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Health Information Exchange, Interoperability, and Network Effects

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Abstract

Health information exchange (HIE) is the electronic exchange of patient medical records among hospitals. I investigate how two defining characteristics of HIE can cause under-adoption. First, HIE represents an information-sharing network, and participation for any hospital is valuable if others participate. This is a network effect. Second, HIE involves exchange of medical records, which may be competitive assets for hospitals. Therefore, hospitals may have disincentive to exchange with competitors despite social benefits. This is a competitive effect. I present a theoretical framework of hospitalsâ?? decisions to adopt HIE and show how presence of network and competitive effects can result in under-adoption relative to the social optimal. I then test for evidence of network and competitive effects in hospital HIE adoption. In the empirical analysis, I use two measure of HIE adoption. The first is a measure of general adoption in which all hospitals that have adopted any HIE capability are assumed to be able to exchange information with each other. The second takes into account that much information-sharing occurs through interoperable IT systems and currently, most IT systems of different vendors are not interoperable. I find evidence of network effects in general HIE adoption and vendor choice. I find that a 10% increase in market adoption rate results in a hospital being 9.2% more likely to adopt HIE. I also find that a 10% increase in adoption rate of a vendor results in a hospital being 1.5% more likely to adopt the vendor. I also find evidence of competitive effects. Specifically, hospitals that are more vulnerable to losing market share are less likely to adopt a prominent vendor in a market. I estimate a model of patientsâ?? hospital preferences and hospitalsâ?? HIE adoption decision. Through counterfactual simulation, I show effects of widespread HIE adoption on market share redistribution. Finally, I evaluate current policies such as the federal governmentâ??s $30 billion adoption incentive program (HITECH Act). The program may be inadequate to promote widespread interoperability in the presence of competitive effects. I also discuss the implications of network effects for competition and innovation in the health IT industry.

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HEALTH INFORMATION EXCHANGE,

INTEROPERABILITY, AND NETWORK EFFECTS

Dedicated to Mom

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ABSTRACT

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Health information exchange (HIE) is the electronic exchange of patient medical records among hospitals. I investigate how two defining characteristics of HIE can cause under-adoption. First, HIE represents an information-sharing network, and participation for any hospital is valuable if others participate. This is a network effect. Second, HIE involves exchange of medical records, which may be competitive assets for hospitals. Therefore, hospitals may have disincentive to exchange with competitors despite social benefits. This is a competitive effect. I present a theoretical framework of hospitals' decisions to adopt HIE and show how presence of network and competitive effects can result in under-adoption relative to the social optimal. I then test for evidence of network and competitive effects in hospital HIE adoption. In the empirical analysis, I use two measure of HIE adoption. The first is a measure of general adoption in which all hospitals that have adopted any HIE capability are assumed to be able to exchange information with each other. The second takes into account that much information-sharing occurs through interoperable IT systems and currently, most IT systems of different vendors are not interoperable. I find evidence of network effects in general HIE adoption and vendor choice. I find that a 10% increase in market adoption rate results in a hospital being 9.2% more likely to adopt HIE. I also find that a 10% increase in adoption rate of a vendor results in a hospital being 1.5% more likely to adopt the vendor. I also find evidence of competitive effects. Specifically, hospitals that are more vulnerable to losing market share are less likely to adopt a prominent vendor in a market. Finally, I estimate a model of patients' hospital preferences and hospitals' HIE adoption decision. Through counterfactual simulation, I show effects of widespread HIE adoption on market share redistribution. Finally, I evaluate current policies such as the federal government's $30 billion adoption incentive program (HITECH Act). The program may be inadequate to promote widespread interoperability in the presence of competitive effects. I also discuss the implications of network effects for competition and innovation in the health IT industry.

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CHAPTER 1 : INTRODUCTION

Health information exchange (HIE) is the electronic exchange of patient medical records between health care providers. HIE has the potential to reduce costs and improve the quality of health care by reducing duplicative services and providing complete medical histories at the point of care. Several policy efforts have targeted the widespread adoption of HIE technology (Vest and Gamm 2010). Despite potential benefits and significant policy efforts, rates of HIE technology adoption remain low (Adler-Milstein and Jha 2014).

Two defining characteristics of HIE could lead to under-adoption. First, HIE represents an information-sharing network, and participation for any given provider is only valuable if there are other participants with whom to exchange information. The increasing value of HIE in the number of participants is the network effect. Second, HIE involves the exchange of patient records, but exclusive access to medical records may be a competitive asset for providers. As a result, providers may be reluctant to engage in information sharing with competitors. This disincentive to share patient medical records is the result of the competitive effect.

The objective of this dissertation is to investigate the conditions under which these features can lead to under-adoption and to test for evidence of network and competitive effects in hospital HIE. I develop a theoretical framework to identify conditions under which suboptimal adoption can occur. I show that the presence of network and competitive effects can lead to under-adoption relative to the social optimal. I also discuss the mechanisms by which each of the effects operates.

I empirically test for network and competitive effects in hospital HIE adoption. In the empirical analysis, I take into account that there are many methods by which electronic informations sharing occurs. I distinguish between two broad forms of HIE. The first is a general form of HIE, which assumes that all hospitals that have adopted some HIE technology can exchange information with each other. This form is analogous to a single-network system in which hospitals can either adopt or not adopt the technology. The second is a key form of HIE that occurs through interoperable IT systems. In the current technological state, the IT systems of different vendors are generally not interoperable (Weber-Jahnke, Peyton, and Topaloglou 2012). In such an environment, only hospitals that have adopted the same vendor can exchange information through interoperable IT systems. The result is multiple, proprietary networks effectively run by competing health IT vendors. I discuss the implications of network effects in a single- versus multiple-network environment.

The empirical analyses have several implications. First, testing for the presence of network effects and competitive effects in HIE sheds light on whether current rates of HIE adoption are suboptimal. If network and competitive effects do not exist, low rates of adoption may be socially optimal and reflect that the technology is not valued. On the other hand, if the effects exist, they could indicate less-than-optimal adoption rates. Second, understanding the mechanisms for under-adoption can provide insight into policy mechanisms to reach optimal adoption. Therefore, using results of the theoretical and empirical analysis, I evaluate current and alternative policies. I consider recent legislation aimed at incentivizing electronic information-sharing and other health reforms. Additionally, I consider implications for competition and innovation in the health IT industry.

1.1. Institutional Background

A primary purpose of HIE is to overcome the challenges of slow record transfer that often occur in paper-based systems.[1] There is anecdotal evidence of inefficiencies resulting from poor transferability of medical records (Lohr 2015; Rosenthal 2014). A common complaint is that record transfer can have significant time and monetary costs for patients. It can take weeks for the transfer to occur, and providers often charge a fee. Even if transferred, records may be incomplete or illegible. As a result, labs and imaging are reordered creating waste and inefficiency. Moreover, treatment decisions may be made with incomplete knowledge of the patient's medical history possibly leading to low-quality care.

1.1.1. Forms of HIE

HIE is an early-stage capability and the relevant technology continues to evolve. As a result, there are many forms by which information sharing takes place and many characteristics by which it can vary. [2]

For the purposes of this dissertation, I define two measures of HIE: general HIE and information sharing through interoperable IT systems. In the first measure, a hospital is defined as having adopted if it has adopted any form of information-sharing

1. HIE can also facilitate population health surveillance and management, data access for observational research studies, and identification of subjects for clinical trials (Shapiro 2007).

2. For example, the Office of the National Coordinator of Health Information Technology (ONC) identifies three key forms of HIE (ONC 2013). The first is directed exchange, which is the ability to send and receive patient information through email-like messages. Second, query-based exchange refers to the ability to search and discover patient information. Data is often accessed through a portal from a data repository. Third, consumer-mediated exchange refers to direct record-access by patients who then can transfer the records. I do not consider the third form of information sharing in this work. However, in such patient-facilitated exchanges, concerns around the competitive effect remain and would potentially be amplified for providers who would lose many patients due to reduced switching cost. The extent of the network effect would depend on the technological details of the consumer-mediated exchange.

technology. An implicit assumption in this measure is that any hospital that has adopted information-sharing capabilities can exchange information with any other hospital that has adopted such capabilities. This is analogous to a single-network environment in the network economics literature. In such an environment, hospitals choose whether to adopt, and all hospitals that adopt can share information with each other. If hospitals report adopting any type of HIE or participating in any information exchange initiative, they are assumed to have adopted HIE according to this measure. This is the measure of HIE adoption that is used in the previous literature.[3]

The second measure takes into account that much information sharing takes place through interoperable IT systems. Generally, in the current state of technology, only IT systems from the same vendor are interoperable (JASON 2014).[4] This measure relies on the lack of interoperability between IT systems of different vendors to define multiple information-sharing networks. By choosing a vendor, hospitals are effectively choosing to join one of several networks. This is analogous to a multiple-network environment in the network economics literature.

I use these two measures of information sharing for their institutional and economic

3. There are other factors on which HIE differ that could be significant in the context of network and competitive effects. For example, information exchange can be unidirectional or bidirectional. In a unidirectional network, a hospital can receive data from hospitals without sending data or vice versa. In a bidirectional network, hospitals must supply their patients' records to access records from other hospitals. If hospitals want to restrict competitor access to their patients' records, they would have differing incentives to adopt depending on whether the network is unidirectional or bidirectional. There is also heterogeneity in how data is stored. For example, in some HIE networks, such as regional health information organizations (RHIOs), hospital medical records are stored in a centralized repository. Other networks may be decentralized, so data is stored by the originator of the records and sent to other hospitals upon request. If hospitals retain greater control over their records in decentralized compared to centralized systems and if competitive effects exist, hospitals may be more likely to join a decentralized network. While such characteristics of HIE could be relevant to adoption decisions, considering such features is beyond the scope of this dissertation because they cannot be observed in the data (McCarthy et al. 2014).

4. Even if the systems can be technically interoperable, vendors charge significant fees to allow data sharing (ONC 2015b).

significance. Most early policy efforts have been focused on developing geographically based HIE networks or adoption of messaging capabilities, which fall under the first measure of HIE. These efforts include development of RHIOs and the Nationwide Health Information Network. However, there has been increased focus on exchange through interoperable IT systems. Specifically, interoperability refers to ability of IT systems to exchange and use electronic health information from other systems without the special effort of the user (ONC 2015a). It is considered an ideal form of information sharing because the exchange is smoother. However, the current lack of interoperability between different systems results in competing proprietary networks. The formation of competing proprietary networks has implications for competition, innovation, and policies at the vendor level, which I discuss in this dissertation.

1.2. Policy Background

In 2009, the federal government enacted the Health Information Technology Act for Economic and Clinical Health (HITECH) under the American Recovery and Reinvestment Act of 2009 (Dranove et al. 2014). This legislation represents the most significant program to promote the widespread adoption of health IT in history. The program is administered by the ONC. The Meaningful Use program of HITECH allocated almost $30 billion in incentive payments to hospitals and providers for adopting and using specified IT capabilities. Incentives are paid in several stages, each requiring increasingly advanced IT capabilities. Meaningful Use Stage I, which began in 2011, focuses on basic health IT capabilities aimed at capturing patient data digitally. Meaningful Use Stage 2, which began in 2014, is aimed at more advanced clinical processes, including the ability to engage in information sharing to support transitions of care. Meaningful Use Stage 3 continues to be developed. By 2011, the average hospital is estimated to have collected $2.2 million in Meaningful Use payments. The size of the incentive payment is a function of the percent of a hospital's Medicare and Medicaid inpatient discharges and the number of total inpatient discharges.

HITECH legislation also affects health IT vendors by making Meaningful Use payments contingent on adoption of technology that is certified by the ONC. Some certification criteria are aimed at facilitating HIE and interoperability between IT systems.

There are additional federal initiatives to support the development of HIE infrastructure, as well. For example, the government has allocated an additional $550 million to states for the development of HIE infrastructure (Mosquera 2010). The long-term goal is to connect these state networks into the National Health Information Network.

Several policy efforts to promote HIE predated HITECH (Vest and Gamm 2010). These past efforts provide evidence for the broad recognition of HIE's potential value as well as the challenges of developing a robust information-sharing infrastructure. In the early 1990s, several states and cities established community health management information systems (CHMISs). These were regionally based data repositories designed for billing, clinical, and research purposes. In the mid- to late-1990s, community health information networks (CHINs) were developed through provider and vendor collaborations. In contrast to the earlier generation of CHMISs, CHINs were decentralized so that providers could retain control of their own databases. However, most did not survive. Also, in 2004, President George W. Bush issued an executive order to develop a nationwide health information network, which led to the establishment of RHIOs across the country. RHIOs are initially government funded, and most have struggled to develop a self-sustaining revenue base. While some RHIOs continue to operate, most have failed or are not being used broadly (Adler-Milstein, Bates, and Jha 2009). In discussing the history of policies aimed at developing functioning HIE, Vest (2010) cites competition among providers and lack of a sustainable business model as two reasons for the failures of past attempts.

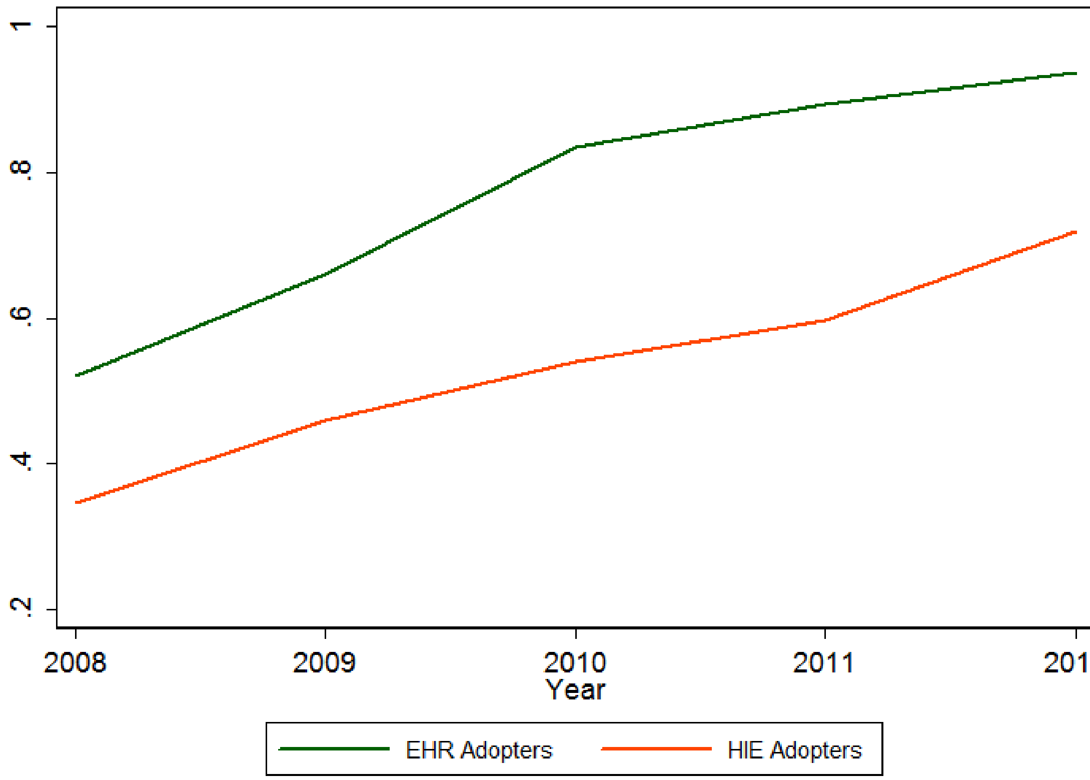
1.3. Evidence on HIE Effectiveness

Evidence on the effectiveness of HIE at reducing costs and improving quality of care is mixed (Rahurkar, Vest, and Menachemi 2015). Some studies find moderate effects from HIE on various outcomes, while others do not find any effect. Lammers, Adler-Milstein, and Kocher (2014) find that hospital HIE capability can reduce duplicative imaging by 9% to 13%. They extrapolate that full-scale HIE diffusion could translate to savings of $19 million in annual costs just by reducing duplicative imaging (Lammers, Adler-Milstein, and Kocher 2014). Vest et al. (2015) find that HIE system usage in the 30 days after a hospital discharge is associated with 57% reduction in odds of readmission. Using data from Israel, Nirel et al. (2010) find HIE leads to fewer lab tests and CT tests in internal medicine. The authors find no effect on general surgery costs, length of stay, or readmissions. Several randomized controlled trials in emergency department (ED) settings find no effect of HIE on outcomes such as ED visits, visits to primary care physicians or specialists, length of stay, lab orders, or cost measures (Hansagi et al. 2008; Overhage et al. 2002; Lang et al. 2006). The lack of strong evidence of HIE effectiveness could reflect poor technology or lack of need for such information-sharing technology. Evaluating the effectiveness of and need for HIE is beyond the scope of this dissertation.

