Hospital Networks of Shared Patients and Engagement in Health Information Exchange

by

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ABSTRACT

Although the healthcare delivery system is composed of an array of organizations that are linked through important, enduring, and complex ties, the healthcare delivery system is rarely explicitly conceptualized or measured as a network. In consequence, we know little about how the enduring but often informal relationships between organizations shape their behavior in terms of the decisions that they make, the quality of care that they provide, and the efficiency of that care. Using techniques developed in the multidisciplinary field of network analysis, I sought to better understand two important facets of health care that are intrinsically linked to the network perspective: the fragmentation of patients' treatments between multiple hospitals, and hospitals engagement in electronically sharing patient information. By analyzing networks of shared Medicare patients treated at multiple hospitals, I first identified dense networks of hospitals that are closely interlinked through many high volume shared patient connections and are therefore likely linked through complex collaborative and competitive relationships. I then characterized these networks to identify arrangements of patient sharing that allowed hospitals to better manage care fragmentation. I found that more concentrated networks, in which hospitals shared most of their patients with few important partners rather than a large number of other hospitals, and more centralized networks, in which the network is arranged in a hub-and-spoke model, were associated with more efficient, higher quality care.

I next described three different approaches to health information exchange and the logic of participation in each approach with specific emphasis on the value of the enterprise approach

for connecting a smaller number of providers and the community approach for facilitating broader connections between more partners. I then investigated whether the choice that hospitals made about how to electronically share patient information was shaped by their networks. I found that hospitals *with* and *within* more concentrated patient sharing networks were more likely to engage in enterprise exchange while hospitals *with* and *within* less concentrated networks engaged in community exchange more frequently.

Together, these findings offer novel insights into the network features of hospitals and how they relate to important healthcare processes and outcomes. More concentrated, centralized networks appear to perform better and these features may be one reason for variation in the cost and quality of care across the nation. Similarly, policy changes designed to shape how healthcare organizations interact and who they interact with—like accountable care organizations, bundled payment initiatives and patient center medical homes—may be more successful if they reinforce beneficial network attributes. Further, as policy efforts designed to facilitate the sharing of information between healthcare providers continue, it will be crucial to allow flexible adoption of different approaches to health information exchange and to support hospitals that engage in an approach to information exchange that benefits communities.

CHAPTER I

Introduction

Since the 1960s, sociologists and healthcare scholars have understood that the healthcare delivery system can be thought of and measured as a network—that is, as a system of interconnected entities (doctors, hospitals and patients) —and that the structure of the network and the position of healthcare providers within the network are associated with their behavior (1, 2). Beginning with work by Coleman, Katz and Menzel in 1966, the vast majority of network research in the healthcare field has focused on the network of inter-connected physicians (3, 4). While network research investigating physician interactions remains an extremely important area of research that can facilitate understanding of how professionals share information, engage in care coordination and collaborate, the importance of hospitals and other organizations to the functioning of the healthcare delivery system has increased over the last half century (5). As such, continued focus on physician networks may overlook other important networks that make up the whole healthcare delivery system, including hospitals, clinics, nursing homes, labs and other organizations that provide care to patients. Relatively little work has investigated how the interconnections between these organizations shape the care their patients receive.

My goal in this dissertation is to contribute to our limited knowledge of how inter-organizational networks shape the healthcare delivery system by focusing on the inter-hospital network formed by sharing in the care of the same patients. To do so, I begin by defining these networks, and investigate the implications of the network as it relates to two important features of the healthcare system that have not been widely studied using a network framework but that intuitively relate to the patient sharing network: the fragmentation of patient care between hospitals and the decisions about how to electronically share patient health information between hospitals. To contextualize the contribution of this dissertation, I first describe network analysis and review the literature on healthcare networks.

A Networked System

A network, as defined in the broad field of network analysis, is any system made up of entities—often called nodes—that are connected by some sort of tie (6). The nodes and ties that make up a network can take many different forms: perhaps the most commonly studied network is defined by the network in which the nodes are individuals and the ties connecting them represent friendship between the individuals. However, networks can also be made up of organizations that are connected in other ways. For instance, network research has studied advertising firms connected through their shared clients and R&D firms connected through alliances (7, 8). This flexibility allows the tools of network analysis to be applied to an enormous range of networks comprised by many different entities represented by nodes that share many different types of affiliation, and this flexibility has led to the application of network analysis in many diverse fields, including physics, epidemiology, sociology, ecology, and neurobiology. Across these disciplines and research settings, an enormous range of measures have been developed to characterize features of networks.

With this methodological flexibility in mind, it may seem obvious that almost any system could be analyzed as a network. It is therefore useful to temper this flexibility with a sense of the types of systems and attributes that are most usefully conceptualized and measured as networks. Powell (1990) argues that the network organizational form represents a third type of organizing, distinct from two contrasting forms previously defined in transaction cost economics: markets and hierarchy (9). Markets occur outside of formal organizations and are based on negotiation over the terms of a contract. According to Powell, in a pure market system, the primary means of communication is through price, contracting defines the normative basis for relationships, the commitment between parties is relatively low, and the tone is precise such that obligations are clearly spelled out through the negotiated contract. Hierarchy, in which transactions that might occur through a market structure are instead internalized to a formal organization, sits in direct contrast to markets: in hierarchies, communication occurs through routines within organizations, employment forms the normative basis for relationships, commitment is relatively high, and the dominant tone is bureaucratic. Networks function differently from both of these forms. The defining attribute of the network form of organizing is that interactions are not (only) bound by precise contractual language and are not defined by organizational boundaries and employment relationships but instead are defined by open ended, indefinite, mutually beneficial relationships. Therefore, in contrast to both other forms, networks allow communication through relationships, with a normative basis in complementary strengths, a high level of commitment and a tone defined by mutual benefit. Network analysis, then, is best suited to capture the aspect of systems made up by repeated interactions that carry content beyond formal contracts or hierarchy. However, these three forms of organizing interact to shape one another in a complex system: network relationships can inform decisions leading to market transactions, while market transactions in turn help to build towards enduring relationships (10). Similarly, network relationships can form the rationale for the development of formal hierarchical relationships (7), and these hierarchical relationships create parameters for network interactions both within and between hierarchies (11).

The question then becomes, to what extent is the healthcare field comprised of attributes associated with a network form of organization, such that it is important to understand the network? Because of the specialized nature of healthcare and the fact that in most cases no one individual and, often, no one organization, can or does provide all necessary care to a given patient, healthcare providers and organizations are linked together by an enduring relationship: shared patients (12). The network of shared patients between providers is important to the functioning of the healthcare delivery system because of the fundamental content carried through the act of sharing patients, the behavior the resulting network demands and the ways this network interacts with other important types of networks. By definition, the shared patient network is composed of patients that move between settings who carry information, expectations and preferences from prior experiences to new settings, and organizations must respond to these views. The flow of patients to an organization from other organizations is also key for its financial success because revenue flows with patients. In addition, for the treatment of many conditions, a shared patient tie between organizations defines a need for those organization to communicate and coordinate in the care of their shared patients lest important information is overlooked when providers treat their patients. Nevertheless, the existence of shared patients between organizations does not imply that those organizations fulfill this need through communication or cooperation—shared patient care may be uncoordinated or lack communication, may form a basis for competition for the continued provision of services to the patient or may be incidental (13). Finally, in many cases, the shared patient tie may reflect intentional referrals between physicians and the organizations at which those physicians practice, such that the shared patient network forms and is formed by other types of network such as trust, friendship, and reputation based networks (14). In other words, the health care field embodies the network form of organization because providers and organizations are interlinked through shared patients and this network shapes and is shaped by patient expectation and preferences, financial success, a need for coordination, learning, reputation and behavior. These shared patient links persist and likely shape behavior regardless of formal affiliation, hierarchy or contracts that may bind individuals and organization. While in an ideal world it would be preferable to discretely capture each of these network forms, the shared patient network is likely to be a useful—if simplified—model of the relationship between organizations that can be employed at a national scale to understand how these relationships shape organizational behavior.

While the extent to which these network ties are the sole form of organizing varies, the importance of the network is likely to persist in many contexts. The solo or small group practice physician represents a very pure form of network organization. For a solo practitioner, the extent of hierarchy and contractual relationships with other physicians or organizations is very low; however, the sustained relationships built on reputation and trust between the solo physician and other physicians in their referral network as well as hospitals and organizations where they treat their patients are essential for the physician's success, and the physician's medical knowledge may be closely tied to the information they gain through their network and interacting with other specialists and organizations with complementary technologies and knowledge. While the health care industry is changing such that fewer providers work in small offices, a large proportion of physicians remain employed in these types of environments (15). When these physicians are employed by large health systems, their professional status lends them more autonomy and lower organizational affiliation than other employees, such that the importance of informal relationships remains essential (16). Physician autonomy within a formal organization is likely particularly high when practicing within their own clinics in locations that may be rarely visited by the organization's management. In addition, continuing medical learning and behavior is also likely to be shaped by peers and collaborators regardless of official employment structures. For physicians within a hierarchical organizations, the importance of their collegial and referral network remains high and likely stretches beyond the walls of the formal organization (17).

