Health Information Exchange, System Size and Information Silos

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Abstract

There are many technology platforms which only bring benefits when users share data. In healthcare, this is a key policy issue, because of the potential cost savings and quality improvements from sharing patient data across medical providers. 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.

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1 Introduction

Many new technology platforms are devoted to making information exchange easier. Nowhere has this need been more pressing than in healthcare, where there is 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, 2011). However, it is unclear what steps policy makers and technology vendors should take to best ensure that information exchange actually happens.

One commonly-advocated strategy for kick-starting a network product is for the network operator to secure a 'marquee' user to help kick-start the platform and attract other users to the platform (Eisenmann et al., 2006; Eisenmann and Hagiu, 2008). As described by Gowrisankaran and Stavins (2004), such users not only attract users to the platform but also, because of their scale and size, can internalize some of the network effects inherent in the platform. 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. If multiple firms merge, then the set of firms that adopts weakly increases. This is due to the newly merged firm's ability to internalize the network benefits from adoption at different locations.

This paper studies how the integration of a subset of network users into a coordinated unit affects the scope of their network *usage*. We use newly available data on the exchange of health information within a local health network. We 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.

We find that hospitals with more hospitals in their system are indeed more likely to exchange electronic information internally. However, surprisingly, they are also 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 is incapable of reciprocal operation with other similar systems.

A potential explanation for their propensity to create information silos is that larger hospital systems believe that they may lose patients. If the hospital allows data outflow, patients are more likely 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). We offer two pieces of evidence that this may be partly driving our result.

In a healthcare setting, hospitals that have patients with Preferred Provider Organization (PPO) medical insurance are more likely to fear the loss of these patients to other hospitals, because these insurance policies set less stringent rules for referrals, making it easier for patients to transfer between hospitals. In other words, these hospitals have customers with lower switching costs. We find evidence that the pattern of larger hospital systems being less likely to exchange information externally is stronger for hospital systems that have PPO contracts. We also show that hospitals that on average pay more to their staff are less likely to allow data to flow out of their local network, suggesting that it is indeed concern about retaining the competitive advantage bestowed by valuable inputs that is driving decisions to not share data. While not conclusive, both these findings provide some evidence that creation of information silos that we observe is linked to competitive concerns.

This paper offers three substantive contributions. Policy makers and researchers have focused on questions of encouraging compatibility and inter-operability at the vendor level, but we show that users who have already adopted may also choose not to exchange information over a network. That means that to be most effective, policies designed to encourage interconnection may need to be broadened to include users as well as vendors of technologies. Our empirical analysis implies that the response of potential users to network externalities is more complex than has previously been supposed. Often, empirical work calibrates network externalities by measuring the response of users to the adoption of a network good by others. However, this kind of analysis ignores the potential for users themselves, once they have adopted, to choose whether to exchange information across a network and influence the future course of adoption.

This is important because of recent policy emphasis on Electronic Medical Records (EMRs) and the 'National Health Information Network' (NHIN). The federal government in the United States has provided $19 billion in financial incentives to healthcare providers under the 2009 HITECH Act to encourage them to adopt EMR. 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. They also have to demonstrate the ability to exchange information with another provider (which given the wording of the rule could be within the same network) at least one time. The federal emphasis on interoperable technological standards reflects the belief that information exchange between providers at different locations is a critical step to achieving the cost savings and quality improvements from EMRs.[1] However, it is not clear whether

[1] This view is expressed 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."

compatibility or capability alone will be sufficient to ensure that electronic information is actually shared. 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 exchange information before moving to the next phase in the rollout.

The findings are also important from a patient care standpoint. There is much anecdotal evidence that despite the HIPAA rule that mandates that healthcare providers must release records to the patient within 30 days, healthcare providers are reluctant to release records to patients transferring healthcare providers (Cohen, 2010; CNN, 2010).[2] There is also evidence that this reluctance stems 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 policy makers.

Our focus on usage contrasts with the traditional empirical network effects literature that has focused on adoption.[3] Our work also relates 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.

[2]For example, an news article entitled 'Medical records often held hostage' described a situation where a transfer patient's wife begged doctors and nurses for his medical records from the previous hospital, and it was only on the sixth day when the patient could not receive pain medication due to lack of documentation and the wife went physically to the facility that she was able to obtain them.

