixing the health care system. *JAMA 307*(16), 1695–1696.

Augereau, A., S. Greenstein, and M. Rysman (2006). Coordination versus differentiation in a standards war: 56k modems. *RAND 37*(4), 887–909.

Blumenthal, D. and M. Tavenner (2010). The 'meaningful use' regulation for electronic health records. *New England Journal of Medicine 363*(6), 501–504. PMID: 20647183.

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

Brailer, D. J. (2005). Interoperability: The Key To The Future Health Care System. *Health Affairs*, w5.19–21.

Buntin, M. B., S. H. Jain, and D. Blumenthal (2010). Health information technology: Laying the infrastructure for national health reform. *Health Affairs 29*(6), 1214–1219.

Burgess, J. J., K. Carey, and G. J. Young (2005, March). The effect of network arrangements on hospital pricing behavior. *Journal of Health Economics 24*(2), 391–405.

Calcanis, C. (2005, November). Milwaukee group develops EMR to reduce ER costs. *Medical Informatics Insider*.

Chen, J., U. Doraszelski, and J. E. Harrington (2009). Avoiding market dominance: product compatibility in markets with network effects. *RAND Journal of Economics 40*(3), 455–485.

Christensen, M. C. and D. Remler (2009). Information and communications technology in U.S. health care: Why is adoption so slow and is slower better? *Journal of Health Politics, Policy and Law 34*(6), 1011–1034.

Ciliberto, F. (2006, March). Does Organizational Form Affect Investment Decisions? *Journal of Industrial Economics 54*(1), 63–93.

Clark, C. (2009, November). Four Health Leaders Weigh in on Whether EMRs Save Money. *Health Leaders Media*.

Coakley, M. (2010). Examination of health care cost trends and cost drivers: Pursuant to g.l. c. 118g, s6.5(b). *Report for Annual Public Hearing, Office of MA Attorney General*.

Delia, D. and J. Cantor (2009). Emergency department utilization and capacity. *The Synthesis project. Research synthesis report* (17).

Economides, N. (1996). The economics of networks. *International Journal of Industrial Organization 14*(6), 673 – 699.

Eisenmann, T., G. Parker, and M. W. V. Alstyne (2006, October). Strategies for two-sided markets. *Harvard Business Review*.

Farrell, J. and P. Klemperer (2007). *Handbook of Industrial Organization, Vol 3*, Chapter Coordination and Lock-In: Competition with Switching Costs and Network Effects, pp. 1967–2072. North-Holland.

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

Frisse, M. E., K. B. Johnson, H. Nian, C. L. Davison, C. S. Gadd, K. M. Unertl, P. A. Turri, and Q. Chen (2012). The financial impact of health information exchange on emergency department care. *Journal of the American Medical Informatics Association 19*(3), 328–333.

Gaynor, M. and W. B. Vogt (2000). *Handbook of Health Economics*, Chapter Antitrust and Competition in Health Care Markets, pp. 1405–1487. Elsevier.

Goodby, A. W., L. Olsen, and M. McGinnis (2010). *Clinical Data as the Basic Staple of Health Learning:Creating and Protecting a Public Good: Workshop Summary.* IOM Roundtable on Evidence-Based Medicine (Series); Institute of Medicine. National Academies Press.

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

Ho, K. (2009). Insurer-Provider Networks in the Medical Care Market. *American Economic Review 99*(1), 393–430.

Japsen, B. (8 July 2005). Final Volleys Over Evanston Healthcare Merger. *Chicago Tribune*.

Jha, A. (2010). Meaningful use of electronic health records: The road ahead. *JAMA 304*(15), 1709–1710.

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

Knox, R. (2009, Sep 21). Doctors don't agree on letting patients see notes. *NPR*.

Madison, K. (2004). Multihospital system membership and patient treatments, expenditures, and outcomes. *Health Services Research 39*(4p1), 749–770.

Manski, C. F. (1993, July). Identification of endogenous social effects: The reflection problem. *Review of Economic Studies 60*(3), 531–42.

Mata, F. J., W. L. Fuerst, and J. B. Barney (1995). Information technology and sustained competitive advantage: A resource-based analysis. *MIS Quarterly 19*(4), 487–505.

McCullough, J., S. Parente, and R. Town (2011). The impact of health information technology on patient outcomes. *Mimeo, Minnesota*.

Melnick, G. and E. Keeler (2007). The effects of multi-hospital systems on hospital prices. *Journal of Health Economics 26*(2), 400 – 413.

Miller, A. R. and C. Tucker (2009). Privacy Protection and Technology Diffusion: The Case of Electronic Medical Records. *Management Science 55*(7), 1077–1093.