Much like physicians, hospitals themselves vary from close formal integration to only holding loose, informal affiliations with one another, with an ongoing trend towards consolidation into multihospital systems (18). Network forms play a key role for both independent hospitals and hospitals in multihospital systems. Independent hospitals rely on often informal relationships with physicians in the community for their flow of patients and thereby revenue, and rely on other hospitals as sources or destinations for referrals for complex care. The importance of networks remains high for hospitals in multihospital systems: early research on multihospital systems during the 1980s envisioned these systems as a type of network form of organizing in which relatively independent hospitals were linked by membership in a system (19, 20). In reality, the extent to which multihospital systems act as network connections between hospitals as opposed to forming a formal, tightly structured hierarchy likely vary across system arrangements. Nevertheless, the vast majority of systems will not isolate the hospitals within the system from physicians and organizations in the geographic area. Instead, these hospitals will remain connected to the broader ecosystem by caring for patients that are also treated by physicians and hospitals outside of the hospital system. As a result, the shift towards formal organizations is unlikely to insulate hospitals in these systems from pressures to cultivate referral and collaborative networks, as well as competitive advantage, with key outside organizations with whom they frequently interact.

Another trend in the healthcare system that has altered the role that the network form of organizing plays in the organization of the healthcare delivery system is the prevalence of insurance contracts specifying different rates for providers that are within the insurer's 'network,' defined through contracts with providers and provider groups. These contracts could reduce the importance of relationships in driving behavior by limiting the extent to which other organizations could alter their networks towards preferred partners and away from problematic ones (21). However, while it is likely that health maintenance organizations and other insurance arrangements shape and curtail the network, cases in which the insurance structure meaningfully reduces the importance of the network on the behavior of providers are likely limited because many providers and organizations are members of multiple insurance plans.

In sum, the healthcare delivery system is undoubtedly a hybrid of hierarchical organizations, contractual arrangements between insurers and providers, and network relationships defined through enduring referral and shared patient relationships. Despite the enduring importance of the network form of organizing for the healthcare delivery system, our knowledge of how the network influences care remains limited. In the next two sections, I briefly review the state of literature on networks in healthcare to provide a framework for the contribution I make through this dissertation.

Physician-Centered Network Research

As reported in two relatively recent reviews (3, 4), a relatively large volume of work has been done on professional's networks (52 papers (3) and 55 papers are reviewed (3) in each). Much of this literature focuses on networks of professionals within hierarchical organizations, indicating the ubiquitous importance of the network form even within other forms of organizing. In addition, most of studies included in these reviews on professionals have used survey-based data collection methods, which limits the potential scope of the network studied due to challenges collecting primary data. Almost all studies are descriptive or associational—only one study has investigated the change resulting from an intervention (22). Although this substantial literature does exist, an enormous amount about social networks remains unknown because of the potential of these networks to interrelate with many important concepts. For instance, Tasseli et al. divides research on professionals' networks into two groups: antecedents of networks (demographic attributes, professional groups, organizational arrangements) and consequences of networks (satisfaction at work, leadership, professionals' behavior, knowledge transfer, diffusion of innovation, and performance) and these numerous sub-topics indicate the ground to cover. Important findings within this literature indicate that closed physician teams may be conducive to discussing problem solving techniques, surgeon-surgeon interactions explained the timing of adoption of a new treatment and that pro-change organization members use strong interpersonal ties to others opposed to change in order to coopt them to accept the change (23-25). While these and other findings are provocative, only a few articles exist in any of these domains such that much more could be learned and confirmed about the way networks are created and lead to provider behavior and patient outcomes.

In addition to the predominately survey-based work included in these reviews, recent work analyzing physician networks has begun to leverage insurance claims data to identify physicians that care for the same patient. An early validation study demonstrated that physicians frequently identified other physicians that appeared on many of the same patients' claims as important partners and sources of information (26). The validated claims-based approach allows the scale of network analysis to be greatly increased from the few physicians targeted by a survey towards a national scale in which theoretically all physician relationships can be identified through insurance claims data. Several other studies using variations on this method have identified a range of relationships between physician networks, the patient population that they serve, and outcomes. Key findings from this work indicate that the network can play an important role in the quality of care provided. For instance, one study found that networks in which primary care providers are highly central to the overall network—as opposed to being on the periphery—featured fewer specialist visits and lower spending on diagnostic tests (27). Another paper found that physicians can be assigned to specific communities within the overall intertwined healthcare delivery system and that these different communities have different performance on ambulatory care sensitive readmissions (28). Interestingly, networks that serve disadvantaged populations are more isolated along a range of network measures than networks serving other populations (29).

To be sure, a great deal remains to be learned about physician networks and many opportunities exist to improve the current knowledge base. For instance, because of the newness of this research, few of these findings have been replicated, and almost all of the existing research is observational and associational. Therefore, a key avenue for research is to better understand if we can change these networks through targeted interventions and if those changes produce higher quality performance. In addition, part of this work might be to identify whether we *have* changed these networks through prior interventions and what the effect of that change was on physician performance.

Health Care Organization-Centered Network Research

In contrast to the literature on physician networks, which is comprised of a rich survey-based literature and a growing literature leveraging claims-based analysis, data on inter-organizational networks in healthcare is relatively limited. This is surprising because, as argued above, organizations are embedded within a network of relationships with other organizations in much the same way that physicians are. As physicians become members of these organizations and the organizations continue to become more important loci of decision making, understanding the web of relationships these organizations must work to navigate will likely become even more important.

One line of research has focused on the multihospital systems as a network form of organizing, envisioning individual hospitals as nodes connected by formal multihospital system affiliation (19, 30, 31). However, the extent to which systems act as networks—where hospitals are largely independent but linked through an affiliation—as opposed to more formal hierarchies is not clear. More recent scholarship has not as frequently defined system membership as a network form, rather considering it to be a merger into a single organization, though the impact of system membership on hospital performance remains a topic of research (32, 33). In contrast to systems, which share ownerships, hospitals also participate in multihospital networks in which ownership is not shared but hospitals join into an alliance or partnership. Network membership has been less directly studied than multihospital system membership; however, it is often included in models studying hospital behavior.

While research into formal affiliations between hospitals dates to the 1980s, research focused on informal affiliation through transfers and patient sharing has mostly occurred in the last decade. Nevertheless, several studies have begun to investigate the role that the inter-hospital network of shared patients has on hospital behavior. Two studies investigated the inter-hospital transfer of critical care patients and found that patients were frequently transferred towards better resourced hospitals, but not solely through a 'hub and spoke' model, and that patients were not always transferred to the closest, highest quality hospital (34, 35). Lee et al. identified the inter-hospital network of shared patients in one county, measured both as direct transfer of patients and as patients that are treated by both hospitals over an interval of time, and noted that hospitals were highly interconnected through many shared patients and that larger hospitals and hospitals that treated more cancer patients were more influential to the network (36). Further pointing towards the ways hospitals are connected through network ties, Pallotti found that hospitals' proximity in the social network was associated with similar performance (37, 38). Mascia and Di Vincenzo furthered our understanding of the complexity of these ties by identifying that many hospitals that elect to share patients (i.e. cooperate) also treat patients in geographically similar areas—that is, are in competition for the same population (13). One paper worked to expand our understanding of organizational ties by using community detection methods to identify the association between unaffiliated ambulatory surgical centers and hospital systems they share the most patients with,(39) while another focused on hospital's relationships to long-term care centers (40). The current research on the inter-hospital network of shared patients indicates potential inefficiencies in the naturally developed network, the role that networks play in influencing performance, and provides additional insight into the interplay between cooperation and competition between hospitals treating a similar population of patients. These provocative findings point towards the importance of developing a greater understanding of the way that the network of shared patients influences hospital behavior and performance.

My Contribution in This Dissertation

In this dissertation, I seek to advance our knowledge of the inter-hospital network of shared patients. Better measurement of this network and understanding of its implications can lead to designing public policies that effectively adapt the structure of the network to facilitate better coordinated care or to employ approaches that are well designed to the existing structure of the network. To characterize the network, I first identify the dense sub-networks within the sparse overall network of hospitals interlinked through shared patients. These dense networks comprise groups of hospitals that are interlinked by many inter-hospital linkages comprised of a high volume of shared patient connections and are therefore likely linked through complex collaborative and competitive relationships. Using these networks, I then investigate two concepts in health services research that have been widely studied and that inherently relate to networks of shared patients but have rarely been studied through a network lens: healthcare fragmentation—the extent to which patients' care is divided between multiple providers, leading to the possibility of poor care coordination—and electronic health information exchange (HIE)—the ongoing effort to develop electronic links between providers that facilitate the effective sharing of important patient information. I pursue these goals over the course of five subsequent chapters.

In the second chapter, I identify the national hospital network of shared patients leveraging publicly available network data derived from Medicare claims. I then apply a community detection algorithm to identify dense sub-groups within this overall network to facilitate identifying salient network boundaries of interconnected hospitals. While other methods have been used to identify groups or markets of hospitals, each available method has clear limitations. I show that the groups identified through this detection method are reliable over time, robust to different assumptions, and insensitive to the use of different algorithms. Finally, I demonstrate that these groups are as or more valid than prior methods. Accurately identifying the groups of hospitals that are interlinked through shared patients is essential (1) to characterize the groups that need to share information and coordinate in the care of these patients to avoid fragmentation; (2) to define logical groups for competition over how and where these patients are shared; and (3) to identify meaningful variation in the care that patients receive across different groups of hospitals. Relative to prior methods of identifying groups of hospitals, this approach identifies relatively larger hospital communities, indicating the potential need to consider interactions between hospitals at a higher level of analysis than supported by prior methods. However, because of the hierarchical nature of this method, investigation into lower-level interactions between the most tightly linked clusters of hospitals is also facilitated, providing a level of flexibility to investigate shared features at multiple levels of analysis.