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

(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. 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 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 beat their competition. Instead, we study hospital end-users who deploy standards-based technology and get a direct benefit (or not) from inter-connection.

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 members of the American Hospital Association.[4] This survey 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

[4] In earlier versions of this paper, we show the results are robust to controlling for potential survey-response bias.

lists, discharge summaries, and radiology reports. We also show that the results are similar if we analyze the decision to exchange clinical and patient data separately.

Since the 2007 survey failed to be comprehensive, the American Hospital Association repeated the survey with different supplementary questions in 2008 and 2009. We use these additional responses 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 long lead time for IT implementations (around 2 years (Miller and Tucker, 2011).) and the antitrust scrutiny attendant on hospital system mergers and acquisitions.

The survey did not ask whom these hospitals exchanged data with. It is necessary to devise 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 health referral regions (HRRs) as our definition of a local area within which patients plausibly might transfer between hospitals.[5] 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.

[5]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.

2.2 Further Controls

We matched this data on patient data exchange with the most recent rounds 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, defined as the number of hospitals owned, leased, sponsored or contract-managed by a central organization. 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 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. 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 explanatory measures.

In all our analyses, 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. For just under 46 percent of systems in our data, some hospitals share information and some do not. Therefore, in the majority of hospital systems that do exchange data externally at all, there is a diversity in individual hospital exchanging behavior.

3 Analysis and Results

3.1 Conceptual Framework

In traditional theoretical models of network externalities (Katz and Shapiro, 1985; Farrell and Saloner, 1985; Economides, 1996), network participants are assumed to be symmetrical

[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 1996-2006 AHA surveys.

Table 1: Summary Statistics for Hospitals in the EMR Survey

	Mean	Std Dev	Min	Max	Observations
External exchange	0.17	0.38	0	1	4060
External patient	0.11	0.31	0	1	4060
External clinical	0.16	0.36	0	1	4060
Internal exchange	0.68	0.47	0	1	2573
Internal patient	0.66	0.47	0	1	2573
Internal clinical	0.64	0.48	0	1	2573
Exchange Insurance	0.75	0.43	0	1	2956
Not member RHIO	0.19	0.39	0	1	4060

Internal exchange dependent variables only applicable to hospitals in systems.

	Mean	Std Dev	Min	Max	Observations
# hospitals in system in HRR	1.48	2.87	0	20	4060
# hospitals outside system in HRR	28.4	21.6	1	92	4060
Admissions (000)	7.53	9.47	0.0070	108.6	4060
Proportion Medicare Inpatients	45.7	22.2	0	99.0	4060
Proportion Medicaid Inpatients	18.1	16.4	0	97.4	4060
No. Doctors (000)	0.023	0.085	0	2.07	4060
PPO	0.64	0.48	0	1	4060
HMO	0.56	0.50	0	1	4060
Per Capita Payroll	0.050	0.016	0.000045	0.42	4060
Independent Practice Association	0.11	0.31	0	1	4060
Group Practice Association	0.020	0.14	0	1	4060
Integrated Salary Model	0.30	0.46	0	1	4060
Non-Profit Hospital	0.43	0.50	0	1	4060
Speciality Hospital	0.39	0.49	0	1	4060
Cerner System	0.077	0.27	0	1	4060
Eclipsys System	0.028	0.17	0	1	4060
Epic System	0.044	0.20	0	1	4060
GE System	0.018	0.13	0	1	4060
Mckesson System	0.071	0.26	0	1	4060
Meditech System	0.17	0.37	0	1	4060
Siemens System	0.045	0.21	0	1	4060
Other System	0.0049	0.070	0	1	4060
# hospitals outside HRR in system	19.7	42.7	0	196	4060

in size and consequently the issue of network user size is not discussed.[7] However, later empirical papers such as Gowrisankaran and Stavins (2004) argue that user size itself can be used to detect the presence of network externalities. The 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.

Such network arguments assume that post-adoption network use of the technology is pre-determined and cannot be influenced by the user. 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. These arguments suggest that when it comes to usage, the fixed costs of investing in the additional technological capacity to exchange information should on a per-transaction basis be lower for larger firms.

Hospitals 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.[8] 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 with patients who are unable to communicate their medical history or allergies (Brailer, 2005). Also, larger firms may have a higher profile which leads them to expect

[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.

[8] 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).

larger inflows of data from the external network if customer switching costs are reduced across all firms in the local area.