1.4. Progress in HIE Adoption and Interoperability

National statistics on the extent of information sharing are not available, but rates of adoption of HIE capabilities can provide a proxy for actual information sharing. The proportion of general medical and surgical hospitals that reported engaging in HIE with a hospital outside their system or participating in an information exchange initiative increased from 35% in 2008 to 72% in 2012 (shown in figure 1).[5]

Figure 1: EHR and HIE Rates by Year



Despite the increase in HIE adoption in recent years, many policymakers consider the progress slow and inadequate. Meaningful Use Stage 2 was supposed to establish robust information sharing and interoperability, but these goals have not been realized. In addition to adoption rates that are considered lackluster relative to the magnitude of the investment, policymakers are concerned about the lack of progress in achieving interoperability. HIE adoption and interoperability are considered key

5. Estimates on the rate of adoption vary based on the sample and precise definition of HIE. For example, a survey by the American Hospital Association (AHA) reports an increase in the proportion of hospitals that engage in HIE with providers outside of their organization. According to the survey, the percent of hospitals that reported engaging in HIE with hospitals outside of their system increased from 15% in 2008 to 40% in 2013 (Association n.d.). This survey includes hospital-types other than general medical and surgical. General medical and surgical hospitals are likely to higher adoption rates relative to the average.

challenges (Adler-Milstein and Jha 2014).

1.5. Previous Literature

This dissertation contributes to theoretical and empirical work in health and network economics.

1.5.1. Health Economics

Two papers in health economics provide evidence of competitive effects in hospital HIE adoption. Miller and Tucker's (2014) study most directly relates to this dissertation. The authors use 2009 AHA IT Supplement data to test how the size of the hospital system relates to HIE adoption. Controlling for the number of other hospitals in the market and hospital characteristics, the authors find that hospitals in larger hospital systems are less likely to participate in HIE. Miller and Tucker attribute this finding to lock-in behavior, which is similar to what I call the competitive effect. The authors also examine how the number of other hospitals that are using HIE in a market affects use by a given hospital to test for network effects. Given the use of cross-sectional data, they are not able to control for hospital fixed effects, which would account for unobservable characteristics affecting adoption behavior. Moreover, with cross-sectional data, Miller and Tucker cannot observe year-to-year *adoption* of HIE as I do through panel data analysis.

Baker, Bundorf, and Kessler (2014) use 2001 to 2007 hospital-level data from Health Information Mangement Systems Society(HIMSS) Analytics to study how state caps on copy fees are associated with hospital adoption of electronic health record (EHR) systems. They find that hospitals in states with caps on how much a provider can charge to copy medical records are more likely to adopt EHR systems. This result suggests that hospitals may avoid adopting technology that facilitates information sharing to maintain switching costs for patients. Once government policies prevent hospitals from maintaining these costs, they are more likely to adopt EHR. In another analysis, the authors study how state copy fees affect the likelihood of patients switching between physicians. They find that patients in states with caps on copy fees are more likely to switch physicians in an outpatient setting. Such switching resulting from reduced costs of record transfer is the mechanism by which competitive effects operate. This result provides evidence that switching costs may, in fact, inhibit patient mobility between providers.

Other research finds suggestive evidence of a competitive effect in HIE adoption. Two studies find that HIE adoption is negatively correlated with market competition. In both studies, competition is measured by the Hirschmann-Herfindahl Index (HHI). HHI is also a measure of market fragmentation with low HHI (high competition) indicating greater fragmentation. HIE would be most useful in more fragmented markets where patients are more likely to receive care from multiple hospitals. However, the finding that competition is negatively associated with HIE adoption indicates there may be other mechanisms at play, such as a competitive effect. First, Adler-Milstein, DesRoches, and Jha (2011) use 2009 AHA IT Supplement data to examine how hospital- and market-level characteristics are associated with participation in RHIOs. They find that hospitals in more competitive markets are less likely to participate in RHIOs compared to those in less competitive markets. They find that for-profit hospitals are less likely to participate as are hospitals with low market share. Additionally, hospitals in markets with less Medicare spending have lower odds of participation. Second, Vest (2010) uses 2009 HIMSS Analytics data to study determinants of participation in HIE initiatives, including but not limited to RHIOs. Results largely support those of Adler-Milstein, DesRoches, and Jha. Notably, Vest finds that hospitals in more competitive markets are substantially less likely to participate in HIE compared to counterparts in less competitive markets.

There is also anecdotal evidence of the competitive effect as a strategic barrier to HIE adoption as providers attempt to protect market share. For example, a survey of hospital CEOs revealed that their greatest concern when deciding whether to engage in HIE was losing competitive advantage by giving up control of medical records (Grossman, Kushner, and November 2008). Additionally, though providers are legally required to share medical records when their patients request them to, there is evidence that many providers attempt to prevent patients and other providers from accessing records (Knox 2009).

This dissertation makes several contributions to the health economics literature on HIE adoption. First, I empirically test for and concurrently consider implications of both network and competitive effects. To my knowledge, this is also the first study to test for network effects in vendor choice and consider the implications of network effects in multiple networks for health IT. Interoperability is a key goal of the HITECH Act, so examining patterns of vendor choice can give insight into the challenges of achieving interoperability. This is also the first study to use details on hospitals' patient populations to test for evidence of competitive effects. Additionally, by combining IT adoption data from two sources, I have data on close to the full population of general medical and surgical hospitals. Near-complete coverage is especially important because market adoption rates are a key variable in measurement of network effects. Finally, I study HIE adoption across time with panel data. Including hospital fixed effects allows me to control for certain unobservables and idiosyncrasies at the hospital level that may affect hospital behavior. In addition, by using panel data, I can examine year-to-year adoption of HIE rather than just use of HIE.

1.5.2. Network Economics

This dissertation draws on theoretical and empirical frameworks in the network economics literature. There is a large theoretical literature in network economics, and several reviews insightfully summarize and discuss the literature (Farrell and Klemperer 2007; Shy 2011; Economides 1996; Matutes and Regibeau 1996).

Historically, network economics has focused on the telecommunications industry following the divestiture of AT&T in the early eighties and the hardware-software industry when IBM dominated hardware and Lotus dominated compatible software. More modern settings in which network effects play an important role are social media and dating websites. The value of joining these networks for any given consumer increases as the number of other users increases. Few studies in network economics have examined this phenomenon in a health care setting.

Literature has considered both direct and indirect network effects. Direct network effects refer to the increasing incentive to adopt as the number of adopters rises. Indirect network effects refer to the increased supply of goods resulting from increased adoption by other buyers. For example, if increasing adoption of iPhones increases availability of iPhone apps, increased availability of iPhone apps is an indirect network effect. This study considers direct network effects—the increasing value of HIE as more hospitals adopt it.

Network effects and the adoption decision can occur at different vertical levels. In the setting of HIE, patients receive the benefits of network effects, and hospitals internalize patients' network effects into their own profit function. Hospitals make the decision of whether to adopt HIE; however, by assuming that hospitals internalize network effects, the problem is similar to one in which the entity that receives the network effect also makes the adoption decision.

Several papers have studied equilibrium adoption outcomes in the presence of network effects under various conditions. In a standard, simultaneous game between two players with equal network effects, there are two equilibria: both adopt or neither adopts. The under-adoption outcome occurs due to a coordination failure or chicken-and-egg problem (Farrell and Klemperer 2007). Several papers consider adoption outcomes under different conditions. For example, in a dynamic setting in which players can observe behavior of others and then decide to adopt, researchers are less concerned about such a coordination failure. However, either too-slow adoption or excess inertia leading to under- or over-adoption can still result. Some papers also consider the adoption decision when there are multiple networks to choose from. Assuming that switching networks is costly, coordination failure is more likely to occur with multiple networks compared to a single-network environment. Moreover, if multiple networks are proprietary, then there are additional implications in terms of competitive strategy of the network owners. This condition is relevant in my study setting in terms of vendors de facto operating competing HIE networks through their incompatible IT systems.

Klemperer and Farrell (2006) examine how network effects and the firm's decision to adopt can be affected by competition. They show that under-adoption of a network can result from a coordination problem and lack of incentive to adopt at the margin if adoption benefits other competitors. Economides (1993) studies opposing network externalities and the competitive effect faced by a monopolist in the telecommunications industry.

Economides notes that a key reason for network externalities is the complementarity between goods. As a result, as competitors enter a monopolist's network, there are two opposing effects on profits. On the one hand, the network externality leads to increased profits. On the other hand, because the number of competitors increases, profits fall. Though the mechanisms of these two effects are different in my framework, the intuition is similar.[6]

Several papers argue that past literature has often wrongly called network effects externalities (Liebowitz and Margolis 1994). In general, these criticisms have focused on indirect network effects because they are generally internalized in price. The network effect considered in this analysis is a network externality because the value that an adopter adds to the network for other participants is not internalized by the adopter (unless there are side payments).

My work also relates to literature on compatibility and standardization. Compatibility refers to coordination that allows for communication, and standardization refers to the process of achieving compatibility. Katz and Shapiro (1985) construct a seminal model of firms' compatibility decisions and consider different conditions, such as the method of standardization and the feasibility of side payments between firms. Although standardization can be beneficial in terms of improving compatibility, Farrell and Saloner (1985) show how standardization can lead to excess inertia and cause an industry to widely adopt an inferior standard. The authors show that firms may fail to achieve compatibility when compatibility is socially optimal. There are two levels in my study setting at which a compatibility decision is being made. At the hospital level, the adoption of HIE technology to allow for more seamless information-sharing can be considered a decision to become compatible. At a higher vertical level, the lack of interoperability of IT systems refers to the non-compatibility of health IT products from different vendors. Economides (1988) finds that firms that are dominant may

6. In the Economides model, the competitive effect operates through price and quantity, but in my model, the competitive effect operates through reduction in switching cost.

not have incentives to become interoperable or compatible with other firms in the market.

Many industries with network effects also have switching costs as in the model used in this dissertation. Past work has studied the effects of switching costs on firm behavior in these industries. Shapiro and Varian (1999) discuss implications of various types of lock-in and associated switching cost. The patient switching cost that I propose to study is most similar to information- and database-related lock-in. It represents the cost of transferring medical records easily and completely and rises with time as more information resides in the originating providers' files. Shapiro and Varian note that agreement on standardized, compatible, or "open" information systems would limit switching costs. Several papers have shown how firms have an incentive to maintain switching costs or even create artificial switching costs in order to "lock-in" a customer base and deter entry by competitors.

Although the empirical literature is much smaller than the theoretical literature, several studies test for network externalities using time-series and cross-sectional data. The first part of my empirical analysis adapts the approach of Gowrisankaran and Stavins (2004), who use panel data to test for network externalities in banks' adoption of automated-clearinghouse electronic payment systems. The authors examine how adoption and usage by a bank is affected by adoption and usage of other banks in the network. They instrument for adoption of other banks by adoption of large branches in different markets. The authors find evidence of moderately large network externalities. Because electronic payment systems are a secondary product in the banking market, their model only allows for network externalities and does not need to consider that such technology could affect the switching cost that consumers incur as I do.

Goolsbee and Klenow (2002) examine network externalities in diffusion of home computers by studying how household computer adoption is affected by the fraction of adopting households in a city. The authors instrument for individual characteristics with city means of those characteristics. They find evidence that household computer adoption is associated with adoption by other households in the city.

1.6. Outline

The remainder of this dissertation proceeds as follows: In Chapter 2, I develop a theoretical framework for studying network and competitive effects. In Chapter 3, I describe my data sources and describe construction of data sets used in the analyses. Chapter 4 presents the empirical test for existence of network effects in HIE technology adoption and vendor choice. Chapter 5 presents empirical tests for evidence of competitive effects in HIE adoption and vendor choice. Chapter 6 discusses policy implications of the theoretical and empirical findings. Chapter 7 discusses limitations, future directions, and conclusions.

CHAPTER 2 : THEORETICAL FRAMEWORK

In this chapter, I present a theoretical framework of hospitals' decisions to adopt HIE. First, I present two models - one with network effects and one with competitive effects. I then present a combined model with both.

The purpose of the theory is to show how these effects can lead to under-adoption of HIE. It also illuminates the mechanisms by which under-adoption can occur in the presence of each type of effect. Understanding their mechanisms provides insight into appropriate policy responses for each scenario.

I assume that profit-maximizing hospitals simultaneously decide whether to adopt HIE. In the network effects model, patients receive a network effect if both hospitals adopt HIE, and hospitals internalize that network effect. In the competitive effects model, hospitals compete on quantity, and patients face a switching cost. If hospitals adopt HIE, patients' switching cost is reduced. I assume hospitals operate in a monopolistic competition environment in which they compete on quantity. I assume patients are insured, so price is fixed. I also assume constant marginal cost. As a result, the profit per patient is fixed.

2.1. Duopoly Model with Network Effects

I first present a model of hospitals' decisions to adopt HIE under network effects. It is adapted from the simple model of network effects presented in (Farrell and Klemperer 2007). I show that under-adoption can occur with network effects as a result of a coordination failure.