In the third chapter, I investigate key characteristics of the networks identified in chapter two that capture the extent to which hospitals' patient sharing relationships are fragmented or arranged to facilitate the development of well-functioning information sharing processes and collaboration. Prior work has investigated the topic of care fragmentation from the patient's perspective—measuring fragmentation as the extent to which a patient's care is divided between multiple providers. However, the extent to which patients that are seen by multiple providers experience fragmented care likely depends on how well those providers collaborate, and the structure of the patient sharing network is likely to shape how hospitals develop coordination processes with one another. Therefore, I complement existing work on care fragmentation by investigating the provider side of fragmentation and find that hospitals with and in highly concentrated networks—that is, hospitals that share many patients with few other hospitals, and whose partners also share many patients with few other hospitals—have lower spending and readmissions than hospitals with and in more dispersed networks. I also find that the degree of centralization of the hospital network relates to lower cost and readmissions. In sum, these findings indicate that the structure of a hospital's network is associated with the quality and efficiency of care that they offer. Likely more important, the findings indicate that concentrated and centralized collective networks of hospitals within which each individual hospital is embedded are associated with higher quality and more efficient care, and that this relationship is more influential than the hospital's direct network of shared patient relationships. Because the association between network structure and performance relates specifically to the geography of where care is received, the associations identified might explain variation in care offered in different geographic areas.

These findings also point to the type of network that hospitals might seek to create while indicating the fundamental importance of considering higher units of analysis to understand forces that shape the performance of individual hospitals. The importance of considering the collective network structure has implications for designing policy efforts and organizational strategic choices: Policy efforts such as accountable care organizations and bundled payment initiatives that aim to alter the interaction between hospitals should be designed to account for the impact of changes on the collective network, not just the individual participating hospitals. Similarly, organizational efforts that only consider the hospital's direct relationships with others may be misguided if these efforts alter the collective network in deleterious ways or do not consider the ways in which the collective network might influence the success of the effort.

In the fourth chapter, I review the literature on HIE and identify three different approaches to HIE: community, enterprise and vendor-mediated HIE. I argue that provider participation in each type is motivated by different goals—open cooperation, strategic cooperation with key partners, and the benefit of electronic health record vendors. I review the literature on each type and find that the clear majority of studies on HIE focus on community HIE. This review identifies missed opportunity for researchers to further our understanding of the empirical impact of each type of HIE on participants and non-participants. Further, my findings have important considerations for policymakers as they continue to incentivize engagement in HIE by highlighting the tradeoffs involved in allowing each approach to be adopted and by identifying the different types of gaps in information sharing created by each approach to HIE. In large part, this discussion sets the groundwork for my later analysis of the network structures that are associated with hospital participation in either community or enterprise HIE.

In the fifth chapter, I investigate how network structure influences hospital participation in two types of HIE. Because community HIE is designed to connect all hospitals in a geographic region, I hypothesize that it should be more appealing to hospitals with and in more dispersed networks, while enterprise HIE might be more appealing to hospitals with and in more concentrated networks where hospitals generally share a large proportion of their patients with few key partners because it is designed to facilitate connections between key partners. I find some support for these hypotheses, and in particular find evidence that the structure of the collective network—not just the hospital's individual network—is important for influencing hospital's selection of HIE approach. This finding is particularly important considering recent concerns that hospitals and other providers may be choosing an approach to HIE based on their competitive or strategic interests, rather than the needs of their patients. I find that hospitals are responsive both to the needs of their patients and to the needs of partner hospitals in their networks, indicating a more pro-social orientation than usually ascribed to healthcare providers as they approach HIE. This finding supports the current public policy approach, which does not actively support specific approaches to HIE by indicating that hospitals may work together as a collective to influence one another to adopt the type of health information exchange that most benefits one another.

Finally, I conclude this dissertation with a review of the implications of my findings for our understanding of the healthcare delivery system, for public policy, and for future research. This dissertation is a contribution to a larger conceptual goal: to build a stronger understanding of the implications of the healthcare delivery system's network structure. By revealing the role of network structure in the performance and decision making process of hospitals, I contribute to our developing knowledge about the healthcare network. In general, my findings build towards the somewhat conflicting conclusion that better understanding how the network functions may lead policy makers to consider new interventions into the way care is provided to foster high performance networks while more nuanced understanding of the ways in which the network promotes self-governance and reinforces salutary norms may lead policy makers to avoid policy prescription and instead to rely on flexibility guided by social capital to lead to desirable outcomes.

CHAPTER II

Identifying Hospital Networks of Shared Patients

INTRODUCTION

The identification of groups of hospitals that provide care for a shared population of patients is essential to allow measuring and understanding features of the healthcare system that encompass multiple organizations and the population of patients for whom they provide shared care. These system-level features, including competition among healthcare delivery organizations, collaboration in the accountable care of a population, unwarranted regional variation in healthcare prices, quantity and quality, and the interplay between demography and healthcare access (41-45), are central to improving the quality, efficiency and equity of the healthcare system. As a result, researchers have developed several definitions of hospital groups (7, 46-48) that are widely used throughout the literature on health services.

Despite the usefulness of identifying groups of hospitals, existing strategies have important shortcomings. One of the earliest ways to group hospitals was simply to divide them by metropolitan statistical area (MSA) or county (for rural hospitals), but while still widely used, definitions based on geopolitical lines unrelated to the healthcare system have been shown to frequently misrepresent the size of the health care and hospital market (49). In the 1990s, the Dartmouth Atlas of Healthcare developed what remains the most prominent method for grouping hospitals: Hospital Referral Regions (HRRs). To define HRRs, the Dartmouth Atlas first grouped ZIP codes by the city in which the plurality of residents in each ZIP code received acute hospital care, thereby creating hospital service areas (HSAs) and then grouped HSAs into HRRs by the city in which the plurality of residents in the HSA received hospital-based neurosurgical and cardiovascular surgical care in 1992-1993 (50). This method may misidentify hospital groups by focusing on a limited set of patients, by using a potentially arbitrary cut-off rule, or by use of data that are now outdated. Recently, researchers have defined local multihospital systems (LMS) which identified groups of hospitals that belonged to the same multihospital system (and thereby shared a common owner) and were also in close proximity so that they likely collaborated in the shared care of patients (51). While this method may be useful to identify the role of LMS in shaping the provision of care in an area, it excludes hospitals and providers that are not part of a system and therefore cannot be used to identify whole markets. Although widely used, all of these methods for identifying hospital groups have some limitations that may curtail their use to special cases or lead to unreliable or invalid groups. Further, little work has been done to show that these grouping strategies are reliable over time or to varied assumptions about how groups are identified, or that they result in externally valid groups of hospitals.

New analytic tools generated by studying a variety of naturally occurring networks allow for the identification of subgroups of closely intertwined entities in a network (52-54). These tools can be applied to hospitals by focusing on the network of shared patients between hospitals, which is generated through readmission, intentional facility-to-facility transfers, hospital referral choices by physicians, and patient choice—informal processes that are not fully controlled by any hospital. In the resulting network, hospitals are represented as individual nodes connected to one another through ties formed by the number of patients shared between the two hospitals. Densely interconnected communities of hospitals can then be identified from within this overall network following a logic used recently to define communities of physicians that share patients (28, 55). The interconnection of hospitals through shared patients is a logical basis on which to group hospitals because shared patients may underlie hospital membership in a community to learn practices and norms from one another, hospital position in a market to compete for the provision of care to these patients, and hospital's necessity to coordinate in the care of patients when the patient moves between care locations.

In this study, I identified the network of shared patients defined by hospitals (including hospital-based clinics) filing inpatient and outpatient Medicare claims for the same patients within 30 days of one another. I then applied a hierarchical community detection algorithm, developed in the field of network analysis,(56) to the hospital network of shared patients in order to define communities of interrelated hospitals, and assessed the reliability and validity of the resulting communities. The community detection method holds theoretical advantages over previous methods: it uses a mathematically rigorous algorithm to group hospitals into the communities with which they are closest in the network of shared patients, leverages data on patients undergoing care for all conditions, and can be updated as newer data becomes available. Furthermore, due to the hierarchical nature of this method, hospital communities can be identified at multiple levels of fidelity allowing for flexible use of different sized communities based on the underlying research question.

To demonstrate the quality of this method, I first generated communities using several different underlying assumptions and types of algorithms, and identified the results of one algorithm at three levels of fidelity: 38 communities of hospitals nationwide, 150 communities and 300 communities. I then measured how similar each community grouping was and identified the approach that appeared to be the most similar to all other groupings. Next, I demonstrated the reliability of the method over time by comparing communities identified in 2014 to those identified in 2012 and 2013. Having shown that the community method identified a reliable grouping of hospitals, I examined summary characteristics and created network graphs and maps of the resulting communities. I investigated the performance of the primary method at identifying larger and smaller communities by evaluating the distinctiveness of the communities at each level of fidelity and the ability of these communities to predict outcomes that vary geographically and therefore should be better characterized by methods that identify the correct grouping of hospitals: 30 day All-Cause Readmissions and Medicare Spending Per Beneficiary (MSPB). Finally, I evaluated the validity of the method by assessing its similarity to the LMS method of hospital grouping, assessing the relative predictive power of the community detection method and HRRs on these two outcomes, and testing the grouping measure's ability to create meaningful groups by examining the reliability of each outcome measure over time and using the split-half reliability method.

DATA AND METHODS

For each year beginning in 2009, the Centers for Medicare and Medicaid Services (CMS) has released the "Physician Shared Patient Patterns" network data files derived from Medicare claims housed in the Integrated Data Repository (57). These files contain information on all healthcare providers appearing on Medicare claims, including hospitals and other institutional providers appearing on inpatient, outpatient and carrier claims. For a hospital to appear on a patient's claim, that patient must receive care that includes a facility or technical fee for that hospital; as a result, this data is unlikely to include patients seen at hospital based clinics who do not undergo a test or procedure.