However, the need for external information exchange may be less for larger firms 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 data from the rest of the network.

Also, larger firms may fear that an overall reduction in customer switching costs 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 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.

3.2 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:

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

and $ExchangeInternal_{ij} = 1$ 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 (2009), 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. Thereforem 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.

Table 2 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 on whether or not that hospital exchanges data with other hospitals in its 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 decision does not appear to be 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.

In Columns (2)-(4) we show that the results remain robust when we add controls for hospital characteristics, the age of the technology and the manufacturer of the system. 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 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]

3.3 Exchange outside a system

However, of crucial importance for network operators and policy makers who are relying on these large users to kick-start the network is whether these hospitals exchange information *externally*.

For this decision, we similarly estimate a separate equation where

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

and $ExchangeExternal_{ij} = 1$ if hospital i in HRR j exchanges information externally. The controls remain the same as before.

Table 3 reports the incremental results where we build up to our final specification. Column (1) of Table 3 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 from the sign in Table 2. Larger hospital systems are less likely to exchange information outside their system. Importantly, the decision to exchange information outside a system does not appear to be positively affected by the number of potential partners outside of the system. The coefficient for this is negative and insignificant.

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

[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.

Table 2: Larger Hospital Systems are More Likely to Exchange Information Internally

	(1) Internal exchange	(2) Internal exchange	(3) Internal exchange	(4) Internal exchange
# hospitals in system in HRR	0.0556***	0.0621***	0.0650***	0.0613***
	(0.0105)	(0.0107)	(0.0109)	(0.0108)
# hospitals outside system in HRR	-0.00198	-0.00376**	-0.00375**	-0.00319**
	(0.00143)	(0.00148)	(0.00149)	(0.00150)
Admissions (000)		0.0250***	0.0248***	0.0209***
		(0.00417)	(0.00416)	(0.00409)
Proportion Medicare Inpatients		-0.00904***	-0.00877***	-0.00847***
		(0.00149)	(0.00152)	(0.00155)
Proportion Medicaid Inpatients		-0.0133***	-0.0135***	-0.0129***
		(0.00203)	(0.00206)	(0.00209)
No. Doctors (000)		0.873	0.873	0.827
		(0.633)	(0.614)	(0.602)
PPO		-0.233**	-0.255**	-0.244**
		(0.102)	(0.102)	(0.102)
HMO		0.324***	0.350***	0.330***
		(0.0991)	(0.0990)	(0.0991)
Per Capita Payroll		4.703*	4.610*	4.426*
		(2.704)	(2.695)	(2.574)
Independent Practice Association		-0.0527	-0.0754	-0.0565
		(0.0991)	(0.0996)	(0.101)
Group Practice Association		0.0652	0.0653	0.0809
		(0.229)	(0.232)	(0.236)
Integrated Salary Model		-0.0447	-0.0405	-0.0419
		(0.0660)	(0.0667)	(0.0672)
Non-Profit Hospital		0.248***	0.245***	0.193***
		(0.0717)	(0.0726)	(0.0734)
Speciality Hospital		0.166**	0.162**	0.130*
		(0.0676)	(0.0680)	(0.0685)
Cerner System				0.491***
				(0.124)
Eclipsys System				-0.0444
				(0.193)
Epic System				0.669***
				(0.177)
GE System				0.222
				(0.220)
Mckesson System				0.198
				(0.127)
Meditech System				-0.0997
				(0.0924)
Siemens System				0.448***
				(0.170)
Other System				0.822**
				(0.413)
Constant	0.255	0.361	0.238	0.269
	(0.360)	(0.419)	(0.458)	(0.445)
State Controls	Yes	Yes	Yes	Yes
Deploy Year Controls	No	No	Yes	Yes
Observations	2571	2571	2571	2571
Log-Likelihood	-1539.0	-1440.1	-1426.1	-1403.2

Probit estimates. Robust Standard Errors. * $p < 0.10$, ** $p < 0.05$,*** $p < 0.01$

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 outside hospitals within the same HRR from whom they could potentially gain patients. However, this is not what we find.