In the model, hospitals 1 and 2 simultaneously decide whether to adopt HIE. In order to realize the network effect, both hospitals must adopt. The network effect can be considered to stem from the patient. Patients value having the option to electronically transfer medical records to another provider at some point and receive additional utility from a hospital if both hospitals have adopted HIE. I assume hospitals internalize the network effect of the patient.[1]

Without loss of generality, patient utility for hospital 1 is given by

$$u_i = u_i' + \mathbb{1}(Adopt_i = 1) \cdot \mathbb{1}(Adopt_{-i} = 1) \cdot n,$$

where u_i' represents patients' baseline utility for hospital i and n, a constant, is the network effect. The indicators $\mathbb{1}(Adopt_1 = 1)$ and $\mathbb{1}(Adopt_2 = 1)$ indicate whether hospital 1 and hospital 2 have adopted HIE, respectively, and the patient only realizes the network effect n if both hospitals adopt HIE. In a multi-firm market, the network effect would be a function increasing in the number of other providers that have adopted HIE.

Hospitals internalize the network effect in their profit function. Hospital 1 profit from adoption is

$$\pi_1^{Adopt} = pq_1 + \mathbb{1}(Adopt_2 = 1)N(n) - c,$$

where p is a fixed profit per patient, q_1 is hospital 1's quantity of patients, c is the cost of adoption, and $N(n)$ is hospital's network effect. It is increasing in the patient's network effect, n. Hospital 1's profit function is dependent on hospital 2's adoption

1. It is also possible that hospitals directly realize the network effect as a reduction in costs. In the empirical analysis, I will not be able to distinguish whether this network effect is at the patient or hospital level.

decision. Hospital 1 can only realize network effects if hospital 2 also adopts. Hospital 1's profit from not adopting is given by $\pi_1^{NoAdopt} = pq_1$. Payoffs from adoption are presented in Table 1.

Table 1: Payoffs under Network Effects

	Hospital 2	
Hospital 1	Adopt	No adopt
Adopt	$N - c$, $N - c$	$-c$, 0
No adopt	0,$-c$	0, 0

If $N \geq c$, it is optimal for both hospitals to adopt. If $N < c$, neither hospital will adopt, and it is not optimal to adopt. However, if $N \geq c$, there are two equilibria: both hospitals adopt, or neither hospital adopts. The no-adopt equilibrium represents under-adoption due to a coordination or "chicken-and-egg" problem.

Under-adoption could also occur if there is heterogeneity in hospitals. If hospitals' heterogeneity results in differing network effects, one hospital may not have the marginal incentive to adopt HIE. For example, if network effects scale with hospital size and if there is a large difference in size between the two hospitals, larger hospitals would realize greater network effects because they would have a larger patient base that values HIE. The payoff matrix in such a setting is given in Table 2.

Table 2: Payoffs under Increasing Network Effects

	Hospital 2	
Hospital 1	Adopt	No adopt
Adopt	$N(q_1) - c$, $N(q_2) - c$	$-c$, 0
No adopt	0,$-c$	0, 0

The network effect $N(q_1)$ is increasing in hospital quantity. If $q_1 = q_2$, this is the same as in the previous section. But suppose hospital 1 is larger than hospital 2 such that $q_1 > q_2$. This inequality implies that $N(q_1) > N(q_2)$.

It is socially optimal for both hospitals to adopt if $N(q_1) + N(q_2) > 2c$. If $N(q_1) > c$ and $N(q_2) > c$, there are two equilibria as in the previous section: both adopt or neither adopts. However, if $N(q_1) > c$ and $N(q_2) < c$, hospitals will not adopt even if $N(q_1) + N(q_2) > 2c$. This example demonstrates how under-adoption can occur if the differential network effect is large enough.

2.2. Duopoly Model with Competitive Effects

In the previous section, differential network effects occur as a result of scaling. Another form of differential network effects can result from competitive effects. Under competitive effects, some hospitals lose market share after adoption as a result of reduced switching cost for its patient base. Conversely, some hospitals will gain market share. The competitive effect stems from a different patient utility function than that of network effects. Specifically, the utility is relevant for patients who have already visited a hospital in the past and incur a switching cost to receive treatment from another hospital. This switching cost results from the cost of having paper records transferred. The switching cost is reduced if the patient's incumbent hospital and the other hospital adopts HIE. Patient utility for hospital 1 is given by

$$u_1 = u_1' - \mathbb{1}(Adopt_1 = 1) \cdot \mathbb{1}(Adopt_2 = 1) \cdot s,$$

where u_1' represents the base utility for hospital 1 and s represents the switching cost that is reduced if both hospitals adopt HIE.

Without loss of generality, hospital 1's profit from adoption is given by

$$\pi_1 = p(q_1 - \mathbb{1}(Adopt_1 = 1) \cdot \mathbb{1}(Adopt_2 = 1)(\sigma q_1 + \sigma q_2)) - c,$$

where $0 < \sigma < 1$ represents the portion of each hospital's patients that would switch if both adopt. I assume σ is equal for both hospitals.[2]

Table 3: Payoffs under Competitive Effects

	Hospital 2	
Hospital 1	Adopt	No adopt
Adopt	$p(\sigma q_2 - \sigma q_1) - c$, $p(\sigma q_1 - \sigma q_2) - c$	$-c$, 0
No adopt	0,$-c$	0, 0

If the welfare gain from reduction in patient switching cost is greater than the cost of adoption for both hospitals, it is socially optimal for the firms to adopt. However, hospitals will not take into account the gains from reduced switching cost.

Assuming again that $q_1 > q_2$, the incentive to adopt is different from the incentive to adopt in the previous section. Specifically, hospital 1 will only have an incentive to adopt if $p(\sigma q_2 - \sigma q_1) > c$. However, this is a zero sum game, so one hospital's profit gain will be weakly larger than the others. Therefore, in this stylized model, only one hospital at most will have an incentive to adopt.

In contrast to the previous model of scaling network effects, if q_1 is sufficiently larger than q_2, hospital 1, the larger hospital, will want to retain its installed base of patients and will not have an incentive to adopt. As in the above section, this results in an

2. However, σ could vary by hospital. If $q_1 > q_2$, it could be that σ is endogenous with market share and represents preferences so that $\sigma_1 > \sigma_2$. This would lead to different model results. However, I follow the convention used in existing literature in emphasizing the importance of initial market share in markets with switching costs. In the theoretical literature, several studies illustrate how a large firm with a locked-in consumer base would resist compatibility with a smaller but competitive rival (Katz and Shapiro 1985; de Palma and Leruth 1996; Crémer, Rey, and Tirole 2000). Past case studies highlight anecdotal evidence of larger firms resisting compatibility with smaller firms. For example, the Bell System, the dominant system of firms in the telephone industry, refused to interconnect with newer and and smaller companies. AOL did not interlink with rival instant messengers (G. Faulhaber 2002; G. R. Faulhaber 2004). In HIE adoption, Miller and Tucker (2014) find empirically that hospitals in large systems are less likely to engage in electronic information-sharing compared to hospitals in small systems.

equilibrium in which neither hospital adopts HIE.

2.3. Duopoly Model with Network and Competitive Effects

Now, I model hospitals' decisions to adopt HIE accounting for both network and competitive effects. Hospitals and patients benefit from hospitals' HIE adoption as a result of network effects. Patients' switching cost is reduced if their hospital adopts HIE; this benefit results from the competitive effect.

Initially, patients are assumed to not know their preferences and so are randomly allocated between the two hospitals. Initial market shares are q_1 and q_2 for hospital 1 and hospital 2, respectively. After the first encounter, patients can remain with the incumbent hospital or switch. I again assume an insured market and fixed price of service, so p represents the per patient profit of the hospital.

Hospital 1's profit from adoption is

$$\begin{aligned}\pi_1^{Adopt} = \quad & p(q_1 + \mathbb{1}(Adopt_2 = 1)(\sigma_2 q_2 - \sigma_1 q_1)) \\ & + \mathbb{1}(Adopt_2 = 1)(N)(q_1 + \sigma_2 q_2 - \sigma_1 q_1) - c,\end{aligned}$$

where c is the cost of adoption. $\mathbb{1}(Adopt_2 = 1)$ is an indicator function equal to 1 if hospital 2 adopts and 0 if hospital 2 does not adopt. The fractions of patients who would switch as a result of reduced switching costs if hospital 1 and hospital 2 adopt are σ_1 and σ_2, respectively. Unlike in the previous model, I allow the amount of switching to vary by hospital. If both hospitals adopt, $q_1 + (\sigma_2 q_2 - \sigma_1 q_1)$ represents the new market share for hospital 1. Hospital 2's profit function from adoption is symmetric..

Table 4: Payoffs under Network and Competitive Effects

	Hospital 2	
Hospital 1	Adopt	No adopt
Adopt	$p(\sigma_2 q_2 - \sigma_1 q_1) + N(q_1 + \sigma_2 q_2 - \sigma_1 q_1) - c$ $p(\sigma_1 q_1 - \sigma_2 q_2) + N(q_2 + \sigma_1 q_1 - \sigma_2 q_2) - c,$	$-c$, 0
No adopt	0,$-c$	0, 0

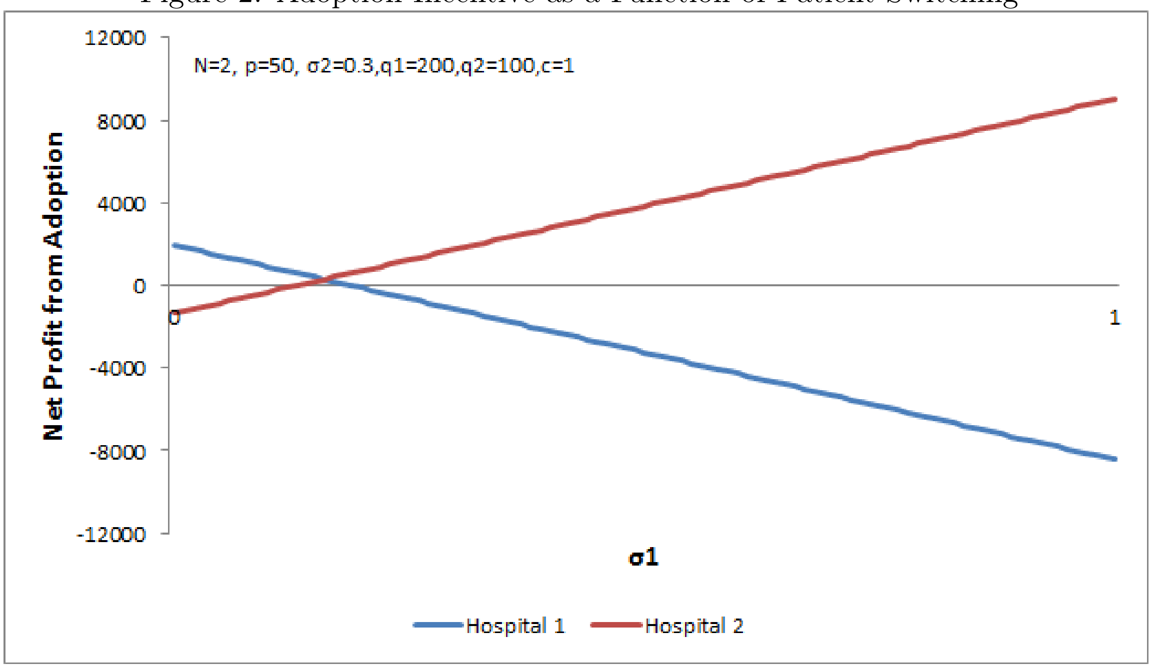
Although it is socially optimal to adopt if the benefits from adoption are greater than the cost of adoption, hospitals 1 and 2 will only adopt if the benefit of adoption outweighs both its cost and any profit loss resulting from patient switching. The socially optimal condition for adoption by both hospitals is $N > \frac{2c}{q_1+q_2}$. Hospitals' condition for adopting is more restrictive.[3] Hospital 1 will adopt if $N > \frac{c-p(\sigma_2 q_2 - \sigma_1 q_1)}{q_1+\sigma_2 q_2 - \sigma_1 q_1}$. Hospital 2 will adopt if $N > \frac{c-p(\sigma_1 q_1 - \sigma_2 q_2)}{q_2+\sigma_1 q_1 - \sigma_2 q_2}$. Heterogeneity among hospitals will determine the extent of redistribution that occurs in the market. In the model, hospital heterogeneity and its effects are reflected by asymmetry of patient preferences, σ_1, and initial market share, q_i. If σ_1 and σ_2 are small, there will be little patient switching. Additionally, if $\sigma_1 q_1$ and $\sigma_2 q_2$ are similar in magnitude, the net loss for each hospital will be small. Specifically, if $\sigma_1 = \sigma_2 = 0$ or if $\sigma_1 q_1 = \sigma_2 q_2$, then hospitals' condition for adopting will be equivalent to the condition for the social optimal. However, if there is a large disparity in σ_1 and σ_2 or in $\sigma_1 q_1$ and $\sigma_2 q_2$, the redistribution of patients will be uneven such that one hospital will not have an incentive to adopt. The result is an equilibrium in which neither hospital adopts.

I present a simple numerical simulation to demonstrate how patient switching and

3. Taking into account the reduction in switching cost for patients would make the value of adopting even greater.

initial market share affect hospitals' adoption behavior. First, I show that there is a small range of σ_i in which both hospitals have an incentive to adopt. Figure 2 shows hospital 1 and hospital 2's profit from adoption assuming the other hospital adopts as a function of σ_1 and holding all other parameters constant. There is only a small range of σ_1 where both hospitals receive positive profit from adoption. Similarly, Figure 3 shows the profit from adoption as a function of the difference in installed base between the two hospitals. Again, there is a small range in which it is profitable for both hospitals to adopt the technology. This simple simulation demonstrates the possibility of a no-adopt outcome despite the presence of network effects if a competitive effect exists.

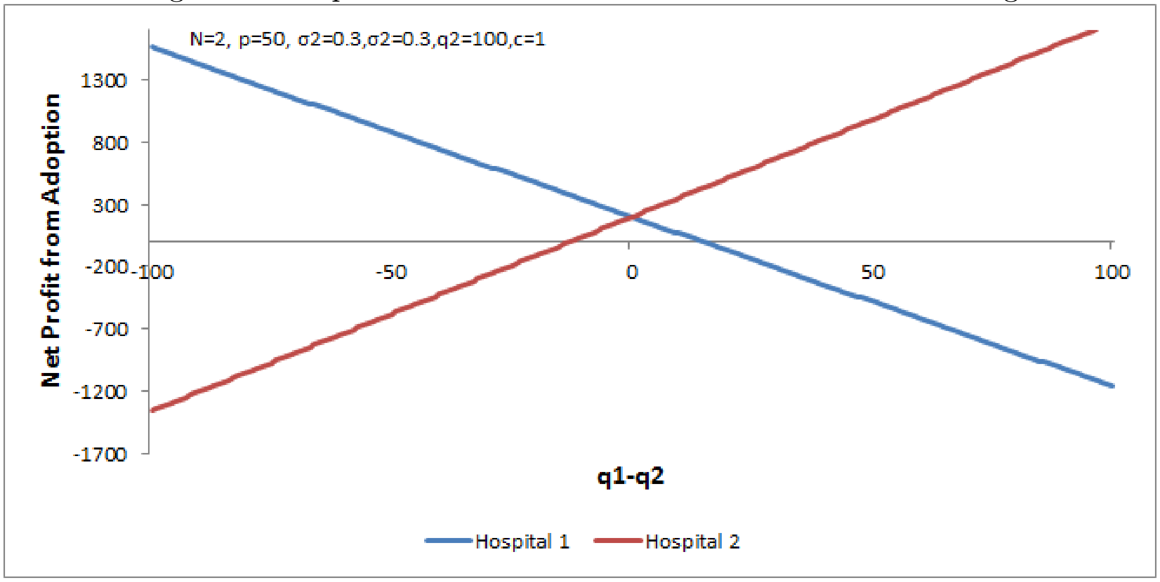
Figure 2: Adoption Incentive as a Function of Patient Switching



2.3.1. Network and Competitive Effects Under Alternate Conditions

The standard results in the simultaneous adoption model may differ under other conditions. For example, coordination problems may be less of a concern in a dynamic

Figure 3: Adoption Incentive as a Function of Patient Switching



setting where hospitals can observe adoption decisions of other hospitals. They can then adopt or not adopt when the network effects are adequate. In terms of competitive effects, hospitals that are more likely to lose market share may wait to observe adoption behavior by other hospitals before deciding whether to adopt. Hospitals that are not concerned about losing market share and have potential to gain market share are more likely to adopt earlier. However, such hospitals must also receive some other benefit from adoption in addition to the network effect which is dependent on other adopters.