Each observation in these data consists of three variables: the two providers that share patients (i.e., dyads), identified by their National Provider Identifiers (NPIs), and the number of patients for whom both providers appeared on a Medicare claim within 30 days, aggregated over the course of the year. This data is directed such that the first provider to file a claim for a patient within 30 days is in the first column of the data, allowing some sense of directionality. Provider dyads that shared fewer than 11 patients over the course of a year are not included in these files.

To identify hospital networks, I started with the 2014 American Hospital Association (AHA) Annual Survey, 2014 network data from CMS, and the National Plan & Provider Enumeration System (NPPES) file (http://download.cms.gov/nppes/NPI_Files.html) which contains the National Provider Identifiers and provider information for all Medicare institutional and individual providers. Using these data, I sought to identify all 4,634 non-federal, acute care hospitals located in the 50 United States and District of Columbia that were listed in the 2014 AHA database within the network data. I first matched hospitals with NPIs listed in the AHA file directly to the network data, resulting in 3,534 (75%) matches. I next matched 863 (18%) hospitals with Medicare numbers listed in the AHA to NPIs using Medicare claims that included both the Medicare provider number and NPI. In some cases, the Medicare provider number was associated with multiple NPIs in claims data (33 hospitals). When this occurred, I selected the NPI with the most shared patients in the network data. On average, this NPI accounted for 82% of the shared patients associated with that hospital's Medicare provider number. I was unable to match 280 hospitals by Medicare provider number or NPI. To identify these hospitals, I looked up NPIs in the NPPES Masterfile using the hospital's name, address, nine-digit ZIP code, latitude and longitude. This resulted in identification of another 252 (5.4%) hospitals. In total, I identified 4,602 (99.3%) hospitals in the network data. The hospital network of shared patients is very sparse: out of a total of 21,173,802 possible directed links between hospitals, there are only 91,120 links.

I used the hospital identifiers found in the 2014 data to identify the hospital network for each year from 2012 to 2014. For hospitals that were in the AHA in prior years but not in 2014, I repeated the procedure above to match hospitals to the correct network NPI. I validated that measures of shared patients were reliable over time, that the number of total patients each hospital shared was closely associated with hospital size and teaching status, demonstrating validity, and that the number of patients shared between pairs of hospitals was strongly associated with the size of each hospital, the distance between hospitals, and membership in the same multihospital system, further validating the quality of the data (See Appendix 1).

Defining the Strength of a Tie

Each tie between two hospitals is comprised of a specific number of shared patients, which can be used as a measure of the strength of the relationship between the hospitals. The distribution of the number of shared patients between hospitals is highly right-skewed such that over 75% of ties are comprised of 107 patients on average, but that the top 1% of ties is composed of 13,155 patients on average. I transformed the strength of these ties by taking the natural log of the number of shared patients. By doing so, I adjusted increases in the number of shared patients to be equivalent to increases in the percentage of shared patients. For example, after taking the natural log, the difference between 100 shared patients and 200 shared patients is equal to the difference between 200 and 400 shared patients. This approach assumes that there are diminishing marginal returns to more shared patients in terms of the influence of each tie between hospitals on the hospitals' behavior and therefore community membership. Further, this approach avoids distorting community detection by applying a very high weight to few strong ties. In contrast to the HRR method which followed only patients receiving care for two types of specialty care, these communities are identified by all patients so that it does not only track the movement of patients that might be referred to hospitals with more sophisticated ability to treat complex patients but also captures other types of patient sharing that may be more incidental.

Defining Communities of Hospitals

Several approaches have been developed to identify communities within an overall network (58-60). All of these methods share a common goal of maximizing the distinctiveness of the identified communities, but use differing approach to define communities. I used Pons and Latapy's 'walktrap' community detection algorithm to identify community structure (56). This algorithm has been shown to perform well across a variety of networks, and is fully hierarchical so that the resulting structure can be divided into subcomponents (61). The algorithm begins with 'random walks' through the network, a repeated process in which at each step a 'random walker' is first placed on a hospital in the network and has a chance of moving to any connected hospital relative to the strength of the tie between each pair of nodes and the number of other hospitals the first hospital is connect to (62). The algorithm then computes a measure of distance between each node based on the probability that the two nodes are on the same random walk. Using this distance measure, hospitals are first combined into communities by combining individual hospitals that are closest together and then initial communities are combined into larger communities to minimize the distance between each hospital and the merged community. This results in a hierarchical process of combining close hospitals into small communities and then close small communities into larger ones at each step. A final grouping is selected that maximizes the distinctiveness of the communities in the network using a measure known as modularity. I used the igraph software package in R to implement this algorithm and all other network analyses (63). I selected this approach because of its intuitive similarity to the process by which patients might move between hospitals like the 'random walker'. In addition, this method is likely to be preferable to more commonly used methods designed solely to maximize modularity because those methods often do not identify smaller sub-communities even when they are present and, given that hospital communities are likely to have reasonable levels of interconnection these methods may not provide optimal solutions (64). One advantage of the Walktrap method is that, because of its hierarchical structure, greater numbers of communities can be selected than the solution that maximizes community distinctiveness. I adjusted the number of communities from the number selected by the algorithm, 38, up to 500 communities and observed changes in the communities identified.

Reliability of Group Identification

To check the reliability of the communities defined by this method to different underlying assumptions, I created five alternative approaches. In the first reliability check, I used the untransformed number of shared patients between hospitals as a measure of tie strength rather than the log transformation. Next, I redefined the strength of ties between hospitals by weighting ties such that two directed ties existed between each pair of hospitals, with each tie weighted by dividing the number of patients shared between the two hospitals by the total number of patients shared by the sending hospital and all other hospitals. This approach allows for identification of the importance of the tie to the sending hospital. I then used an alternative community detection algorithm, the Infomap algorithm developed by Rosvall and Bergstrom, to re-identify communities based on the untransformed, log transformed, and hospital-proportional shared patients (65). While the Infomap algorithm performs well on a variety of tasks (61), unlike Walktrap, the Infomap algorithm is not fully hierarchical and therefore cannot simply be divided into multiple sub-communities. Finally, I compared the similarity of the main method used—logged walktrap—with 150 and 300 communities selected with each other method. I compared the similarity of the communities identified through these methods with the primary method using a measure known as the Normalized Mutual Information ("NMI"). The NMI, based on the entropy measure from information theory is a measure of the amount of joint information contained in both community partitions divided by the sum of the information in each community partition, and can be considered as analogous to a generalized correlation coefficient (66). The NMI varies from 0 when two groupings are independent to 1 when two groupings are identical and therefore contain completely mutual information (54, 62).

Overtime Reliability of Communities

To determine whether community membership was stable over time, I examined the reliability of communities by comparing community membership in 2014 to 2013 and 2012 networks. To do so, I focused on the 4,484 hospitals that were identified in the hospital network in all three years. I again used the NMI to describe the similarity of the groupings of communities across years. While I expected some movement in community definition based on changing relationships between hospitals, I would find evidence for reliable communities if the NMI is close to 1.

The Structure of Hospital Communities

After examining the reliability of the community method, I characterized the main selected community detection method-- the walktrap algorithm on logged patient ties—by the average size and range of size of the communities when different numbers of communities are selected as well as the proportion of ties and proportion of shared patients that occur within communities. To provide a visual sense of the communities selected, I graphed the network and communities identified using the walktrap algorithm on logged patient ties using the large graph layout projection, an iterative projection using ties as springs exerting force on the placement of nodes equivalent to the weight of the ties (67), and display these communities on a map of the United States.

Community Distinctiveness

To assess the community method's success at creating distinct communities of hospitals at each level of fidelity, I used a common measure of distinctiveness called modularity. This measure represents the proportion of ties between actors that are within each community as opposed to between communities, relative to the expected value given randomly drawn communities. In networks where ties between actors are weighted, like the hospital network of shared patients, the modularity score is weighted by the strength of each tie. In general, the modularity score varies from 0, when the communities are no better than random, to 1 when the communities are perfectly differentiable. While modularity is a useful summary measure to compare the performance of different grouping methods, it does not provide an intuitive sense of how well the method performed in an absolute sense. To provide that intuition, I presented the number of ties that are within each community (as opposed to crossing between communities) and the number of patients shared within each community. In principle, a better grouping of hospitals would have more links within each community, balanced for the fact that as there are more communities there will be more ties between communities.

<u>Predictive Power at Different Communities Sizes</u>

I investigated the performance of the community detection method at each level of fidelity at predicting two key outcomes: Readmissions and MSPB. I drew these measures from CMS's Hospital Compare website for 2014. To measure predictive power, I ran a series of ordinary least squares regression models predicting each outcome using fixed effects for each community at varying levels of community fidelity from 38 to 500 communities. I then compared the adjusted R-squared, which alters the standard R-squared to eliminate the tendency to increase even when variables that have little explanatory power are added to the model. This procedure allows me to determine the number of communities at which further division did not explain additional variance and simply created divisions with little meaning. This process allowed for identification of the number of communities that was most parsimonious in this case and may be most generally useful in other cases.