Column (2) of Table 3 adds other hospital characteristics to control for observable differences in hospitals' underlying propensity to exchange information. Many are insignificant. We also include controls for hospital organizational structure. More of the controls for organization form such as independent practice association (IPA) were not significant.[10] The coefficient for an integrated salary model organizational form suggests a positive, though marginally significant effect. 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 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 2 shows that hospitals with high per-capita payrolls are more likely to exchange information within their system (though this estimate was not precise). 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 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

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

patients to take their data from a consultation with a famous consultant 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.[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, in Column (3) of Table 3 we include fixed effects for the year that the EMR system was installed. In Column (4) we also 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.

3.4 Robustness

Since the findings in Table 3 are new, we go on to explore the robustness of our results in Table 4.

Column (1) simply reports the results for a simple linear probability model. This makes

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

Table 3: Larger Hospital Systems are Less Likely to Exchange Information Externally

	(1) External exchange	(2) External exchange	(3) External exchange	(4) External exchange
# hospitals in system in HRR	-0.0287***	-0.0301***	-0.0283***	-0.0285***
	(0.00933)	(0.00965)	(0.00962)	(0.00961)
# hospitals outside system in HRR	-0.00164	-0.00147	-0.00131	-0.00130
	(0.00128)	(0.00129)	(0.00130)	(0.00130)
Admissions (000)		0.00705**	0.00687**	0.00685**
		(0.00287)	(0.00293)	(0.00303)
Proportion Medicare Inpatients		0.00271**	0.00275**	0.00326**
		(0.00131)	(0.00133)	(0.00135)
Proportion Medicaid Inpatients		0.00269	0.00256	0.00285*
		(0.00170)	(0.00171)	(0.00172)
No. Doctors (000)		0.681**	0.651**	0.599*
		(0.296)	(0.313)	(0.315)
PPO		-0.153*	-0.173**	-0.170**
		(0.0799)	(0.0809)	(0.0812)
HMO		0.0484	0.0578	0.0622
		(0.0781)	(0.0790)	(0.0789)
Per Capita Payroll		-5.163***	-5.538***	-5.293***
		(1.915)	(1.908)	(1.905)
Independent Practice Association		-0.0393	-0.0329	-0.0293
		(0.0876)	(0.0886)	(0.0886)
Group Practice Association		-0.0480	-0.0581	-0.0660
		(0.198)	(0.195)	(0.194)
Integrated Salary Model		0.107*	0.101*	0.101*
		(0.0551)	(0.0554)	(0.0556)
Non-Profit Hospital		-0.000170	-0.00329	-0.00211
		(0.0622)	(0.0630)	(0.0633)
Speciality Hospital		-0.0157	-0.00702	-0.00902
		(0.0607)	(0.0614)	(0.0617)
Cerner System				-0.167
				(0.106)
Eclipsys System				-0.0223
				(0.156)
Epic System				0.141
				(0.125)
GE System				-0.390**
				(0.188)
Mckesson System				-0.0807
				(0.0999)
Meditech System				-0.148*
				(0.0790)
Siemens System				-0.0419
				(0.128)
Other System				-0.314
				(0.383)
Constant	-0.314	-0.117	-0.222	-0.173
	(0.312)	(0.351)	(0.398)	(0.399)
State Controls	Yes	Yes	Yes	Yes
Deploy Year Controls	No	No	Yes	Yes
Observations	4060	4060	4060	4060
Log-Likelihood	-1781.4	-1764.2	-1747.0	-1741.4

Probit estimates. Robust Standard Errors. * $p < 0.10$, ** $p < 0.05$,*** $p < 0.01$

sure that the large number of indicator variables and the fact our key explanatory variable of interest is a count variable does not bias our results when placed in a non-linear specification. The results are similar to before. They also give an idea of the magnitude of the effect. A hospital that has 10 hospitals within the same system in the same HRR is 6.4% less likely to exchange data with external hospitals. Given that only 17 percent of hospitals are exchanging data externally, this is quite a large decrease.

Columns (2) and (3) check robustness to alternative dependent variables. These distinguish between 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). 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.

In Column (4), we check whether our results hold 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.

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 check for this, we exclude observations of hospitals that had experienced mergers in the past 10 years in Column (5) of Table 4. The results remain similar. This suggests that the pattern we find is not a result of previous merger activity.

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.[12] 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.

Column (6) shows that our results are robust if we isolate our analysis to hospitals that are part of some kind of system (that is the same sample we use for the analysis in Table 3). This is reassuring that the mass-point of hospitals that had zero system size is not driving our results when we use the full data.