Also, coordination failures may be more likely in the case of multiple networks. For example, consider if instead of $Adopt$ or $NoAdopt$, hospitals are deciding between $AdoptA$ and $AdoptB$. In this case, one hospital may adopt vendor A and another hospital may adopt vendor B. Assuming switching vendors is costly, a coordination failure would result in which both hospitals have adopted different networks so they cannot electronically exchange information with each other.

CHAPTER 3 : DATA

I construct four related panel data sets from four data sources for the empirical analyses in this dissertation. The data sets include hospital HIE adoption status and vendor choice as well as other hospital-level characteristics. Some of the data sets include additional information on the patient population of hospitals.

The first data set is national, hospital-level panel of HIE adoption status, vendor choice, and other hospital characteristics. Second, I construct a multi-state hospital-level panel data set that adds patient population information aggregated to the hospital. Third, I construct a multi-state panel of hospital pairs within a region with information about vendor choice and patient population. Finally, I construct a single-market, discharge-level data set merged with data on hospital HIE adoption status.

3.1. Construction of National Hospital Dataset

I construct a national hospital-level panel data set to empirically test for network effects in HIE adoption and vendor choice described in Chapter 4. The data ranges from years 2008 through 2012 and consists of non-federal, general medical and surgical hospitals. I choose years 2008 to 2012 for two reasons. First, I expect increased adoption of IT in these years, particularly with the start of the HITECH Meaningful Use incentive payments. Second, the number of hospitals that appear in the data set increases in these years, particularly with the availability of the AHA IT Supplement described below.

3.1.1. Data Source: AHA Annual Survey

Data on non-IT hospital characteristics is drawn from the American Hospital Association (AHA) Annual Survey. It is a verified survey of community hospitals and hospital systems across the country. It contains information on characteristics including organizational factors, personnel employed, services, revenues, and expenses. The AHA Annual Survey provides data on system membership and location. This data is used to delineate markets and hospital systems. In addition, it provides hospital characteristics such as ownership status and primary services provided by the hospital which are used to identify the sample. Other characteristics including number of admissions, the portion of inpatient days attributable to Medicare patients, the number of inpatient days attributable to Medicaid patients are control variables in the analysis.

3.1.2. Data Source: HIMSS Analytics Database

The Healthcare Information Management Systems Society (HIMSS) Analytics database provides data on IT-related characteristics of hospitals. It is a survey administered by The Dorenfest Institute for Health Information and represents several thousand hospitals across the country. Among other IT-related information, it contains data on whether the hospital participates in HIE. The HIMSS Analytics survey also provides data on vendor adopted for various IT capabilities, including clinical data repository software.

3.1.3. Data Source: AHA IT Supplement

While the HIMSS Analytics data covers the majority of the hospitals, the AHA IT Supplement provides additional data, particularly for hospitals not covered in the HIMSS Analytics database. It includes information on whether hospitals have adopted HIE technology.

To construct the panel, the three aforementioned data sources were merged for years 2008 to 2012. The AHA Annual Survey and AHA IT Supplement are merged using the AHA hospital identifier. The AHA data is merged to the HIMSS Analytics data in two stages. First, hospitals are merged using Medicare number. The remaining unmatched hospitals are matched by zip code, and matches between the two data sets are identified manually. Hospitals in the HIMSS Analytics data that do not match the AHA are dropped.

3.1.4. Key Variable Construction

A key variable in the construction of this data set is hospitals' HIE adoption status. I construct this variable by using data reported by both surveys - the HIMSS Analytics data and the AHA IT Supplement. I assume a hospital has adopted HIE if it is reported as having HIE in either the HIMSS data or the AHA IT Supplement.

The HIMSS survey reports whether a hospital participates in any type of information exchange initiative. Hospitals specify the form of HIE they partake in, with options including a regional health information organization, a federal information exchange initiative, or a proprietary information exchange. I define hospitals as participating in HIE according to the HIMSS if they report participating in any type of information exchange. There are two drawbacks to the HIMSS Analytics survey. First, it does not distinguish between a missing data element and not having the technology. In the analysis, I assume that missing data is equated to not having the technology. This is consistent with past studies that have used the HIMSS data (Vest 2010). Moreover, I do not allow for disadoption in the data. If a hospital reports having adopted HIE at some point during the study period, it is assumed to have it for the remainder of the study time. The second drawback is that all of the data elements for hospital information exchange are missing in year 2011. Therefore, the increasing sample size of the AHA IT Supplement is important in the construction of the data set.

The AHA IT data reports the types of information that are electronically exchanged and with whom it is exchanged. Specifically, the survey reports whether the hospital electronically exchanged data on patient demographics, clinical care records, labs, medication reports, and radiology reports. The AHA also reports whether hospitals participate in a RHIO. I define hospitals as having HIE according to the AHA if they report electronically exchanging at least one type of data with hospitals outside of their hospital system or being part of a RHIO. As with the HIMSS data, disadoption is not allowed for in the analysis. There are 1,199 instances in the data set in which a hospital is reported as not having HIE after it reported having HIE in the previous year. However, with my assumption for disadoption these hospitals are assumed to have HIE for the remainder of the study period.

About 55% of the observations on HIE adoption status agree between the HIMSS Analytics database and the AHA IT Supplement. There are a couple possible reasons for the poor match between the two. First, it is possible that the poor match reflects the broad and varying definition of HIE. The two surveys specify different questions about the exact form of HIE participation, and the different responses could be responses to the specific questions. By combining both measures, I am creating an even broader definition of HIE. Second, the assumption that missing data elements in the HIMSS survey indicate no HIE adoption could be under-reporting rates of HIE in the HIMSS data. Finally, the poor match could reflect poor data quality of one or both of my data sources, despite being the two best sources of data on hospital IT characteristics. These data are self-reported so it is possible that there are errors.

Moreover hospitals in the AHA that do not match the HIMSS or AHA IT data are retained. Responders to the HIMSS and AHA IT Supplement may be more likely to have IT capabilities compared to non-responders. Therefore, to account for this potential bias towards greater IT adoption, these hospitals are assumed to not have IT. In sensitivity analyses, these hospitals are dropped and results are qualitatively robust.

The dependent variable in the first analysis is whether a hospital adopts HIE in a given year. Adoption in year t is defined as yes if a hospital has the capability in year t and does not have it in year $t-1$. After a hospital adopts, it is dropped from the analysis sample so as not to penalize a hospital for already having adopted. Furthermore, as discussed previously, if a hospital has adopted technology, it is assumed to have the capability for the remainder of the study period. Given the short study range and the high costs of implementing an IT system it is unlikely that there is significant actual disadoption in the time period. Moreover, because the analysis focuses on adoption, disadoption behavior is not as relevant. The construction of the dependent variable on adoption in time t requires data from years t and $t-1$. As a result, data from years 2008 through 2012 is used in construction of the data set, but only years 2009 through 2012 are represented in the analysis sample.

A variable used in the multiple-network analysis is hospitals' vendor choice. I focus on hospitals' vendor choice for clinical data repository software, which stores electronic patient medical records. I choose this particular IT capability because it is most directly related to HIE and is likely to be accessed when engaging in HIE. In the vendor choice variable, I allow for hospitals to change vendor from year-to-year. In the study period, there are 1,137 observations in which a hospital reports changing vendors from one year to the next. Hospitals using the same clinical data repository vendor are defined as being interoperable.

3.1.5. Market Definition

I delineate markets by hospital referral regions (HRRs) as defined by the Dartmouth Atlas. HRRs are defined by documenting where Medicare patients are referred for major cardiovascular surgical procedures and neurosurgery. I use HRR as the market definition because it represents a fairly large market size in which we could expect to see network effects operating. There are 305 HRRs represented in my data set. I fix markets at 2008 HRRs to avoid hospitals moving in and out of markets over time.

3.2. Construction of Multi-State Hospital Dataset

I construct a multi-state hospital-level panel data set to empirically test for competitive effects described in Section 5.1. The data set represents hospitals in California, Florida, and New York from years 2008 through 2011. This multi-state panel incorporates information on a hospital's patient population. The measures on patient population are constructed and merged to hospital characteristics described in Section 3.1 for the three states of interest.

3.2.1. Data Source: State Inpatient Data

The patient data is drawn from the Healthcare Cost and Utilization Project (HCUP). The HCUP database represent comprehensive state inpatient data. The data are at the discharge-level and allow me to track patients across facilities and time. I aggregate the patient data to the hospital-level. California, Florida, and New York are selected for two reasons. First, data is available to me for these three states. Second, these states have patient-level identifiers that allow me to track patients across time and multiple facilities.

3.2.2. Key Variable Construction

The state inpatient data provide a key independent variable - the patients shared or the portion of patients treated by a hospital who also visit at least one other hospital in that year. The numerator of the fraction is the number of patients who visit the given hospital and at least one other hospital in the given year. The denominator is the total number of patients the visit that hospital in that year. Patient identifiers are not attributed to about 20% of discharges in the state inpatient data. These discharges are assumed to each represent unique patients.

3.3. Construction of Pairwise Hospital Dataset

I construct a multi-state pairwise data set of hospitals for the empirical test for network effects described in Section 4.3. The data set represents California, Florida, and New York in years 2008 through 2011. It represents the same set of hospitals as the data set described in Section 3.2, but it is oriented differently. The observations are at the hospital-pair level. Any two hospitals that are in the same market form an observation. In addition, any pair of hospitals for which there is at least one patient who has an inpatient stay at both hospitals form an observation. The data set is constructed using state inpatient data from HCUP and hospital-level data described in the previous sections.

3.3.1. Key Variable Construction

A key variable that is constructed in this data set is the portion of patients shared between the two hospitals in a pair. This measure is constructed from the discharge-level inpatient data. The numerator in this variable is the number of patients who visit both hospitals in a given year. The denominator is the average number of unique patients that visit the two hospitals in the given year.

Another measure used in this analysis is the distance between the two hospitals. I use hospital latitude and longitude measures from the AHA Annual Survey. I measure straight-line distance between hospital pairs in kilometers.

A third measure is whether or not the hospital pairs are in the same system. I use system membership data from the AHA Annual Survey to identify hospital systems. While there are a couple instances where hospitals are reported to have changed systems from one year to the next, I assume hospitals remain in their 2008 system through the study period.

3.4. Construction of Discharge Dataset

I construct a discharge-level data set representing the Manhattan HRR from years 2008 through 2011 for the patient flow analysis described in Section 5.2. The data is extracted from the New York HCUP inpatient files. Specifically, the sample represents all discharges in hospitals in Manhattan that were in one of the top ten major diagnostic categories. This includes discharges for which the patient lived outside of Manhattan. Hospital characteristics are merged with the discharge data for the hospitals represented in the data set.

float

CHAPTER 4 : EMPIRICAL TESTS FOR NETWORK EFFECTS

In Chapter 2, I show that presence of network and competitive effects can lead to suboptimal rates of HIE adoption. In this chapter, I empirically test for network effects in hospital HIE and vendor choice.

If network effects exist, the value of adoption for a given hospital increases in the number of other hospitals that have adopted the technology. Therefore, the decision of whether to adopt can be expressed as

$$Adopt_i = \mathbb{1}(\pi_i(HIE_{-i}) > 0) = \mathbb{1}(\gamma X_i + \beta f(HIE_{-i}) + \epsilon_i > 0) \tag{4.1}$$

where $Adopt_i$ indicates whether hospital i adopts the technology, $f(HIE_{-i})$ is the fraction of other hospitals that have adopted the technology in hospital i's market, X_i is a vector of hospital i characteristics, and γ is a vector of parameters. If β is positive, network effects exist and adoption by hospitals in the market increases the likelihood of adoption by hospitals that have not yet adopted.

This chapter consists of three main analyses. The first two are based on Equation 4.1. First, I test for network effects in HIE adoption, using the first measure of general HIE adoption, by studying how adoption is affected by the fraction of other adopters in the market using the national panel data set. I address potential endogeneity by exploiting exogenous variation in market adoption rates stemming from variation in hospital system adoption rates. I also test for heterogeneity in adoption behavior in response to market adoption rates. Second, I test for network effects in vendor choice by studying how likelihood of adoption is affected by market adoption rates of a vendor. I use variation in system vendor choice to address potential endogeneity.

The first two analyses assume that adoption by other hospitals is equally valuable regardless of which hospitals have adopted. However, network effects should be stronger when hospitals are more clinically integrated. In the third analysis, I test whether more clinically integrated hospitals are more likely to be interoperable. I measure clinical integration by the portion of patients shared by two hospitals. If network effects exist, it should be more valuable to be interoperable with a hospital with which a high patient population is shared.

4.1. Empirical Strategy: Network Effects in HIE Adoption

Adapting the method of Gowrisankaran and Stavins (2004), I test for network effects by studying the effect of market adoption rates on HIE adoption. I estimate the following model, adapted from Equation 4.1:

$$Adopt_{isjt} = \beta_0 + \beta_1 f(HIE_{-i-sjt}) + \gamma X_{isjt} + \alpha_i + t + \epsilon_{isjt} \tag{4.2}$$

where $Adopt_{isjt}$ is a binary measure indicating whether hospital i in system s and market j adopts the technology in time t, $f(IT_{-i-sjt})$ is the fraction of other hospitals in market j but not in system s that have adopted by time t, X_{isjt} represents a vector of hospital characteristics, α_i are hospital fixed effects, t indicate year fixed effects, ϵ_{isjt} is the error, and β_0, β_1, and γ are parameters.

The explanatory variable of interest, $f(HIE_{-i-sjt})$ is the adoption rate in the market and is calculated as

$$f(HIE_{-i-sjt}) = \frac{\text{\# hospitals in market } j \text{ and not in system } s \text{ at time } t \text{ with HIE}}{\text{\# hospitals in market } j \text{ and not in system } s \text{ at time } t}.$$

Hospitals in hospital i's system are excluded because the decision process to adopt within a system may be related to factors other than network effects. For example, if a hospital system and an IT vendor negotiated a rate to purchase an IT system for all hospitals in a system, that would confound the network effect.