Comparing Communities and Other Definitions of Hospital Communities

To validate the community detection process, I next assessed the similarity between the hospital communities and two other measures of hospital groups: LMS and HRR. The LMS is defined as a group of hospitals that are in the same multihospital system and are within 150 miles of the same large hospital in the system (61). By comparing the community method with LMS, I assessed the ability of the community method to identify nearby hospitals that are preferentially linked by formal affiliation through shared ownership. Because not all hospitals are in an LMS, I could not compare community membership and LMS membership directly using the NMI; instead, I used sensitivity and specificity to describe the performance of the community method in predicting whether hospitals within 300 miles of one another (the farthest theoretical distance two hospitals could be while belonging in the same LMS) are in fact in the same LMS. In addition, I ran a logistic regression predicting whether or not two hospitals are in the same LMS based on their membership in the same community and same HRR. I compare the success of the community method at predicting LMS membership to HRRs ability to predict LMS membership to provide a grounded sense of how successful the community method is at identifying LMS membership—without this comparison it may be challenging to interpret whether the community method is successful.

Next, I compared the result of the community detection approach to the most commonly used current definition of hospital groups: HRRs. I compared these methods on the modularity and NMI of each method and compared the results of the community detection method at three different levels: 38 communities, 150 communities, and 306 communities. I chose 150 communities because it performs well on measures of reliability and validity, captures the tendency of the community method to detect larger groups than the HRR approach, and provides a useful contrast to the smaller groups identified by HRRs. I chose 306 communities to match the number of HRRs and because it is close to the point above which no more information about the selected outcome is gleaned by further dividing the communities.

Prediction of Variation in Hospital Expenditures and Readmissions

Finally, I compared the performance of the community detection method to HRRs in predicting variation in two measures of hospital care: Medicare spending per beneficiary and 30-day all cause readmissions drawn from CMS's Hospital Compare quality website. One of the original goals in developing hospital groupings was to characterize regions of hospitals with high and low spending, outcomes and utilization,(42) and successful grouping methods should group hospitals that are similar and therefore explain variation in hospitals' behavior. The ability of the community method to predict outcomes as well as or better than HRRs is therefore an important measure of validity. To measure variation, I ran ordinary least squares models with fixed effects for each community and compared the resulting adjusted R-squared.

Reliability of Outcomes

In classical psychometric test evaluation, the reliability of a set of questions is defined by the extent to which they provide consistent answers and are therefore measuring the same underlying construct. One way to assess the success of these grouping methods is by testing the reliability of outcomes within groups. If hospitals belong to the same 'true' community, their performance on outcomes should be similar because hospitals in the same community are linked together to a sufficient degree that their outcomes are more similar than random, unconnected hospitals. The grouping method that identifies hospitals with more reliable scores can then be considered to be more successfully identifying the true shared relationship between hospitals than grouping methods with lower reliability. I evaluated reliability in two ways. First, I evaluated the reliability of hospitals in the same community or HRR in 2014 over time—that is, in 2013 and 2014. Next, I randomly split each community or HRR in half and tested the reliability of the score on outcomes of the two halves of each community.

RESULTS

Reliability of Group Identification

An important characteristic of group identification is its robustness to alternative specifications. The primary approach to community detection identified 38 communities (Table 1), while the five alternative approaches to identifying communities (using unlogged patient sharing numbers, patient sharing numbers proportional to sending hospital size, and a different detection algorithm) all identified more naturally occurring communities than the main method. This indicated that 38 is a lower bound on the number of distinct communities but may not be the single 'right' number of communities. To explore the features of higher numbers of communities within my main approach, I divided the 38 communities identified by the primary method into larger numbers of communities, and focused on the 150 and 300 community sets. In general, the alternative methods of defining communities were more similar to the main Walktrap method with 150 communities selected: this method had an NMI over 0.82 in all cases and over 0.90 in 5 of 7 cases. This high similarity indicates that the methods generated similar communities but that the most likely number of highly meaningful communities was in the range of 100-250 communities.

Table 1. Reliability of Group Identification to Alternative Measure of Tie Strength and Detection Algorithm

	Prim Walktrap	Walktrap Unlogged	Walktrap Prop.	Infomap	Infomap Unlogged	Infomap Prop.	Main Walktrap 150	Main Walktrap 300
Primary Walktrap	--							
Walktrap Unlogged	0.83							
Walktrap Proportional	0.88	0.85						
Infomap	0.86	0.90	0.79					
Infomap Unlogged	0.77	0.90	0.85	0.88				
Infomap Proportional	0.77	0.89	0.79	0.87	0.99			
Main Walktrap 150	0.83	0.90	0.82	0.91	0.90	0.90		
Main Walktrap 300	0.77	0.86	0.77	0.87	0.91	0.91	0.94	
# of Communities	38	125	41	92	260	253	150	300

Overtime Reliability of Communities

Next, I investigated whether the community method produced consistent groupings over time. 4,484 (97.4%) hospitals in the 2014 network data were also present in the 2013 and 2012 years. Using the methods described above, 38 communities were identified in 2014, 39 identified in 2013 and 41 in 2012. The communities identified were relatively similar, with an NMI of 0.89 between 2014 and 2013 communities, 0.91 between 2013 and 2012 and 0.92 between 2014 and 2012. When the number of communities generated in each year was set to 150, the similarity between the communities increased to 0.94 between 2014 and 2013, 0.95 between 2013 and 2012 and 0.95 between 2014 and 2012. As a result, the community structure of the hospital network appears stable over time, and this stability was more apparent at higher numbers of communities. Longitudinal analyses using the community method might employ an ensemble method to combine community structures identified in different year to identify a community structure that is consistent over time (68) or may employ a multilayer community structure to better depict changes over time (69).

The Structure of Hospital Communities

The community method produced the most distinctive communities of hospitals by dividing the whole network into only 38 communities across the United States, rather than identifying smaller groups like the HRR method. On average, these communities were comprised of 121 hospitals, with the largest community containing 356 hospitals and the smallest containing just 13 (Table 2). With 38 communities, 88.9% of ties and 94.7% of patients were shared within the communities. As this initial identification was divided into a greater number of communities, the average number of hospitals in each community decreased and some hospitals were placed into single-hospital communities. Similarly, the percentage of ties that occurred within communities decreased as more communities were identified, as did the percentage of shared patients.

Table 2. Descriptive Characteristics of Hospital Communities

	38 Communities	150 Communities	300 Communities	500 Communities
Average Size	121	31	15	9
Minimum	13	1	1	1
Maximum	356	102	60	55
% of ties within	88.9%	72.6%	56.6%	42.6%
% of patients within	94.7%	87.1%	76.8%	64.7%

In the network of hospitals divided into 38 communities (Figure 1a), each community was relatively distinct and contiguous within the overall network: there was little overlap in communities within this network projection. When 150 communities are graphed (Figure 1b), the communities were closer together and in some cases overlapped in the graph, indicating some reduction in the ability of the algorithm to divide hospitals into distinctive communities.

Figure 1a. The Network of Hospitals Through Shared Patients, 38 Communities

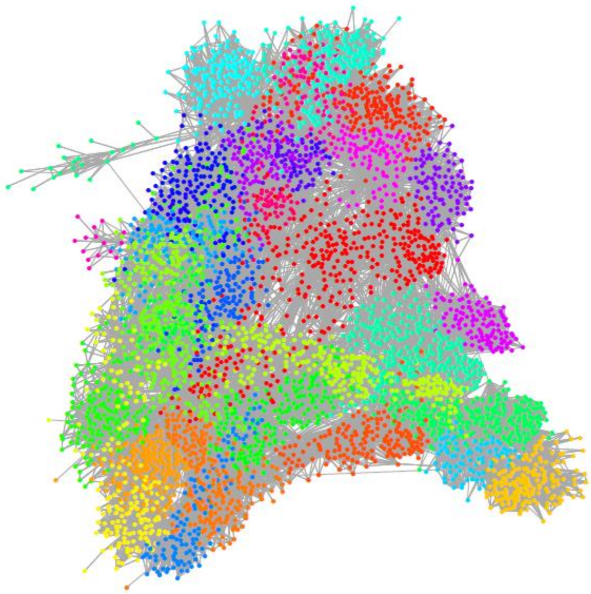
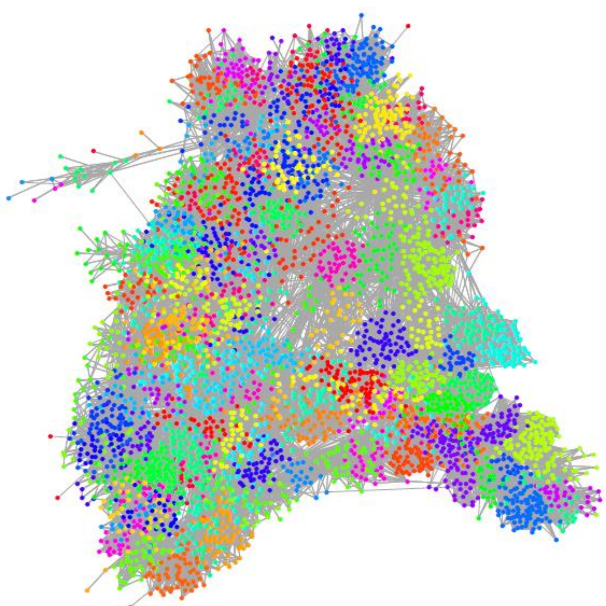


Figure 1b. The Network of Hospitals Through Shared Patients, 150 Communities



When plotted on a map of the United States, the 38 hospital communities clearly fell along geographic lines (figure 2a). In some cases, the hospital communities seemed to parallel state lines closely, such as in Michigan and Florida. When the 38 communities are separated into 150 communities, the communities remain geographically contiguous but are by definition of smaller size (figure 2b). In most cases, areas surrounding major urban centers were not divided into multiple communities. Instead, major cities and their suburban areas were treated as a single community of hospitals.