In Columns (7) and (8), we move on to two falsification checks. In the first column 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 the organizational capacity, for example that larger systems move slower, we would expect this to have a similar negative and significant effect. However, Column (7) shows that we do not find such an effect. In Column (8), we report results for a falsification check where we look at how these metrics affect 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

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

a similar result for this metric since it is also external exchange of data. We have fewer observations as this question was only asked in the 2009 survey, and also we do not know about the details of the insurance system implementation from the AHA survey so cannot include system age or manufacturer as controls. However, the results in Column (8) suggest that indeed there was not a negative relationship between system size and the decision to exchange information with insurers, as the coefficient was positive and insignificant.

Table 4: Checking the robustness of our results

	OLS (1) External exchange	Alt DV (2) External patient	(3) External clinical	(4) Not member RHIO	No Merger (5) External exchange	Only Systems (6) External exchange	(7) External exchange	(8) Exchange Insurance
# hospitals in system in HRR	-0.00621***	-0.0345***	-0.0240**	0.0147*	-0.0288***	-0.0328***		0.00126
	(0.00210)	(0.0112)	(0.00991)	(0.00878)	(0.0106)	(0.0114)		(0.00848)
# hospitals outside HRR in system							-0.000853	
							(0.000659)	
# hospitals outside system in HRR	-0.000255	0.00140	-0.00237*	-0.00186	-0.00215	-0.00185	-0.00175	0.00116
	(0.000296)	(0.00144)	(0.00135)	(0.00137)	(0.00139)	(0.00180)	(0.00130)	(0.00125)
Admissions (000)	0.00159**	0.00994***	0.00733**	0.0147***	0.00758**	0.00703**	0.00581*	0.0433***
	(0.000762)	(0.00324)	(0.00310)	(0.00297)	(0.00328)	(0.00341)	(0.00299)	(0.00486)
Proportion Medicare Inpatients	0.000794**	0.00115	0.00353**	0.00232*	0.00343**	0.000141	0.00272**	0.00308**
	(0.000312)	(0.00151)	(0.00140)	(0.00135)	(0.00142)	(0.00174)	(0.00134)	(0.00120)
Proportion Medicaid Inpatients	0.000725*	0.000362	0.00318*	0.00434***	0.00274	0.000239	0.00239	0.00301*
	(0.000428)	(0.00196)	(0.00177)	(0.00166)	(0.00181)	(0.00232)	(0.00172)	(0.00155)
No. Doctors (000)	0.181*	0.375	0.687**	-0.393	0.546*	0.678*	0.589*	-0.869**
	(0.105)	(0.300)	(0.325)	(0.339)	(0.324)	(0.349)	(0.321)	(0.401)
PPO	-0.0395*	-0.249***	-0.140*	-0.161**	-0.171*	-0.113	-0.174**	-0.0743
	(0.0207)	(0.0910)	(0.0832)	(0.0780)	(0.0877)	(0.115)	(0.0812)	(0.0744)
HMO	0.0138	0.0656	0.0471	0.167**	0.0358	0.0535	0.0530	0.221***
	(0.0198)	(0.0893)	(0.0808)	(0.0761)	(0.0844)	(0.112)	(0.0788)	(0.0724)
Per Capita Payroll	-0.978***	-4.492**	-4.115**	1.910	-5.572***	-6.705***	-5.516***	3.680*
	(0.346)	(2.169)	(1.892)	(1.465)	(2.057)	(2.330)	(1.928)	(2.220)
Constant	0.371***	-0.757*	-0.396	-0.793**	0.0490	-0.0591	-0.158	-0.0474
	(0.133)	(0.448)	(0.403)	(0.378)	(0.436)	(0.462)	(0.399)	(0.363)
State Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hospital Type Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Vendor Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Deploy Year Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Observations	4060	4016	4060	4060	3420	2561	4060	3527
Log-Likelihood	-1676.6	-1296.5	-1632.4	-1807.5	-1482.4	-1035.3	-1746.6	-1894.1

OLS estimates Column (1). Probit estimates Columns (2)-(7). Robust Standard Errors. * $p < 0.10$, ** $p < 0.05$,*** $p < 0.01$

3.5 Why do large hospital regional systems not share data?

Given that the results of Table 4 appear to rule out an explanation based on technological capacity, we turn to exploring whether the decision by large hospital systems to not share patient data reflects 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, 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. Columns (1) and (2) Table 5 presents estimates by whether or not that hospital has a non-zero number of PPO contracts. The results suggest that that PPO hospitals in larger systems are less likely to exchange 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. We repeat this estimation for the decision to share data internally within a system in Table A1 and find no such relationship.