In the analysis, I control for log number of admissions, portion of inpatient days attributable to Medicare patients, and portion of inpatient days attributable to Medicaid days. I also control for hospital and time fixed effects in certain specifications

I run three specifications of the model. First, I estimate a pooled linear probability model on Equation 4.2 without the time or hospital fixed effects. Second, I estimate a fixed effects linear probability model. A major assumption for identification in the fixed effects linear probability model is that the ϵ's are not correlated across hospitals in a market. Because I control for hospital and time fixed effects, the restriction still allows for peer-group effects and for time-specific shocks. For example, if a hospital or market uses more IT because the residents or consumers in the market have stronger preference for it, this will be captured by the fixed effects. Also, if IT usage is increasing over time because of government policies or decreased price, the yearly fixed effects will be positive. Finally, I run a two stage fixed effects model to address potential endogeneity. The rationale and approach are discussed in the following section.

4.1.1. Addressing the Endogeneity Problem

While the fixed effects model described above is robust to peer-group and time-specific shocks, market- and time-varying shocks are not consistent. Manski (1993) highlights the challenge of distinguishing peer effects from characteristics shared by the the entity of interest and the reference group driving the behavior. In this setting, for example, a market-wide advertising campaign by an IT company that causes many hospitals to adopt in a market may be incorrectly measured as network effects.

To address the concern about endogeneity, I instrument for the explanatory variable, market adoption rate, and estimate a two stage fixed effects model. I instrument for market adoption rate with the fraction of adopters in the same system but different markets as hospitals represented in the explanatory variable. Using variation from adoption rates outside hospital i's market circumvents concern about time-varying market-level factors confounding identification of network effects. The exclusion restriction is that adoption behavior should not be affected by adoption by hospitals in different markets and different systems. The instrument relies on correlation of HIE adoption between hospitals in a system and system-level variation in HIE adoption rates. Such correlation in within-system adoption could stem from factors such as cultural factors or system-level negotiated IT adoption rates. However, for the purposes of the analysis, it is important that the actual adoption decision be made based on profitability of adoption for the individual hospital. In the data, while there is correlation in adoption behavior among hospitals in a system, adoption decisions appear to be made on a hospital-by-hospital basis as there is variation in adoption between hospitals in a system.

The instrument is constructed in several steps. First, I identify the hospital systems represented in market j, excluding system s. I then count the number of hospitals in this set of systems that are in markets other than j. This number constitutes the denominator of the instrument. The numerator is the number of hospitals represented in the denominator that have adopted HIE. About three hundred observations drop out of the data set because the instrument cannot be computed. This can result if the hospital is in a market with only non-system hospitals or is part of the only system in the market.

I estimate the following two stage model:

$$\begin{aligned} f(HIE_{-i-sjt}) &= \beta_0' + \beta_1' g(HIE_{-i-s-jt}) + \gamma' X_{isjt} + \alpha_{is}' + t' + \epsilon_{isjt}' \\ Adopt_{isjt} &= \beta_0 + \beta_1 f(\widehat{HIE_{-i}}_{-sjt}) + \gamma X_{isjt} + \alpha_{is} + t + \epsilon_{isjt} \end{aligned} \tag{4.3}$$

where $g(HIE_{-i-s-jt})$ is the instrument, the fraction of adopting hospitals in the same system but different market as hospitals constituting the denominator in $f(HIE_{-i-sjt})$. As in the fixed effects model, hospital controls, hospital fixed effects, and year fixed effects are included, and both stages are estimated as fixed effects linear probability models.

I conduct several tests on the strength and consistency of the two stage model. I conduct a Durbin-Wu-Hausman to test for endogeneity of the regressor. I also examine first stage results of the two stage analysis. Additionally, since the analysis relies on correlation of adoption between within-system hospitals, I examine how a hospital's technology adoption is associated with adoption rates in its system.

4.1.2. Sensitivity Analyses

I conduct several sensitivity analyses to test the robustness of the main analyses described above. First, adoption by larger hospitals may increase the value of HIE compared to adoption by small hospitals. To allow for this, I weight larger hospitals more heavily in the measurement of fraction of adopters. Specifically, I weight $f(HIE_{-i-sjt})$ and $g(HIE_{-i-s-jt})$ by market share as measured by admissions and then estimate the fixed effects and two stage fixed effects model.

Second, there may be a lag between hospitals' observation of market adoption rates and adoption. To account for this, I lag the independent variable and instrumental variable. Lagged measure may also be appropriate if there is a ramp up period after adoption before hospitals can begin to use the IT and realize the network effects. I estimate the fixed effects and two stage fixed effects models with lagged measures.

In the third sensitivity analysis, I remove the observations for hospitals that do not appear in the HIMSS Analytics data or AHA IT Supplement. In the main analysis, these hospitals are assumed to not have adopted the technology. I estimate the fixed effects and two stage fixed effects models.

In the fourth sensitivity analysis, I include state fixed effects to account for state policies or information-sharing infrastructure that may affect the level of adoption. Again, I estimate the fixed effects and two stage fixed effects models.

In the fifth sensitivity analysis, I test the shape of the network effect. I subset the data by quartile of market HIE adoption rate. I run the analysis on each quartile of the data. The relative magnitude of the coefficients will provide insight into the network effects. If the coefficients are increasing from quartile to quartile, it provides evidence for linearity of network effects in the fraction of adopters.

The sixth sensitivity analysis aims to address the possibility that large hospitals may influence smaller hospitals in a system with respect to their IT adoption. On the other hand, small hospitals are not likely to induce a large hospital in their system to adopt. If this is the case, endogeneity may exist in the adoption decision by large hospitals in a system in the two stage analysis. To address this concern, I remove the largest quartile of hospitals from each hospital system and re-estimate the two stage fixed effects analysis.

4.1.3. Heterogeneity in Response to Market Adoption Rate

I test for heterogeneity in response to market adoption rate on two dimensions - market competition and market share. By examining network effects by market competition, I examine how network effects vary on the basis of heterogeneity by market share. In competitive markets, there is more equal distribution of market share compared to concentrated markets. Therefore, if differential response exists, there should be stronger evidence of network effects for hospitals in competitive markets. Under scaling network effects, the model predicts that larger hospitals realize a larger network effect from adoption. On the other hand, the model of competitive effects predicts that larger hospitals receive a lower marginal incentive to adopt because they are vulnerable to losing more patients. The differential effect between high and low market share hospitals will suggest whether larger hospitals have higher or lower incentive to adopt relative to smaller hospitals.

In the analysis by market competition, I subset the data at the median Herfindahl-Hirschmann Index (HHI) in 2008. The HHI is calculated as the sum of squared market share across hospitals in a market-year. In this analysis, I calculate market share by the number of beds. I then test for network effects in HIE adoption on the subsetted data by estimating Equations 4.2 and 4.3. As in the analysis in Section 4.1, I estimate a fixed effects model and a fixed effects model with an instrumental variable.

In the second analysis, I subset the data by median market share in 2008. Market share is calculated as the number of admissions divided by the total number of admissions in the market. Again, I estimate Equations 4.2 and 4.3.

4.1.4. Data

This analysis uses hospital-level panel data described in Section 3.1. The panel represents hospitals from 2009 to 2012.

4.2. Empirical Strategy: Network Effects in Vendor Choice

In the second analysis, I test for network effects in hospitals' vendor choice. Since hospitals' can choose from multiple vendors, I estimate a multinomial logit model:

$$Vendor_{isjt} = \frac{exp(\beta_1 f(v_{-sjt}) + v + t + \epsilon_{isjt})}{1 + \sum_{k=1}^{K} exp(\beta_1 f(v_{-sjt}) + v_k + t + \epsilon_{isjt})} \tag{4.4}$$

where $Vendor_{isjt}$ is vendor choice of hospital i in system s and market j at time t, $f(v_{-sjt})$ is the fraction of other hospitals in market j and not in system s that have adopted vendor v, v indicates vendor fixed effects, t indicates year fixed effects, and ϵ_{isjt} is an error. The explanatory variable of interest is measured equivalently to the explanatory variable in the previous analysis.

I estimate Equation 5.1 with a conditional logit to estimate a probability of adoption for each vendor for each hospital.

I use two measures of the dependent variable. The first measure is use and it indicates whether a hospital reports having that vendor in a given year. The second dependent variable is adopt and it indicates whether the hospital reports having adopted the vendor in that year. The adopt measure is analogous to the dependent variable used in the previous analysis. The analysis focuses on clinical data repository software and much adoption occurs before the study period. Therefore, analyses with the second measure of vendor choice, adopt have fewer observations. Unlike in the analysis on

HIE adoption, I allow for hospitals to switch vendors during the study period.

4.2.1. Addressing the Endogeneity Problem

Concerns about endogeneity that were discussed in Subsection 4.1.1 may also be a concern in this analysis of vendor choice. The example of a marketing-campaign biasing measurement of network effects in vendor choice may be relevant in this setting. To address potential endogeneity, I use an instrumental variable and a two stage residual inclusion estimation method (Terza, Basu, and Rathouz 2008). The instrument is analogous to that in the previous analysis. I instrument for market adoption rate of vendors with adoption rates of hospitals outside the market in the systems represented.

I estimate a two stage residual inclusion model rather than a two stage fixed effects model because the second stage is nonlinear. The two stage model is as follows:

$$f(v_{-i-sjt}) = \beta_0' + \beta_1' g(v_{-i-s-jt}) + v' + t' + \epsilon_{isjt}'$$

$$Vendor_{isjt} = \frac{exp(\beta_1 f(v_{-i-s-jt}) + v + t + \widehat{\epsilon_{isjt}'} + \epsilon_{isjt})}{1 + \sum_{k=1}^{K} exp(\beta_1 f(v_{-i-sjt}) + v_k + t + \widehat{\epsilon_{isjt}'} + \epsilon_{isjt})}$$

where $g(v_{-i-s-jt})$ is the instrumental variable and $\widehat{\epsilon_{isjt}'}$ indicates the predicted residuals. As in the previous analysis, I will also examine the first stage results for the strength of the instrument.

4.2.2. Data

This analysis also uses hospital-level panel data described in Section 3.1. Years 2008 through 2012 are represented in specifications with the dependent variable indicating use of a vendor. The panel begins in year 2009 for specifications in which the dependent variable is measured as adoption.

4.2.3. Descriptive Statistics

Table 5 reports descriptive statistics of the national hospital data set at the hospital level. Eighteen percent of hospitals adopt HIE during the study period, and 52% of hospitals have HIE. Market adoption rates are 49% on average. Tables 6 and 7 compare HIE adopters and non-adopters by year. In general, hospitals that adopt are larger than hospitals that do not adopt HIE. Adopting hospitals are also more likely to be non-profit and less likely to be for-profits.

Table 8 reports descriptive statistics at the market-level. The data set represents 1,107 market-years. In the average market, 56% of hospitals have adopted HIE. The average hospital has about 15 hospitals and 2.6 systems. Fifty-three percent of hospitals are system-members.

Figure 4 shows distribution of HIE market adoption rates over the study period. The figure illustrates the variation in rates over time and the increasing rates of adoption over the course of the study period.

Table 9 reports system-level descriptive statistics. The data set represents 973 hospital system-years. The average system has about eight hospitals and spans three markets. HIE adoption rates in the average system is 47%.

Table 5: Hospital-Level Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Adopts HIE	8,472	.18	.38	0	1
Fraction HIE	8,472	.52	.21	0	1
Fraction HIE in System	8,472	.49	.19	0	1
Admissions	8,472	6,270.91	7,739.13	50	70,384
Portion Medicare	8,471	.52	.18	0	1
Portion Medicaid	8,471	.19	.15	0	.99
Market Share	8,472	.06	.1	0	.94
Year 2009	8,472	.32	.47	0	1
Year 2010	8,472	.26	.44	0	1
Year 2011	8,472	.22	.42	0	1
Year 2012	8,472	.2	.4	0	1

Table 6: Hospital Characteristics of Adopters and Non-Adopters, Mean (SD)

	2008		2009		2010		2011	
	Yes	No	Yes	No	Yes	No	Yes	No
Admissions	7,879	6,479	8,289	6,068	7,249	5,833	6,080	5,508
	(9,332)	(8,030)	(10,351)	(7,360)	(8,724)	(7,095)	(7,608)	(6,674)
Number Beds	179	153	185	147	170	144	149	142
	(191)	(165)	(200)	(156)	(190)	(151)	(161)	(147)
Number Physicians	19	12	18	12	17	11	19	9.5
	(84)	(66)	(79)	(63)	(59)	(60)	(95)	(38)
Number RN Nurses	221	177	247	170	219	165	183	162
	(309)	(259)	(357)	(241)	(324)	(228)	(263)	(218)
Portion Medicare	.5	.52	.5	.52	.52	.53	.51	.53
	(.18)	(.18)	(.17)	(.18)	(.19)	(.18)	(.19)	(.18)
Portion Medicaid	.19	.18	.2	.19	.19	.18	.19	.18
	(.15)	(.15)	(.15)	(.16)	(.16)	(.15)	(.16)	(.14)
System member	.53	.53	.57	.54	.56	.56	.57	.57
	(.5)	(.5)	(.5)	(.5)	(.5)	(.5)	(.5)	(.49)
Academic Med Ctr	1.7	1.8	1.7	1.8	1.8	1.8	1.8	1.8
	(.45)	(.39)	(.45)	(.38)	(.42)	(.37)	(.4)	(.38)
Market Share	.075	.059	.081	.055	.078	.052	.061	.048
	(.12)	(.095)	(.13)	(.09)	(.11)	(.089)	(.098)	(.085)

Table 7: Hospital Ownership by Adopters and Non-Adopters, Percent

	2008		2009		2010		2011	
	Yes	No	Yes	No	Yes	No	Yes	No
For profit	12	22	8	24	12	27	14	32
Govnonfederal	25	25	25	25	28	23	26	22
Non Profit	63	53	66	51	60	50	60	46
Total	100	100	100	100	100	100	100	100

Table 8: Market-Level Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Market Adoption	1,107	.56	.23	0	1
HHI	1,107	.21	.14	.02	.87
Number Hospitals	1,107	14.9	13.1	2	79
Number Systems	1,107	2.57	2.5	0	17
System Members	1,107	.53	.32	0	1