Figure 2a. The Network of Hospitals Through Shared Patients, Map of 38 Communities

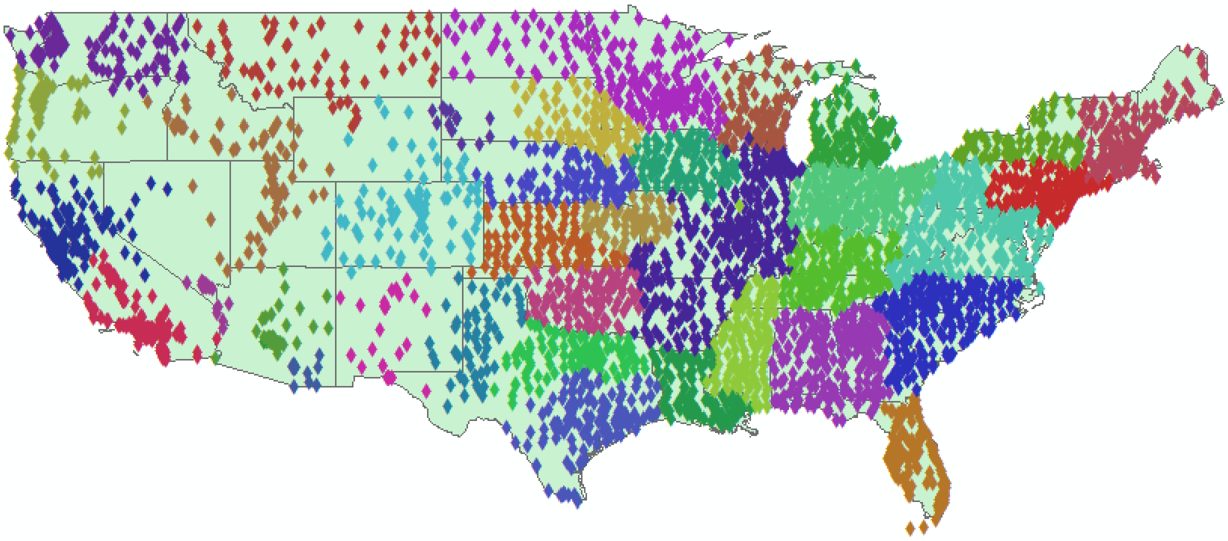
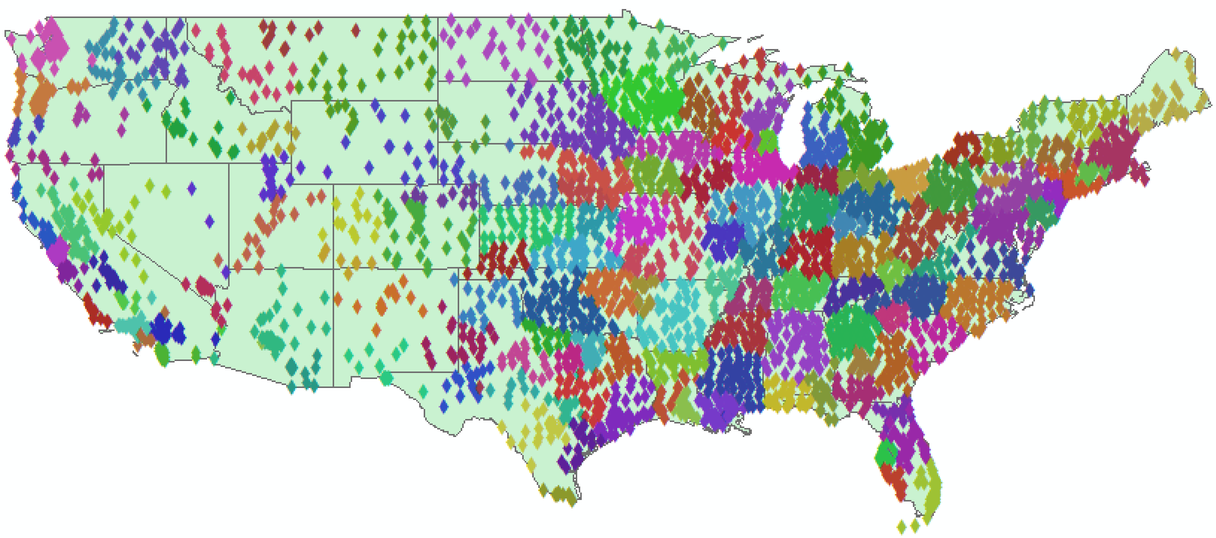


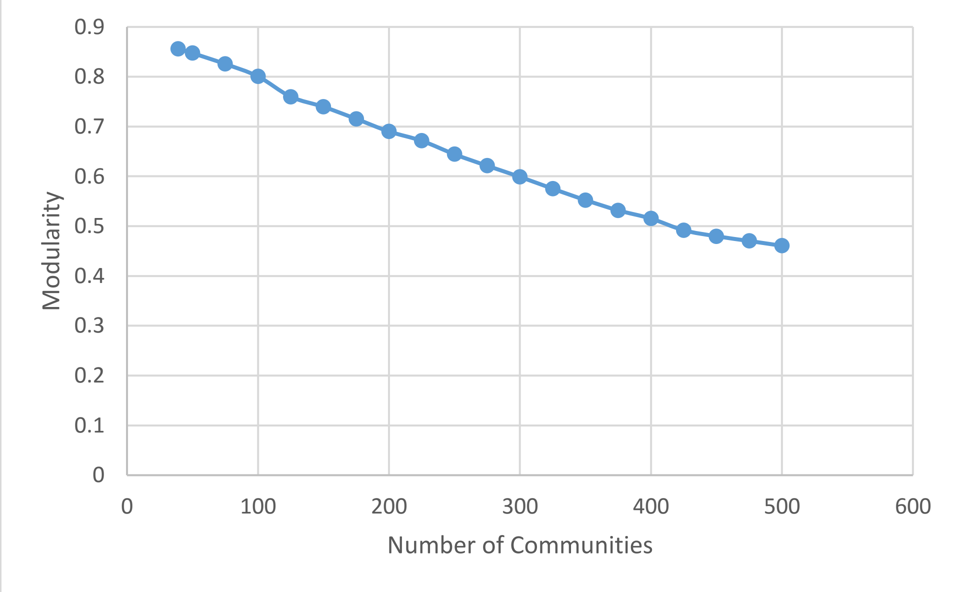
Figure 2b. The Network of Hospitals Through Shared Patients, Map of 150 Communities



Community Distinctiveness

When 38 communities were identified, the modularity of these communities, a measure of how well the network was separated into communities relative to chance, was 0.86. As these 38 communities were divided into smaller sub-communities, the modularity decreased approximately linearly such that when 500 communities were identified, the modularity was 0.46 (Figure 3). This linear trend indicates no clear cut point or drop off below which the identification of communities is much less meaningful but instead points towards a tradeoff between identifying more communities and the distinctiveness of communities.

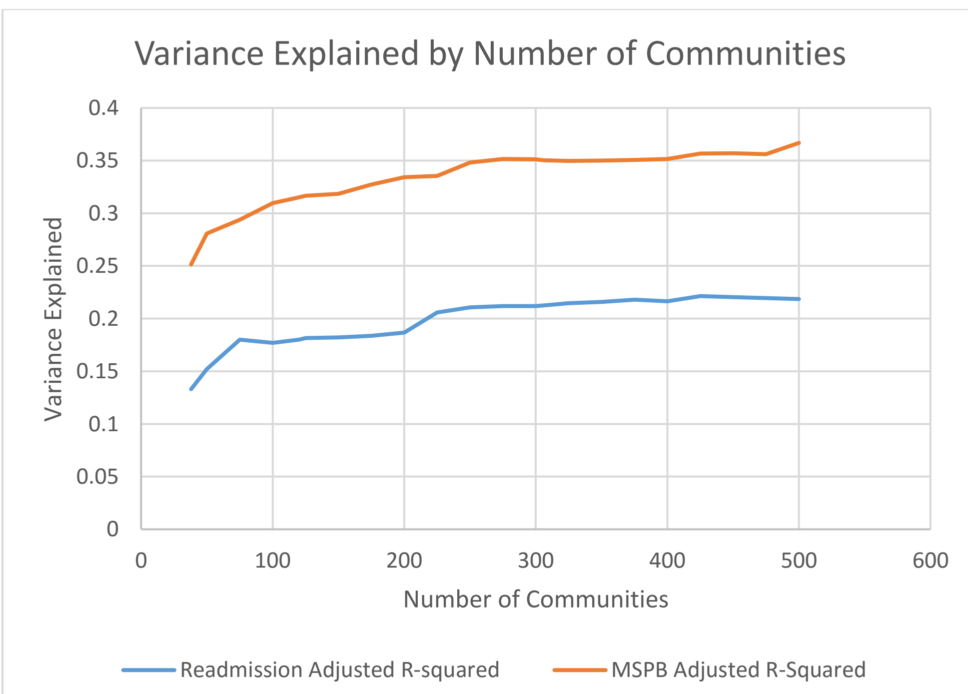
Figure 3. Change in Modularity Based on # of Communities Identified



Prediction of Variation in Hospital Expenditures and Readmissions

One of the key goals of defining hospital groupings is to identify the level of variation in services, behavior and outcomes across the nation. I examined how well the community detection approach explained two hospital-level outcomes: Medicare spending per beneficiary (MSPB) and 30-day all-cause readmission rates (Figure 4). Because each additional set of communities divided the hospitals into smaller pieces, it is reasonable to expect that the R-squared and adjust R-squared would increase as more communities were identified. It is therefore notable that, for both MSPB and Readmissions, the increase in adjusted R-squared flattens as the number of communities increases, indicating that the ability of small groups to explain these outcomes was saturated and additional division into more communities added little predictive power. This flattening is most notable around two points corresponding to the number of communities chosen as examples: the lines begin to flatten around 150 communities, at which 18% of variance in readmissions and 32% in spending and again around 275-300 hospitals, at which 21% of variance in readmissions and 35% of variance in spending is explained. Little additional variance is explained by increasing beyond 300 communities. In other words, about 1/3 of variance in the spending of 4,603 hospitals can be explained by grouping them into 150 communities while only modestly more can be explained by identifying twice as many communities.