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. Columns (3) and (4) of Table 5 explores 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 to

Table 5: PPO Hospitals and High-Paying Hospitals are More Likely to Not Exchange Data Externally if they have large systems

	(1) PPO	(2) No PPO	(3) Above Average Wage	(4) Below Average Wage
# hospitals in system in HRR	-0.0347***	-0.0198	-0.0548***	-0.0177
	(0.0123)	(0.0169)	(0.0176)	(0.0128)
Admissions (000)	0.00848**	-0.00929	0.00242	0.00816**
	(0.00361)	(0.00748)	(0.00633)	(0.00383)
Proportion Medicare Inpatients	0.00138	0.00611***	0.00132	0.00450**
	(0.00224)	(0.00201)	(0.00188)	(0.00203)
Proportion Medicaid Inpatients	0.00276	0.00180	0.00102	0.00488*
	(0.00263)	(0.00274)	(0.00231)	(0.00266)
No. Doctors (000)	0.127	3.727***	0.618	0.820**
	(0.312)	(0.830)	(0.408)	(0.416)
PPO	0	0	-0.196*	-0.107
	(.)	(.)	(0.117)	(0.123)
HMO	0.0983	-0.225	0.0281	0.0641
	(0.0953)	(0.189)	(0.115)	(0.118)
Per Capita Payroll	-4.177	-6.839**	-6.838	-5.860**
	(2.766)	(2.851)	(4.656)	(2.986)
State Controls	Yes	Yes	Yes	Yes
Hospital Type Controls	Yes	Yes	Yes	Yes
Deploy Year Controls	Yes	Yes	Yes	Yes
Observations	2591	1444	1826	2229
Log-Likelihood	-1077.5	-622.5	-798.6	-899.0

Probit estimates. Robust Standard Errors. * $p < 0.10$, ** $p < 0.05$,*** $p < 0.01$

the creation of that data. The more valuable the inputs, the more reluctant firms are to share such data outside their firm boundaries.

4 Implications

This research investigates the relationship between the size of firm that uses a network and the kind of network externalities 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. The reliance by vendors on customers to internalize network externalities can lead to the creation of information silos. This suggests that policies designed to encourage inter-connection may need to be broadened to include users as well as vendors of technologies.

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 markets with network externalities. 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 depends 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 and not silo their data.

Our findings are also of crucial significance for the 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 are capable of doing 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.

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Table A1: Repeating Table 5 for internal exchange

	(1) PPO	(2) No PPO	(3) Above Average Wage	(4) Below Average Wage
# hospitals in system in HRR	0.0700***	0.0434**	0.0629***	0.0552***
	(0.0124)	(0.0178)	(0.0154)	(0.0133)
Admissions (000)	0.0282***	0.0190**	0.0390***	0.0211***
	(0.00483)	(0.00893)	(0.00979)	(0.00470)
Proportion Medicare Inpatients	-0.00359	-0.00896***	-0.00650***	-0.0105***
	(0.00255)	(0.00255)	(0.00240)	(0.00220)
Proportion Medicaid Inpatients	-0.00746**	-0.0125***	-0.00861***	-0.0170***
	(0.00307)	(0.00354)	(0.00308)	(0.00296)
No. Doctors (000)	-0.234	5.340***	2.037*	0.236
	(0.521)	(1.774)	(1.125)	(0.626)
PPO	0	0	-0.0745	-0.341**
	(.)	(.)	(0.156)	(0.141)
HMO	0.377***	0.212	0.147	0.429***
	(0.115)	(0.236)	(0.151)	(0.137)
Per Capita Payroll	10.30***	3.440	1.445	2.545
	(3.211)	(2.183)	(5.796)	(2.210)
State Controls	Yes	Yes	Yes	Yes
Hospital Type Controls	Yes	Yes	Yes	Yes
Deploy Year Controls	Yes	Yes	Yes	Yes
Observations	1639	924	967	1582
Log-Likelihood	-883.2	-495.2	-567.0	-813.7

Probit estimates. Robust Standard Errors. * $p < 0.10$, ** $p < 0.05$,*** $p < 0.01$