Figure 4: Market Adoption Rates

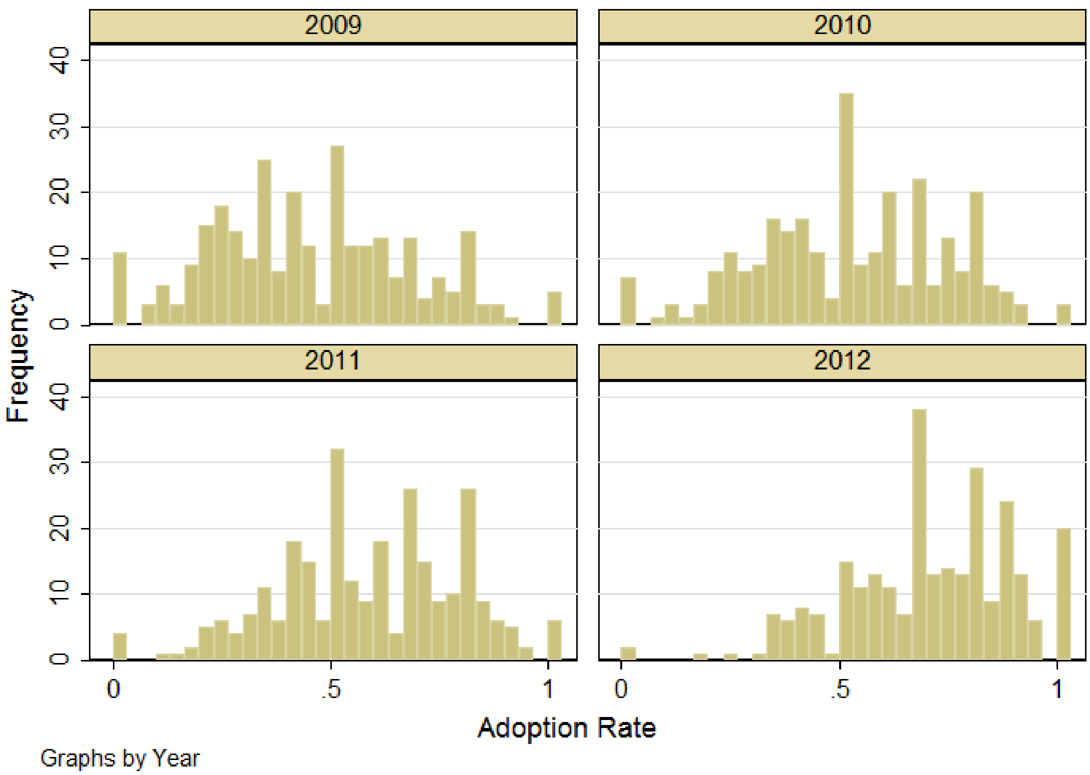


Table 9: System-Level Summary Statistics: 2008 - 2012

Variable	Obs	Mean	Std. Dev.	Min	Max
Number Hospitals	973	8.44	15.25	1	133
Number Markets	973	2.93	5.94	1	64
System HIE Adoption	973	.47	.34	0	1

4.3. Empirical Strategy: Network Effects by Clinical Integration

In the third analysis, I test the effect of clinical integration measured by the fraction of shared patients on the likelihood of two hospitals being interoperable.

I estimate a fixed effects linear regression on the following model:

$$\begin{aligned} Interoperable_{ijt} = \quad & \beta_1 PatientsShared_{ijt} + \beta_2 SameSystem_{ij} \\ & + \beta_3 Distance_{ij} + \alpha_i + \alpha_j + t + \epsilon_{ijt} \end{aligned}$$

where each observation represents a hospital pair ij at time t. The dependent variable $Interoperable_{ijt}$ indicates if hospitals i and j are interoperable at time t. Interoperability is defined as yes if hospitals i and j use the same vendor. $PatientsShared_{ijt}$ is the portion of patients who visit hospitals i and j in time t divided by the average number of unique patients visiting hospitals i and j in year t. I also control for $SameSystem_{ij}$, whether hospital i and j are in the same system, and $Distance_{ij}$, the distance between hospitals i and j. Distance is straight-line measure between the hospitals. I also include year fixed effects and fixed effects for hospitals i and j.

I estimate two versions of the model, handling hospital pairs in which neither hospital has adopted a vendor differently. In the first version, if neither hospital has adopted a system, I define the pair as not interoperable. In the second version, I drop hospitals in which neither hospital has adopted a system.

If network effects exist, β_1 is significant and positive. This indicates that a higher number of patients shared between two hospitals increases the likelihood that they adopt the same vendor.

4.3.1. Data

This analysis uses hospitals from the multi-state panel data from 2008 to 2011 described in Section 3.2. However, the data is organized in a pairwise fashion where each observation represents hospitals i and j at time t. The number and fraction of patients shared between the two hospitals is calculated from the state inpatient data. The sample consists of all hospital pairs that share any patients and all hospital pairs in a given market.

4.3.2. Descriptive Statistics

Table 10 shows descriptive statistics for the hospital pairwise data set. There are 60,245 hospital pairs in the data set. Fifteen percent are interoperable, average distance is one hundred kilometers, and twenty percent are in the same hospital system. The fraction of patients shared ranges from 0% to 15%

Table 10: Hospital-Pair Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Interoperability	60,245	.1529	.3599	0	1
Fraction Shared Patients	60,245	.0029	.0073	0	.148
Distance	60,245	100.6994	116.8353	.0201	877.8791
Same System	60,245	.1968	.3976	0	1

4.4. Results: Network Effects in HIE Adoption

I find evidence of network effects in HIE adoption. Results of the pooled, fixed effects, and two stage fixed effects models are reported in Table 11.

I find evidence of network effects in HIE adoption with hospitals more likely to adopt when other hospitals in the market have adopted. The coefficient on fraction HIE reflects the network effect. Column 1 reports results from the pooled regression analysis, and I find positive and statistically significant evidence of network effects on HIE adoption. Column 2 reports results from the fixed effects linear regression and the coefficent is positive and statistically significant. Column 3 reports results from the two stage fixed effects regression and I find a positive and statistically significant coefficient. Using the coefficient from the two stage fixed effects model, the results indicate that a 10% increase in the fraction of adopting hospitals increases a hospital's likelihood of adopting by 9.2%. It is puzzling that the instrumental variables result is higher than the result without the instrumental variables. Generally, endogeneity is expected to affect adoption by hospital i and adoption by other hospitals in the market in the same direction. However, this result suggests that hospital i is being affected in the opposite directions. One explanation is that some hospitals in markets with high adoption rates resist HIE adoption as a form of differentiation. For example, if some patients have privacy concerns related to HIE, hospitals may not adopt in order to differentiate themselves and appeal to these patients.

In general, hospital characteristics such as log admissions, portion of Medicare inpatient days, and portion of Medicare inpatient days were not statistically significant, indicating that hospital fixed effects absorb much of the variation. The time fixed effects indicate that we see increasing adoption from years 2009 through 2012.

4.4.1. Validity of the Instrumental Variable

The tests support the two stage fixed effects model and instrumental variable. The Hausman test rejects the null hypothesis at the $p < 0.05$ level suggesting the regressor is endogenous. First stage results for the two stage fixed effects model estimated in

Table 11: Effect of Market Adoption Rate on HIE Adoption

	(1) Pooled	(2) FE	(3) FE w/IV
Adoption Rate	0.217***	0.202***	0.883**
	(0.02)	(0.05)	(0.32)
Admissions (log)	0.013***	0.023	0.038
	(0.00)	(0.03)	(0.03)
Portion Medicare	-0.041	-0.005	-0.003
	(0.03)	(0.05)	(0.05)
Portion Medicaid	-0.011	0.068	0.067
	(0.04)	(0.07)	(0.07)
Year 2010		0.133***	0.078**
		(0.01)	(0.03)
Year 2011		0.171***	0.078
		(0.01)	(0.05)
Year 2012		0.364***	0.185*
		(0.02)	(0.09)
Constant	-0.014	-0.261	-0.670*
	(0.03)	(0.22)	(0.30)
Observations	8,470	8,470	8,470
F statistic	35	241	232
Hospital FE	No	Yes	Yes
Year FE	No	Yes	Yes

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Table 12: First Stage - Effect of Out of Market System Adoption on Adoption Rate

	FE
System Adoption Rate	0.176***
	(0.02)
Admissions (log)	-0.022**
	(0.01)
Portion Medicare	-0.004
	(0.01)
Portion Medicaid	-0.001
	(0.02)
Year 2010	0.067***
	(0.00)
Year 2011	0.113***
	(0.00)
Year 2012	0.218***
	(0.01)
Constant	0.525***
	(0.06)
Observations	8,470
F statistic	827
Hospital FE	Yes
Year FE	Yes

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Table 11 are reported in Table 12. The instrumental variable is strongly correlated with the endogenous regressor suggesting a strong instrument. The coefficient on the instrument is positive and statistically significant. The F-statistic is 827. This is high indicating a well-fit model. The large magnitude results from a very small sum of square errors in the data.

Table 13 reports results on correlation of adoption and hospital system adoption rates. The coefficient on system adoption rate is positive and statistically significant. This reinforces the relevance of the instrument, by demonstrating the correlation between HIE adoption and adoption by other hospitals in the system.

Table 13: Association of Adoption and System Adoption Rate

	FE
Fraction HIE in system	1.047***
	(0.03)
Admissions (log)	0.028
	(0.03)
Portion Medicare	-0.036
	(0.05)
Portion Medicaid	0.039
	(0.07)
Year 2010	0.054***
	(0.01)
Year 2011	0.044***
	(0.01)
Year 2012	0.116***
	(0.01)
Constant	-0.576*
	(0.22)
Observations	8470
F statistic	335
Hospital FE	Yes
Year FE	Yes

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

4.4.2. Results: Sensitivity Analyses

I conduct several sensitivity analyses to test the robustness of the main results reported in Table 11. Results of the sensitivity analyses on HIE adoption are consistent with the main analysis.

Table 14 reports results with weighted adoption rate to account for the greater value adoption by larger hospitals may add relative to adoption by smaller hospitals. Column 1 represents the fixed effects regression on HIE adoption and the coefficient on adoption rate is positive but not statistically significant. Column 2 reports the two stage fixed effects results and the coefficient is much larger and statistically significant. Since the fraction HIE variable is weighted by market share as measured by admissions, it is possible that the large coefficients could be a result of collinearity. To address this possibility, I re-estimate the two stage fixed effects regression for HIE adoption and drop the admissions variable. This result is reported in Column 3. The coefficient on weighted adoption rate remains large. The larger coefficients indicate that larger hospitals are more influential in inducing adoption by other hospitals. Overall, the results of this weighted analysis maintain the existence of network effects for HIE adoption even when accounting for size of the participants.

Table 15 reports results of the analysis with lagged adoption rate. Column 1 reports the results from the fixed effects regression and the coefficient is positive and statistically significant. Column 2 reports the two stage fixed effects results and again the coefficient is also positive and statistically significant. These results also are also consistent with the main results.

Table 16 reports results when hospitals that are missing in the HIMSS and AHA IT data are missing. Fifty-five observations were removed as a result. Column 1 reports

Table 14: Effect of Weighted Market Adoption Rate on HIE Adoption

	(1) Pooled	(2) FE w/IV	(3) FE w/IV (2)
Adoption Rate (weighted)	0.316	4.745*	4.796*
	(0.21)	(2.15)	(2.17)
Admissions (log)	0.020	0.040	
	(0.03)	(0.03)	
Portion Medicare	-0.006	-0.008	-0.010
	(0.05)	(0.05)	(0.05)
Portion Medicaid	0.068	0.068	0.064
	(0.07)	(0.07)	(0.07)
Year 2010	0.147***	0.118***	0.116***
	(0.01)	(0.02)	(0.02)
Year 2011	0.194***	0.142***	0.139***
	(0.01)	(0.03)	(0.03)
Year 2012	0.411***	0.327***	0.321***
	(0.01)	(0.04)	(0.04)
Constant	-0.162	-0.462	-0.145
	(0.24)	(0.27)	(0.08)
Observations	8,470	8,470	8,470
F statistic	194	220	256
Hospital FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Table 15: Effect of Market Adoption Rate on HIE Adoption with Lag

	(1) FE	(2) FE w/IV
Adoption Rate(lagged)	0.237**	0.818*
	(0.08)	(0.41)
Admissions (log)	0.028	0.043
	(0.04)	(0.04)
Portion Medicare	-0.035	-0.032
	(0.07)	(0.07)
Portion Medicaid	0.045	0.043
	(0.09)	(0.09)
Observations	5,766	5,766
F statistic	163	198
Hospital FE	Yes	Yes
Year FE	Yes	Yes

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

fixed effects regression result on HIE adoption, and the coefficient of interest is positive and statistically significant. Column 2 reports the fixed effects two stage regression, and I again find a positive and statistically significant coefficient on fraction HIE adoption. The magnitude of the coefficient, 0.921, is comparable to that in the main results.

Table 17 reports results with state fixed effects. Even with state fixed effects, the results confirm the existence of network effects. Column 1 represents the fixed effects linear probability model on HIE adoption, and the coefficient on fraction of adopters is positive and statistically significant. Column 2 reports the results from the two stage fixed effects model on HIE adoption, and the coefficient is also positive and statistically significant. These results are consistent with the findings of the main analysis.

Table 18 reports results of the fixed effects analysis by quartile of the market adoption

Table 16: Effect of Market Adoption Rate on HIE Adoption with HIMSS and IT Data

	(1) FE	(2) FE w/IV
Adoption Rate	0.205***	0.890**
	(0.05)	(0.32)
Admissions (log)	0.030	0.046
	(0.03)	(0.03)
Portion Medicare	-0.005	-0.003
	(0.05)	(0.05)
Portion Medicaid	0.073	0.072
	(0.07)	(0.07)
Year 2010	0.133***	0.077**
	(0.01)	(0.03)
Year 2011	0.171***	0.078
	(0.01)	(0.05)
Year 2012	0.365***	0.184*
	(0.02)	(0.09)
Observations	8,423	8,423
F statistic	195	232
Hospital FE	Yes	Yes
Year FE	Yes	Yes

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Table 17: Effect of Market Adoption Rate on HIE Adoption with State FE

	(1) FE	(2) FE w/IV
Adoption Rate	0.203***	0.887**
	(0.05)	(0.32)
Admissions (log)	0.025	0.041
	(0.03)	(0.03)
Portion Medicare	-0.007	-0.005
	(0.05)	(0.05)
Portion Medicaid	0.071	0.070
	(0.07)	(0.07)
Year 2010	0.133***	0.077**
	(0.01)	(0.03)
Year 2011	0.170***	0.077
	(0.01)	(0.05)
Year 2012	0.364***	0.184*
	(0.02)	(0.09)
Observations	8,470	8,470
F statistic	188	181
Hospital FE	Yes	Yes
Year FE	Yes	Yes

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Table 18: Effect of Market Adoption Rate on HIE Adoption by Quartile

	(1) First	(2) Second	(3) Third	(4) Fourth
Adoption Rate	-0.034	0.387	1.379***	0.434
	(0.23)	(0.41)	(0.40)	(0.23)
Admissions (log)	0.066	-0.029	-0.015	-0.020
	(0.07)	(0.06)	(0.06)	(0.08)
Portion Medicare	-0.037	0.013	0.028	-0.045
	(0.11)	(0.07)	(0.11)	(0.17)
Portion Medicaid	-0.199	0.285*	0.071	0.166
	(0.17)	(0.13)	(0.14)	(0.20)
Year 2010	0.136***	0.079***	0.128***	0.158***
	(0.02)	(0.02)	(0.03)	(0.03)
Year 2011	0.184***	0.130***	0.151***	0.250***
	(0.03)	(0.03)	(0.03)	(0.03)
Year 2012	0.524***	0.362***	0.446***	0.475***
	(0.07)	(0.06)	(0.06)	(0.05)
Constant	-0.408	0.038	-0.716	-0.245
	(0.54)	(0.54)	(0.50)	(0.65)
Observations	2,183	2,199	2,061	2,027
F statistic	25	14	24	38
Hospital FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

rate. The coefficient on market adoption rate is negative in the first quartile as seen in Column 2. It increases to be positive but small in the second quartile. It is the highest in the third quartile and falls by more than half in magnitude in the fourth quartile. This could indicate existence of a "tipping point."