Figure 4. Variance Explained as the Number of Communities Increases



Comparing Communities and Other Definitions of Hospital Communities

I next sought to validate the community detection method by assessing the extent to which hospitals that shared a formal affiliation, captured using the LMS approach, were also sorted into the same community using the community detection algorithm and identifying 150 or 300 communities. This comparison is interesting because it tests the sensitivity of the community method, which is based on a patient sharing network, to identify a different type of network formed by formal affiliations that are likely to alter, perhaps indirectly, the patient sharing network.

To make this result more tractable, I compared the odds that the community method sorted hospitals with an LMS affiliation into the same community to the odds that the HRR method sorted hospitals with an LMS affiliation into the same HRR to provide a baseline for whether the community method is successfully identifying LMS affiliation. There are 8,517 formal links between hospitals created by belonging to the same LMS; 100,129 links between hospitals created by belonging to the same community when 150 communities were identified, 54,244 links created by belonging to the same community when 300 communities are identified, and 62,036 links between hospitals created by belonging to the same HRR, relative to 1,028,604 undirected links between hospitals within 300 miles. The community method was a somewhat more sensitive predictor of LMS membership than the HRR method, especially when fewer communities were identified (sensitivity=0.63 for 150 communities, 0.46 for 300 communities and 0.46 for HRR) and a slightly more specific method when more communities were identified (specificity=0.91 for 150 communities, 0.95 for 300 communities and 0.94 for HRR). Perhaps most interesting, when both same community membership and same HRR membership were included in a logistic regression predicting whether hospitals are in the same LMS, the odds ratio associated with hospitals belonging to the same community membership was larger—that is, in a model including an indicator for whether the hospital pair belongs to the same community in the 150-community group, the odds ratio on this variable was 9.6, while the odds ratio associated with belonging to the same HRR was 2.7. When an indicator was included for whether the hospital pair belongs to the same community in the 300-community group, the odds ratio on this variable was 6.4 and the odds ratio associated with belonging to the same HRR is 4.1. In other words, belonging to the same community appears to be a stronger predictor of belonging to the same LMS than does belonging to the same HRR.

I further compared the identified communities and HRRs in several steps beginning with visually comparing maps of both grouping strategies. Figures 5a-c show the hospitals in five states, Michigan, Ohio, Indiana, Illinois and Wisconsin divided into 150 communities, 306 communities and 306 HRRs, respectively. In contrast to the HRR approach, the network approach using both 150 and 306 communities kept hospitals surrounding the major metropolitan areas of Chicago, Cleveland and Detroit in a single community. The network approach also largely avoided identifying very small communities in this area: for example, while the HRR method divides the western side of Michigan into 5 HRRs, including two very small coastal HRRs, the 150 community method treats all of these as a single community and the 306 community method divides it into two communities. In other areas, such as the areas around Indianapolis and Columbus, the groupings identified by the network approach and the HRR approach are notably similar.

Figure 5a. Map of Hospital Communities in 5 States: 150 Communities

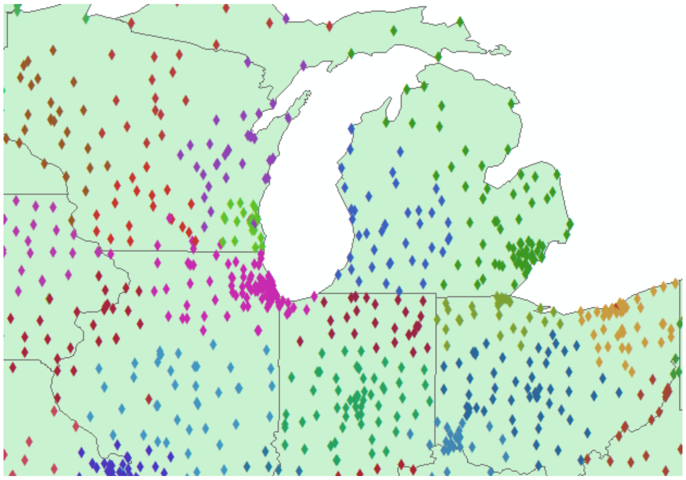


Figure 5b. Map of Hospital Communities in 5 States: 306 Communities

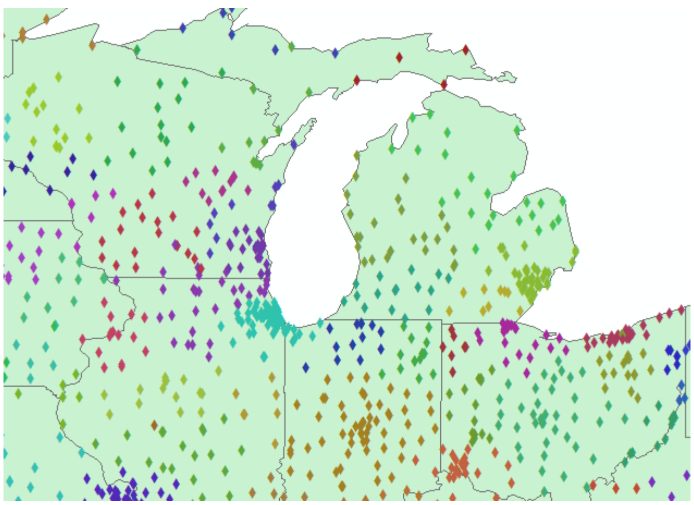
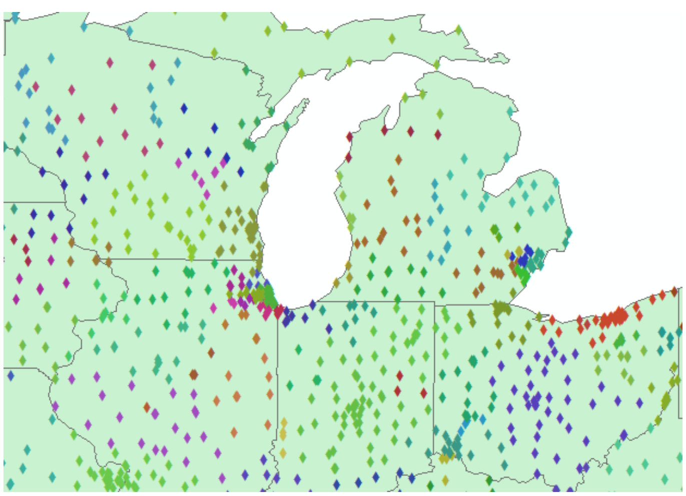


Figure 5c. Map of Hospital HRR Membership in 5 States



The similarity between these methods can be described quantitatively using the NMI (Table 3). Because this measure is in part dependent on the similarity of the number of communities identified, I selected 306 communities to allow for direct comparison with the HRR method. At this level, the community detection method and HRRs identified relatively similar groupings of hospitals, with an NMI of 0.87; however, this similarity is little better than the similarity between the 150-community method and the HRR method.

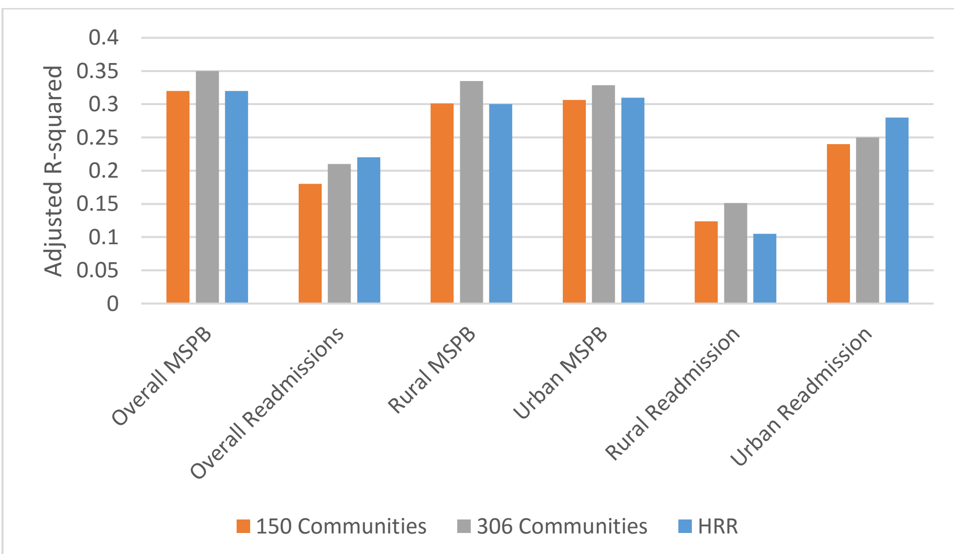
The community method appears to provide more distinctive groupings of hospitals than the HRR method. At the same number of communities, the community method had a modularity of 0.59 and the HRR method had a modularity of 0.55 (Table 3) which is close to the modularity of the community detection method with 350 communities. 51.7% of ties between hospitals occurred within an HRR and 75.1% of shared patients were shared within an HRR, both of which are modestly worse than the performance of the network approach described on Table 1.