Miller, A. R. and C. Tucker (2013). Active social media management: The case of health care. *Information Systems Research 24*(1), 52–70.

Miller, A. R. and C. E. Tucker (2011a, April). Can health care information technology save babies? *Journal of Political Economy 119*(2), 289–324.

Miller, A. R. and C. E. Tucker (2011b). Encryption and the loss of patient data. *Journal of Policy Analysis and Management 30*(3), 534–556.

Miller, A. R. and C. E. Tucker (2012, forthcoming). Electronic discovery and the adoption of information technology. *Journal of Law, Economics, and Organization*.

Murray, E., J. Burns, C. May, T. Finch, C. O'Donnell, P. Wallace, and F. Mair (2011). Why is it difficult to implement e-health initiatives? a qualitative study. *Implementation Science 6*(1), 6.

Prestigiacomo, J. (2012). Overcoming competition in private hies.

Shy, O. (2001). *The economics of network industries*. Cambridge University Press.

Simcoe, T. S., S. J. Graham, and M. Feldman (2009, Fall). Competing on Standards? Entrepreneurship, Intellectual Property and the Platform Paradox. *Journal of Economics and Management Strategy 18*(3), 775–816.

Smith, M., R. Saunders, L. Stuckhardt, and J. M. McGinnis (Eds.) (2012). *Best care at lower cost: The path to continuously learning health care in America.* Committee on the Learning Health Care System in America; Institute of Medicine. National Academies Press.

Song, Y. I. (1995). Strategic alliances in the hospital industry: A fusion of institutional and resource dependence views. *Academy of Management Journal*, 271–275.

Town, R. J., D. Wholey, R. Feldman, and L. R. Burns (2007). Revisiting the relationship between managed care and hospital consolidation. *Health Services Research 42*(1 Pt 1), 219–238.

Tucker, C. (2008). Identifying Formal and Informal Influence in Technology Adoption with Network Externalities. *Management Science 54*(12), 287–304.

Walker, J., E. Pan, D. Johnston, J. Adler-Milstein, D. W. Bates, and B. Middleton (2005). The value of health care information exchange and interoperability. *Health Affairs*, w5.10+.

Wolf, L., J. Harvell, and A. K. Jha (2012). Hospitals ineligible for federal meaningful-use incentives have dismally low rates of adoption of electronic health records. *Health Affairs 31*(3), 505–513.

Table A1: Repeating Table 8 for Internal Exchange

	(1) PPO Mrg Eff./S.E.	(2) No PPO Mrg Eff./S.E.	(3) Above Average Wage Mrg Eff./S.E.	(4) Below Average Wage Mrg Eff./S.E.	(5) Speciality Mrg Eff./S.E.	(6) Not Speciality Mrg Eff./S.E.
# hospitals in system in HRR	0.024***	0.015**	0.023***	0.018***	0.026***	0.018***
	(0.013)	(0.018)	(0.016)	(0.014)	(0.020)	(0.013)
# hospitals outside system in HRR	-0.001	-0.002*	-0.001	-0.001	-0.002***	-0.000
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Admissions (000)	0.009***	0.006*	0.012***	0.006***	0.010***	0.006***
	(0.005)	(0.010)	(0.010)	(0.005)	(0.009)	(0.005)
Proportion Medicare Inpatients	-0.001	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Proportion Medicaid Inpatients	-0.002**	-0.004***	-0.003***	-0.005***	-0.005***	-0.005***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
No. Doctors (000)	-0.122	1.829***	0.811*	0.082	0.080	0.328
	(0.499)	(1.780)	(1.160)	(0.618)	(0.931)	(0.706)
Per Capita Payroll	3.627***	1.241*	1.146	0.888	2.300*	1.031
	(3.291)	(2.218)	(5.989)	(2.251)	(3.441)	(2.140)
o.Other System		0.156	0.330	0.232	0.351	0.320
	(.)	(0.572)	(0.670)	(0.764)	(0.720)	(0.735)
PPO			-0.046	-0.094**	-0.082	-0.092**
			(0.162)	(0.143)	(0.176)	(0.132)
HMO			0.062	0.127***	0.177***	0.080*
			(0.157)	(0.139)	(0.177)	(0.126)
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Hospital Type Controls	Yes	Yes	Yes	Yes	Yes	Yes
Installation Year Controls	Yes	Yes	Yes	Yes	Yes	Yes
Vendor Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1635	924	960	1582	975	1567
Log-Likelihood	-867.19	-483.16	-546.96	-801.69	-518.77	-830.23

Probit estimates. Dependent variable is whether the hospital exchanges electronic data internally within its system. Robust Standard Errors. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$