Table 19 reports two stage fixed effects results in which the top quartile of hospitals in each system are removed. The coefficient on adoption rate is positive and statistically significant. This also suggests that larger hospitals are more influential in inducing smaller hospitals to adopt.

Table 19: Two Stage Analysis Excluding Largest Quartile of Hospitals by System

	FE w/IV
Adoption Rate	1.131*
	(0.49)
Admissions (log)	0.031
	(0.03)
Portion Medicare	-0.003
	(0.05)
Portion Medicaid	0.041
	(0.07)
Year 2010	0.042
	(0.04)
Year 2011	0.026
	(0.07)
Year 2012	0.096
	(0.13)
Constant	-0.705
	(0.36)
Observations	6,818
F statistic	170
Hospital FE	Yes
Year FE	Yes

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

4.4.3. Heterogeneity in Response to Market Adoption Rate

I find evidence that hospitals in competitive markets and low market share hospitals realize greater network effects compared to hospitals in concentrated markets and high market share hospitals, respectively. The finding of greater network effects for hospitals in competitive markets suggests that network effects operate more strongly when there is greater equality of market share divided among hospitals in the market. The fact that low market share hospitals experience a greater network effect suggests that smaller hospitals are more likely to adopt as the adoption rate increases, while large hospitals are less likely to respond to increasing adoption rate.

Table 20 displays results of the analysis subsetted at median HHI. Median HHI is 0.108, which represents a relatively unconcentrated market. Columns 1 and 2 report fixed effects results for hospitals in competitive and concentrated markets, respectively. I find the coefficient on market adoption rate is positive and statistically significant for hospitals in competitive markets. The coefficient for hospitals in concentrated markets is positive and smaller in magnitude but not statistically significant. Columns 3 and 4 reports results from the fixed effects with instrumental variables for hospitals in competitive and concentrated markets, respectively. Again, I find a larger coefficient on market adoption rate for hospitals in competitive markets compared to those in concentrated markets. While the coefficient for the set of hospitals in competitive markets is statistically significant, that for hospitals in concentrated markets is not. This differential suggests that hospitals in markets with even distribution of market share realize greater network effects relative to hospitals in concentrated markets.

Table 21 reports results on network effects in HIE adoption by market share. I subset

Table 20: HIE Adoption by Market Competition

	FE		FE w/IV	
	(1) Competitive	(2) Concentrated	(3) Competitive	(4) Concentrated
Adoption Rate	0.476***	0.100	1.676***	0.503
	(0.11)	(0.06)	(0.43)	(0.42)
Admissions (log)	0.005	0.061	0.022	0.074
	(0.04)	(0.04)	(0.04)	(0.04)
Portion Medicare	-0.012	0.016	0.010	0.010
	(0.07)	(0.08)	(0.07)	(0.08)
Portion Medicaid	0.118	0.037	0.132	0.029
	(0.09)	(0.10)	(0.10)	(0.10)
Year 2010	0.105***	0.148***	0.009	0.114**
	(0.01)	(0.01)	(0.04)	(0.04)
Year 2011	0.118***	0.203***	-0.037	0.145*
	(0.02)	(0.02)	(0.06)	(0.06)
Year 2012	0.274***	0.416***	-0.034	0.306**
	(0.03)	(0.02)	(0.11)	(0.11)
Constant	-0.239	-0.521	-0.883*	-0.787
	(0.32)	(0.35)	(0.38)	(0.44)
Observations	4,209	4,261	4,209	4,261
F statistic	93	102	111	123
Hospital FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

the data at the median market share which is 0.028. Columns 1 and 2 show results of the fixed effects regression for high and low market share hospitals, respectively. Both results are positive and statistically significant and the coefficient on market adoption rate for low market share hospitals is larger than that for high market share hospitals. Columns 3 and 4 show results of the two stage fixed effects regression for high and low market share hospitals, respectively. After introducing the instrument, I again find that the coefficient on market adoption rate is larger for low market share hospitals compared to that for high market share hospitals. However, the coefficient on high market share hospitals is not statistically significant. The results suggest that small hospitals respond more strongly to increasing market adoption rates. The results also suggest that high market share hospitals have enough incentive to adopt absent a high market adoption rate. Low market share hospitals may be followers who adopt in the presence of other adopters.

This analysis provides evidence for differential network effects by competition and market share. I find evidence for stronger network effects among hospitals in competitive markets providing evidence for heterogeneous network effects. I also find evidence of stronger network effects for low market share hospitals compared to high market share hospitals.

4.5. Results: Network Effects in Vendor Choice

I find evidence of network effects in hospitals' vendor choice though the magnitude and significance of the network effect vary depending on the specification.

Table 22 reports results. Column 1 reports results from the conditional logit in which the dependent variable is whether the hospital reported using the vendor in that year, and I find a positive and statistically significant coefficient on adoption

Table 21: HIE Adoption by Market Share

	FE		FE w/IV	
	(1)	(2)	(3)	(4)
	High Share	Low Share	High Share	Low Share
Adoption Rate	0.162*	0.248**	0.569	1.981*
	(0.07)	(0.09)	(0.35)	(0.79)
Admissions (log)	0.006	0.013	0.028	0.039
	(0.06)	(0.03)	(0.06)	(0.03)
Portion Medicare	-0.040	0.002	-0.038	0.008
	(0.12)	(0.06)	(0.12)	(0.06)
Portion Medicaid	0.041	0.068	0.056	0.037
	(0.14)	(0.07)	(0.13)	(0.09)
Year 2010	0.165***	0.101***	0.131***	-0.034
	(0.01)	(0.01)	(0.03)	(0.06)
Year 2011	0.210***	0.132***	0.152**	-0.092
	(0.02)	(0.02)	(0.05)	(0.10)
Year 2012	0.420***	0.309***	0.311**	-0.138
	(0.03)	(0.03)	(0.10)	(0.20)
Constant	-0.094	-0.190	-0.468	-1.087*
	(0.52)	(0.25)	(0.62)	(0.47)
Observations	4,107	4,363	4,107	4,363
F statistic	109	87	126	98
Hospital FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Table 22: Effect of Market Adoption Rate on Vendor Choice

	Multinomial Logit		2SRI	
	Use	Adopt	Use	Adopt
Fraction of other adopters	1.674***	2.009***	3.982***	0.935
	(0.15)	(0.30)	(0.42)	(1.07)
Year 2009	0.241***	-58.341	0.250***	-56.527
	(0.04)	(3428.57)	(0.04)	(2540.04)
Year 2010	-0.026	-39.056	-0.019	-37.793
	(0.04)	(3020.85)	(0.04)	(2205.71)
Year 2011	-0.101**	-20.647	-0.089*	-19.935
	(0.04)	(2891.65)	(0.04)	(2093.09)
Observations	1,392,950	86,840	1,336,400	80,000
Vendor Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

rate. Column 2 reports conditional logit results in which the dependent variable is whether the hospital adopted a given vendor in that year, and again the coefficient on the fraction of other adopters in the market is positive and statistically significant. Column 3 reports results from the two stage residual inclusion with the dependent variable defined as use of the vendor and the coefficient on fraction of adopters is again positive and statistically significant. Finally, Column 4 represents the two stage residual inclusion estimation with adoption as the dependent variable and the coefficient on fraction of adopters is positive though not statistically significant. I find some evidence of network effects in vendor choice, though the two stage residual inclusion result on adoption is not statistically significant.

To provide intuiton on the magnitude of the coefficient from the conditional likelihood results, I use the logit own-elasticity formula $\frac{dp(Vendor_i)}{d(p(Vendor_{-i}))} = \beta_1 p(Vendor_i)(1 - (Vendor_i)$. If the mean probability of adopting a vendor is 0.5, a 10% increase in adoption rate of a given vendor leads to a 1.5% increase in the likelihood of a hospital adopting the vendor using the results from Column 3 in Table 22.

Table 23: First Stage: Effect of System Adoption on Market Adoption Rate

	Adoption Rate
System Adoption (Instrument)	0.284***
	(0.00)
Year 2009	-0.000
	(0.00)
Year 2010	0.000
	(0.00)
Year 2011	0.001***
	(0.00)
Observations	1,336,400
Vendor Fixed Effects	Yes
Year Fixed Effects	Yes

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Table 23 reports results of the first stage regression. I find a positive and statistically significant coefficient on the outside-market adoption rate. This suggests a strong relationship between the instrument and endogenous variable.

4.6. Results: Network Effects by Clinical Integration

Table 24 presents results of the pairwise hospital analysis, and I find that hospital pairs with a high fraction of shared patients are likely to have adopted the same vendor. Column 1 presents the results in which hospital pairs where neither hospital has adopted HIE are considered not interoperable. The coefficient is positive and statistically significant. Column 2 reports results in which these hospital pairs are dropped from the analysis. Again, the coefficient is positive and statistically significant. The coefficient on system is also positive and statistically significant, reinforcing that adoption behavior within a system is correlated.

Using the coefficient from Column 2, the results suggest that a 10% increase in the fraction of shared patients is associated with a 54% increase in the likelihood of

Table 24: Interoperability by Shared Patients

	(1) Interoperability	(2) Interoperability (Alternate)
Fraction patients shared	5.262***	5.356***
	(0.26)	(0.26)
Same system	0.015*	0.015*
	(0.01)	(0.01)
Distance	0.000***	0.000***
	(0.00)	(0.00)
Year 2009	0.023***	0.023***
	(0.00)	(0.00)
Year 2010	0.024***	0.024***
	(0.00)	(0.00)
Year 2011	0.028***	0.028***
	(0.00)	(0.00)
Observations	60,245	59,847
F statistic	23	.
Hospital FE	Yes	Yes
Year FE	Yes	Yes

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

interoperability between two hospitals. While this provides supporting evidence for network effects, it is also possible that an ommited variable is confounding the result. For example, if two hospitals serve a similar type of patient population and vendor design their IT systems with certain specialties in mind, these hospitals have a high portion of shared patients and would be likely to adopt the same vendor.

4.7. Discussion

I find evidence of network effects in HIE adoption and vendor choice. With respect to HIE, I find that a 10% increase in the market adoption rate causes a 9.2% increase in the likelihood of adoption. In the vendor choice analysis, I find that a 10% increase the market adoption rate increases the likelihood of adoption by 1.5 %. As in other networks, the value of participating in HIE increases as the number of other participants increases. In each of the above estimates, hospitals from the same system are not included.

I find additional suggestive evidence for network effects by examining interoperability between hospital pairs that share a high patient population. I find that hospitals that share a high patient population are more likely to have adopted the same vendor.

In this chapter, I find evidence of network effects in HIE adoption and vendor choice. In the next chapter, I test for competitive effects.

CHAPTER 5 : EMPIRICAL TESTS FOR COMPETITIVE EFFECTS

In Chapter 4, I find evidence of network effects in HIE adoption. In this chapter, I test for evidence of competitive effects using two empirical strategies. First, I test whether hospitals that are vulnerable to losing market share are less likely to adopt a vendor that has been adopted broadly in the market. Second, I estimate a model of patient preference for hospitals and hospitals adoption of HIE and simulate market share redistribution resulting from HIE adoption. This analysis allows me to examine market share redistribution resulting from HIE adoption.

5.1. Empirical Strategy: Competitive Effects

The first empirical strategy extends the analysis in Section 4.2. I study whether hospitals that are vulnerable to losing market share are less likely to adopt a vendor that is more prominent in the market.

I estimate the following multinomial logit model:

$$Ven_{visjt} = \frac{exp(\beta_1 f(v_{-i-sjt}) * Sh_{isjt} + \beta_2 f(v_{-i-sjt}) + \beta_3 Sh_{isjt} + v + t)}{1 + \sum_{k=1}^{K} exp(\beta_1 f(v_{-i-sjt}) * Sh_{isjt} + \beta_2 f(v_{-i-sjt}) + \beta_3 Sh_{isjt} + v_k + t)}$$

where ven_{visjt} indicates whether hospital i in system s and market j adopts vendor v at time t, $f(v_{-i-sjt})$ is the fraction of hospitals in market j and not system s that have adopted vendor v at time t, Sh_{it} indicates the fraction of hospital i's patients who also visit another hospital in time t, v is vendor fixed effects, and t is time fixed effects.

Sh_{it} is a measure of the "vulnerability" of a hospital to losing market share. I assume that if a large portion of a hospital's patient population visits another hospital in that year, the hospital is more vulnerable to losing patients as a result of reduced switching cost. I also include vendor and time fixed effects to account for vendor-level effects and time trends. Because of a substantially reduced data set for this analysis, I measure ven_{visjt} as whether or not hospital i reports using vendor v at time t.

The explanatory variable of interest is $f(v_{-i-sjt}) * Sh_{it}$. If β_1 is negative, this is evidence of competitive effects. It would indicate that a hospital is less likely to adopt a vendor that is more widely adopted in the market if the hospital has a higher portion of patients who visit another hospital in that year. If the coefficient β_1 is positive, it would indicate strong network effects, in which hospitals with a patient population that visits other hospitals adopt a vendor that is more prominent in the market.

The coefficient on $f(v_{-i-sjt})$, β_2, indicates the likelihood of adopting a vendor given its prominence in the market if the hospital has no "shared" patient population. I expect β_2 to be positive, consistent with the findings in Section 4.2.

5.1.1. Data

I use the multi-state hospital panel data set described in Section 3.2. The data set represents hospitals in California, Florida, and New York from 2008 to 2011. Discharge-level data is aggregated to the hospital level to calculate the portion of shared patients.

5.1.2. Descriptive Statistics

Table 25 presents descriptive statistics on the hospitals in the data set. Almost 50% of hospitals have HIE. For the average hospital, about 16% of patients also visit another hospital. Average market share is 8% an average HHI is 0.13.

Table 25: Multi-State Hospital-Level Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
HIE	2,554	.49	.5	0	1
Fraction Shared Patients	2,554	.16	.09	.01	.86
Market Share	2,554	.08	.11	0	.81
HHI	2,554	.13	.11	.02	.67

5.2. Empirical Strategy: Endogenizing Patient Preferences

In the second analysis, I estimate a model of hospitals' adoption decisions and patient choice to simulate market share redistribution resulting from HIE adoption.

I assume there is a set of hospitals indexed by $i = 1...I$ and a set of patients denoted by $j = 1....J$. Hospitals' adoption decision in this model is slightly different from that in the above analyses. In particular, I simplify the hospitals' decision by only considering the market share redistribution that would result from HIE adoption. Therefore, adoption decision is

$$\begin{aligned} Adopt_i &= \mathbb{1}(\pi_i(HIE_i(q_i^{Adopt} - q_i^{NoAdopt})) > 0) \\ &= \mathbb{1}(\alpha(q_i^{Adopt} - q_i^{NoAdopt}) + \gamma X_i + \epsilon_i > 0) \end{aligned}$$

Hospital i will adopt if profits from adoption increase. Profits are a function of market share change that results due to switching cost reduction. Market share redistribution, $q_i^{Adopt} - q_i^{NoAdopt}$ is determined by patients' hospital choice. I assume all patients receive care from a hospital in the market (i.e. there is no outside option). The utility that patient j receives from care at hospital i is represented by the utility function,

$$u_{ji} = \beta_1 HIE_i + \gamma X_{ij} + \epsilon_{ji}$$

where β and γ are parameters, HIE_i indicates whether hospital i has adopted HIE, and X_{ij} is a set of patient and hospital characteristics. X_{ij} includes patient to hospital distance, distance squared, hospital fixed effects, HIE and distance interaction, distance and MDC fixed effect interaction, and HIE-distance-MDC fixed effect interaction.

The errors ϵ_{ij} are assumed to be Type I extreme-value distributed and independent over i and j. This yields the multinomial logit form:

$$P_{ji} = \frac{exp(\beta_1 HIE_i + \gamma X_{ij})}{\sum_{i=1}^{I} exp(\beta_1 HIE_i + \gamma X_{ij})}$$

where P_{ij} represents the probability that patient j chooses hospital i.

I sum the probabilities across hospital to determine patient volume for each hospital:

$$s_i = \sum_{j=1}^{J} P_{ji}$$

Using estimates of the demand model, I conduct a counterfactual analysis of the effect that full-scale interoperability will have on market share. I define full-scale interoperability as adoption of HIE by all hospitals. I estimate the difference between actual share and shares under full interoperability. I also estimate the difference between no HIE adoption and full interoperability. I then test the effect of simulated market share change from adoption on HIE adoption to test whether hospitals that are predicted to gain market share are more likely to adopt.

5.2.1. Data

I conduct this analysis on inpatient data from Manhattan from 2008 to 2011. The construction of this data set is described in Section 3.4. The data contains discharge-level information for each inpatient stay in a hospital in the Manhattan HRR. The analysis is restricted to patients who have diagnoses in one of the top ten major diagnostic categories (MDCs). The ten MDCs are described in Table 26. The discharge-level data is merged with hospital-level data which contains information on IT adoption status and other hospital characteristics.

5.3. Results: Competitive Effects in Vendor Choice

Table 27 reports results of the multinomial logit analysis, and I find evidence of competitive effects. Column 1 reports results with no vendor or year fixed effects, Column 2 reports results with year fixed effects, and Column 3 reports results with vendor and year fixed effects. Consistently, across the specifications, I find a positive and statistically significant coefficient for the fraction of adopters of a given vendor. This coefficient can be interpreted as the network effect given no shared patient population. The coefficient on the interaction between fraction of adopters and the portion of shared patients is negative and statistically significant providing evidence for competitive effects. The large magnitude of the coefficient is due to the interaction of two fractions. The negative coefficient on $f(y_{-sjt}) * Sh_{it}$ indicates that a hospital is less likely to adopt a prominent vendor as the portion of its shared patient population increases.

5.4. Results: Endogenizing Market Share Redistribution

Demand estimates for patient hospital choice are reported in Table 28. The coefficient on HIE represents the effect of HIE on probability of choosing hospital i at distance zero. Given that average patient to hospital distance is twelve kilometers, the seemingly odd negative coefficient on HIE is not particularity relevant.

Figures 5 and 6 show distribution of predicted market share change resulting from full HIE adoption relative to the actual adoption rates and predicted no HIE adoption. I find that average volume increases by 5% when moving from current levels of HIE to full interoperability. Volume change ranges from -25% to 255% indicating that some hospitals gain volume while others lose volume. Average volume change when moving from no HIE adoption to full HIE adoption is 6%. Volume change ranges from -74% to 248% when moving from no HIE to full interoperability. This is consistent with existence of a competitive effect in which there are "winners and losers" among hospitals as patients reallocate following reduction of switching costs. Figure 5 shows the simulated difference in volume between current levels of HIE adoption and full adoption. Table 29 presents results of the regression of predicted volume change on HIE adoption. I find a positive and statistically significant coefficient suggesting that hospitals that are predicted to gain volume are more likely to adopt.

5.5. Discussion

The results of this analysis suggest competitive effects may be at play in the decision to adopt HIE and vendor choice. I find that hospitals with a higher fraction of patients who visit other hospitals are more likely to adopt HIE. Assuming that a high fraction of shared patients is a proxy for vulnerability to market share loss, this suggests that vulnerable hospitals are less likely to adopt the prominent vendor. While the first analysis tests whether hospitals are reluctant to adopt a vendor out of concern of patient switching, the second analysis of patient flows studies whether there is actual switching as a result of HIE adoption. The results indicate that there are "winners and losers" from HIE adoption. There are some hospitals who lose market share and others who gain.

Table 26: Description of Ten Major Diagnostic Categories

MDC	Description
1	Nervous System
2	Eye
3	Ear, Nose, Mouth and Throat
4	Respiratory System
5	Circulatory System
6	Digestive System
7	Hepatobiliary System and Pancreas
8	Musculoskeletal System and Connective Tissue
9	Skin, Subcutaneous Tissue and Breast
10	Endocrine, Nutritional and Metabolic System

Table 27: Effect of Shared Patients on Vendor Choice

	(1)	(2)	(3)
Fraction adopters * Shared Patients	-4.209**	-4.208**	-9.223***
	(1.38)	(1.38)	(1.76)
Fraction of Other Adopters	3.765***	3.765***	0.862**
	(0.23)	(0.23)	(0.29)
Fraction Shared Patients	0.278	0.291	0.628
	(1.05)	(1.07)	(1.10)
Year Fixed Effects	No	No	Yes
Vendor Fixed Effects	No	Yes	Yes
Observations	76,620	76,620	76,620

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Note:

Figure 5: Hospital Volume Change: Full Adoption vs. Actual

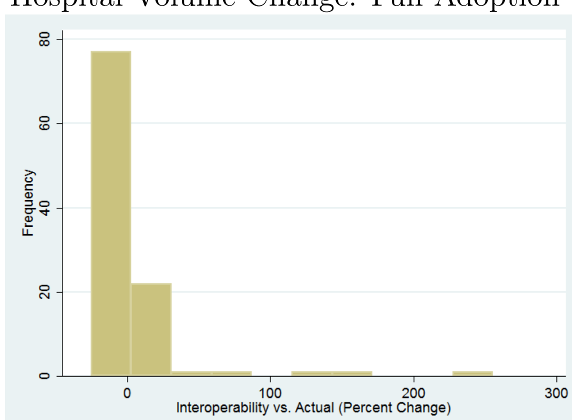


Table 28: Patient Choice Model Estimates

	A1	
choice		
Distance	-0.67***	-244.9
Squared distance	0.01***	363.4
HIE	-1.15***	-86.7
Distance x HIE	0.28***	97.8
Distance x age	-0.02***	-20.3
Distance x female	-0.01***	-15.7
Hospital FE	Yes	
DistxHIE FE	Yes	
MDCxHIE FE	Yes	
MDCxDistxHIE FE	Yes	
Observations	27686594	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Figure 6: Hospital Volume Change: Full Adoption vs. None

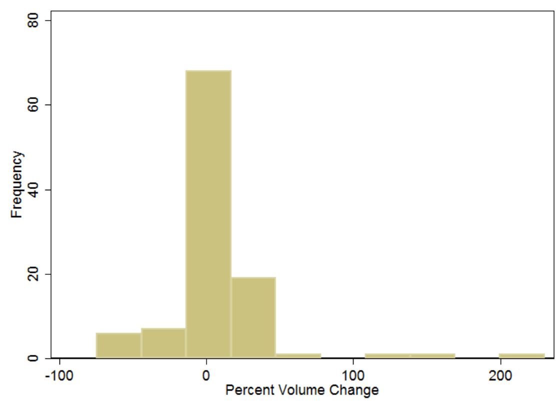


Table 29: Effect of Predicted Volume Change on Actual HIE Adoption

	Coefficient	Standard Error
Predicted Volume Change	0.01*	(0.0027)
Observations	31	
Hospital Char	Yes	
Year FE	Yes	
Hospital FE	Yes	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

CHAPTER 6 : POLICY IMPLICATIONS

The analyses in this dissertation show how network and competitive effects can lead to under-adoption and provide empirical evidence for the existence of network and competitive effects in hospital HIE adoption. These findings suggest that rates of adoption may be suboptimal, and policy interventions could be called for. In this chapter, I consider the policy implications of the theoretical and empirical results. I consider differing implications of single- and multiple-network environments.

6.1. Implications in a Single-Network Environment

In Chapter 4, I find evidence of network effects in the adoption of HIE. Assuming equal incentive to adopt, Section 2.1 shows that under-adoption can occur through a coordination problem. However, a coordination problem is less likely to occur in a dynamic setting when hospitals can observe behavior of others and decide to adopt in the following period. Therefore, despite evidence for network effects, there is lower likelihood of under-adoption resulting from network effects.

As discussed, competitive effects could lead to under-adoption because hospitals that are vulnerable to losing market share may not have enough incentive to adopt. Meaningful Use incentive payments being paid through the HITECH Act may be inadequate to induce adoption in the presence of competitive effects. In order to induce adoption, the payments would have to be large enough to overcome the market share loss induced by adopting hospitals. Such sizeable incentive payments are unlikely to be efficient.

An alternative policy that may at least partially overcome challenges posed by competitive effects is side payments. Marginal payments from the information receiver to the sender could increase the marginal incentive to exchange medical records for hospitals that face market share loss. While side payments are often not feasible in other settings, they could be feasible in the health IT setting because the technological infrastructure for such arrangements are already largely in place through the IT systems (Katz and Shapiro 1985).

Thoughtful design of the technical features of HIE networks could also encourage adoption by attenuating hospitals' concern about market share loss. Of the RHIOs that have been most successful, many have been designed to alleviate hospitals' concerns about loss of market share. For example, an HIE network with decentralized data storage in which hospitals' retain "control" of their patients records may be less threatening than a network in which all data is stored in a centralized repository. Other details such as restricting the time during which the receiver has access to medical records to the time during which a patient is being treated may also alleviate hospitals' competitive concerns (Prestigiacomo 2012).

Other health reforms that are not directly related to health IT could also overcome challenges of the competitive effect. For example, the rise of capitated payments, accountable care organizations, and patient-centered medical homes may realign incentives to encourage coordination among hospitals and information sharing. With capitated payments, providers have incentive to lower global health care costs of the patient. It may then be in their financial interest to share medical records for patients with other providers that are involved in their patients' care. However, some level of competition is likely to remain between independent hospitals or between accountable care organizations, so it is unlikely these reforms will completely overcome the competitive effects.

6.2. Implications in a Multiple-Network Environment

In a multiple-network environment, network effects have implications at both the hospital- and vendor-level. Network effects in vendor choice could result in coordination failures, or they could lead to adoption of an inferior standard. First, coordination problems are more likely to occur in the case of multiple networks compared to single networks. The coordination problem is more likely because hospitals are coordinating between multiple options and switching vendors is costly. A coordination failure in vendor choice can lead to splintering so that many different networks are being used across a market and benefits from network effects cannot be realized. As a result, information exchange through networks is limited to only hospitals that have adopted the same network.

If network effects are very strong, another perverse outcome is that an inferior standard could be adopted. If hospitals adopt a given IT system because it has been adopted by other hospitals, IT systems that were adopted early are more likely to persist. This could lead to newer and better IT systems being forgone for inferior technological standards.

These findings also have implications for competition and innovation in the health IT industry. If HIE occurs through multiple proprietary networks and network effects exist, early entrants have a first mover advantage. Moreover, these early entrants have an incentive to make their systems non-interoperable with systems of other IT vendors. By keeping their systems non-compatible, more hospitals will adopt vendors that are widely adopted in their market in order to realize network effects. Newer and smaller entrants may not be competitive despite having superior technological offerings. This could retard the adoption of welfare-improving technologies and reduce health IT companies' incentives to innovate. It could also induce consolidation among health IT companies as they compete on network size, further dulling competition. There is anecdotal evidence of these effects in the health IT industry. For example, new technologies such as open, API (Application Program Interface) IT systems have struggled to gain market share, even though they are considered superior to the previous generation of IT systems (Mandl and Kohane 2012). Instead, closed IT systems sold by large vendors continue to gain market share, despite their technological disadvantages when it comes to information sharing (Creswell 2014).

One possible policy solution is the establishment of a common standard by which all IT systems must comply, so that systems of different vendors can be interoperable. Several attempts have been made to create such a common standard by government organizations and private alliances (Gaynor et al. 2014). Industry groups have also developed common technical standards such as HL7 for developers so that systems can exchange information. However, these efforts have been largely unsuccessful so far. Government could also play a role in mandating standards. Through the HITECH Act, hospitals are only eligible for Meaningful Use payments if they adopt an IT system that has been certified. To be certified, an IT system must meet requirements such as having the ability to electronically exchange information with other systems. A potential tradeoff to the establishment of a common standard is the stifling of innovation. For example, if standards are not technically robust, it could lead to slow or poor connection. Requiring adherence to such standards could also divert investment from other value-creating innovation. Establishment of such standards is more important when there are strong network effects such that interoperability could substantially enhance welfare but weak incentives to become interoperable among vendors.

A more market-based option is the creation of an adapter to make disparate IT systems interoperable. Such an adapter could be developed and sold by a third party. IT vendors could also make adapters (Katz and Shapiro 1994). Vendors would have greater interest in making one-way adapters, so that other systems could link to their system, while making it difficult for their system to link to theirs. Both the establishment of a common standard and development of adapters effectively create a single-network environment from a multiple-network environment.

CHAPTER 7 : CONCLUSION

This dissertation has several limitations. In this section, I discuss two limitations that can motivate future work. First, in the analysis, I use data on hospital adoption of information-sharing capabilities and assume that adoption implies actual information-sharing. However, it is possible that some hospitals adopt HIE but don't engage in actual information-sharing. The data I use does not allow me to observe actual information-sharing. Future work should examine actual information sharing between individual providers if such data becomes available. Second, an underlying assumption in the motivation of this work is that HIE is valuable. However, as discussed in Section 1.3, the evidence on effectiveness of HIE is mixed. Future work should study whether current evidence on HIE is mixed because technology is poor or if HIE technology does not provide significant inherent value. HIE may not provide significant value if the extent of patient switching is not high or if the value-add of past medical history is not high.

Despite the potential of HIE to improve the costs and quality of care, rates of HIE adoption remain low. In this dissertation, I study how two non-standard features of HIE generate network and competitive effects. I show how these effects lead to under-adoption relative to the social optimal. I empirically test for and find evidence of network and competitive effects in hospital adoption of HIE. I discuss the implications of these findings as it relates to policies directed at hospitals as well as vendors.

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