Table 3. Similarity Between Groupings of Hospitals

	38 Communities	150 Communities	306 Communities	500 Communities	HRRs (306)
38 Communities					
150 Communities	0.83				
306 Communities	0.77	0.93			
500 Communities	0.73	0.89	0.95		
HRRs	0.75	0.87	0.88	0.87	
Modularity	0.86	0.74	0.59	0.46	0.55

To better understand the relative ability of these methods to predict variation in outcomes at different number of groupings, I examined the variation explained by 150 communities, 300 communities and the HRR method (Figure 6). I first estimated the performance overall and then in separate analyses considered urban and rural hospitals (defined by the type of core based statistical area each hospital was located in) because, as observed above, the HRR method divided hospitals in urban areas into several regions while the community method often combined these areas into a single community. Relative to HRRs, the 150 communities approach explained an approximately equal amount of the variation in MSPB for all, urban and rural hospitals and the 300 communities approach predicted significantly more variation than the HRR method. While the community method explained greater variation in readmission rates in rural areas, HRRs explained modestly more variation for readmissions overall, driven by better ability to explain variation in urban areas. This may be due to the HRR approach's ability to identify hospital sub-groups within a larger metropolitan area, which the community method tends to group together. Overall, the ability to explain variation in spending by grouping is greater than the ability to explain readmissions: about 1/3 of variation in spending is explained while about 1/6 of variation in readmissions is explained.

Figure 6. Variance Explained by Grouping Method



I also investigated the reliability of each grouping method over time by comparing the correlation between average MSPB and readmission rate in each community or HRR in 2013 to the average in 2014. As shown in Table 4, the correlation between 2013 and 2014 readmissions is highest in the 150-community partition and approximately equal in the HRR and 306-

community partition. The correlation between years on MSPB is also highest in the 150-communities grouping, followed by HRRs and 306-communities, but all correlations are extremely high.

Table 4. Overtime Correlation of Outcomes

	150 Communities	306 Communities	HRRs
Readmission 2013-2014 Correlation	0.93	0.90	0.90
MSPB 2013-2014 Correlation	0.97	0.95	0.96

Finally, I compared each grouping strategy using split-half reliability. Grouping methods that capture hospitals that truly belong to the same underlying group should have more similar performance on outcomes than hospitals that do not belong to the same group. Therefore, better grouping methods are likely to have higher split-half reliability. I found that the 150-community partition had substantially higher reliability on both measures than the other two groupings (Table 5), while the 306-community partition performed better than HRRs on the readmissions measure and the HRR partition performed better on the MSPB measure.

Table 5. Split-Half Reliability

	150 Communities	306 Communities	HRRs
Readmission Split Half Reliability	0.69	0.53	0.48
MSPB Split Half Reliability	0.77	0.57	0.63

DISCUSSION

I proposed an alternative definition of hospital communities based on the principles of social network analysis. I then showed that the resulting communities were robust to differing methods of community detection and over time, could be divided into smaller groups while retaining the ability to identify meaningfully separate groups of hospitals, were valid in that they were closely related to two other means of identifying hospital groups and performed as well or better than a commonly used method of hospital grouping in predicting hospital-level outcomes, and that the outcomes associated with each community were reliable, indicating that the community method was identifying a consistent underlying construct.

The hierarchical nature of this approach provides an important advantage over other methods of grouping hospitals by allowing additional flexibility that may be valuable as researchers seek to answer varied questions requiring differing levels of analysis. While it may often be useful to leverage the hierarchical nature of the community detection algorithm to identify smaller groups of more tightly knit hospitals, under some assumptions the 'best' solution, which maximizes the distance between communities, created a small number of large communities. As a result, it may be useful for researchers and policymakers to conceptualize hospital groups at the level of these large communities when thinking about the healthcare market and access to uncommon procedures. For instance, larger communities may be useful for assessing the interaction between teaching hospitals or multihospital systems that draw patients from many hospitals and long distances. On the other hand, researchers interested in understanding the role of very local norms in shaping hospital behavior and studying competition among small or rural community hospitals may select smaller networks of tightly interconnected hospitals (70). The choice of number of communities creates a tradeoff: by selecting fewer communities, hospitals are grouped into large but potentially more loosely affiliated communities. When these communities are split into sub-communities, the resulting smaller groups are more tightly interconnected. However, using smaller communities may result in somewhat artificial divisions between hospitals that should be considered members of the same community.

One of the key advantages of this method is that it can be easily updated from publicly available data and as a corollary, is verifiably reliable over time. Other methods of grouping hospitals, such as HRRs or geographic definitions unrelated to healthcare (such as metropolitan statistical areas) either have not been or could not be updated in response to changes in the healthcare delivery system. In contrast, community definitions could change over time in response to changing patient sharing patterns or chance, but in this analysis and over a relatively short period of time, were largely unchanging from year to year. The demonstrated reliability of the community method to different analytic assumptions (how to weight ties between hospitals and the algorithm used to identify communities) provides further evidence of the robustness of this identification strategy while other methods have not been tested for this type of reliability.

The community method was closely related to an alternative definition of hospital groups, local multihospital systems (LMS). This indicates that the informal networks created by shared patients are related to the formal hospital networks generated through shared ownership. However, the analyses performed here could not identify the causal mechanism underlying this similarity: shared ownership may lead to greater shared patients therefore membership in the same community, or shared patients may lead to shared ownership structure. Nevertheless, this similarity provides support for the validity of the community detection approach because it generates groupings that are sensitive to a distinct type of network connection created by formal linkages. While LMS membership was also predictive of HRR membership, the association was not as strong, which may lend further support to the validity of the community method.

Although there were conceptual reasons to suspect that the HRR method did not represent the most meaningful grouping of hospitals due to the age of the underlying data and focus on a limited subset of patients, HRRs and the identified communities were reasonably similar, perhaps because both methods are derived from analyzing how patients move between hospitals. When testing the ability of each grouping to predict hospital outcomes, the HRR method and community detection method performed relatively similarly. However, HRRs identified more groups than the community detection method and in particular separated urban and suburban areas into several HRRs whereas the community detection method did not divide these areas. This difference may be due to the HRR's focus on specific referral patterns for specialty diseases which may capture planned transfers and referrals between community hospitals and specific quaternary care providers but overlooks important linkages between similar hospitals in the care of less acute patients due to geography, patient preference, and random occurrence. Even in robustness tests, no version of the community detection method identified as many naturally occurring groups as indicated by the HRR method. As a result, it seems likely that for most analytic purposes, the best number of groups is lower than that identified by the HRR method and closer to 150-200 communities. These large groups correspond to work showing that hospital markets are often larger than a single MSA (49).

This study is subject to several limitations. First, the network of shared patients used to identify hospital communities was based only on Medicare patients. The network formed by commercially insured patients may be different especially since many of these insurers have contracts with certain hospitals and create incentives for patients to visit those hospitals. Second, these communities were identified solely from shared patients. More formal ties or ties formed by shared physician affiliations may also contribute to the formation of communities. To a certain degree, these networks would be reflected in the network of shared patients as noted by the association between LMS and communities. Third, the content and motivation underlying the sharing of patients is somewhat ambiguous—it may be the basis for either competition or collaboration over those patients. Finally, some very weak ties between hospitals are omitted because the publicly available data is censored at a minimum of 11 shared patients. However, very few ties included in the data are made up of that low of a number of patients so it is unlikely that this is dropping many inter-hospital links. For instance, there are 306 ties comprised of 15 patients and only 17 ties comprised of 11 patients.

In this study, I presented a flexible, reliable and valid method of identifying hospital communities within the network of shared patients. Researchers interested in studying the interaction of multiple hospitals may find this approach useful as they seek to understand hospital interaction, competition, and variation in spending or outcomes. Of particular interest, the number of naturally identified communities was smaller using this method than previous methods. The communities identified here need not be the final word—I plan to make the data and R script that led to this grouping scheme publicly available—and I hope that this work will form the basis for continued improvement of our understanding of informal multihospital relationships.

CHAPTER III

A Network Approach to Care Fragmentation: Association with the Quality and Efficiency of Hospital Care

INTRODUCTION

Patients often receive care from multiple healthcare providers because of the highly specialized nature of healthcare and the preferences of individual patients. However, when patients are treated by different providers, their care becomes fragmented, and providers must communicate and collaborate to provide high quality care for these shared patients. In consequence, care fragmentation can lead to low quality and inefficient care if communication between organizations is ineffective and providers do not coordinate in patient management (71). Evidence indicates that highly fragmented healthcare delivery systems result in higher costs and utilization, and worse patient outcomes including readmissions and mortality (72-74). This fragmentation appears to be a common experience (75, 76) and concerns with fragmentation have in part motivated recent efforts to reform the delivery system, including the establishment of new programs that incentivize better coordination (e.g., accountable care organizations and patient centered medical homes) (77, 78).

Some sharing of patients between healthcare providers and organizations is likely unavoidable due to specialization and patient preference, and the benefits of provider competition also create pressures to avoid solving fragmentation through consolidation. Thus, the key question is not how to reduce patient sharing, but instead how to avoid the negative consequences of patient sharing. Negative consequences may be avoided if the inter-connections between organizations are structured to support high functioning collaboration between parts of the system (27). Conceptualizing and measuring healthcare delivery as a network of connected organizations can help identify features of the inter-connected network associated with successful patient sharing. In particular, two features of the network – concentration and centralization – are likely to result in high functioning patient sharing.

A high level of concentration—such that providers share many patients with relatively few partners—may reduce the negative effects of fragmentation because frequent sharing of patients may compel partnering organizations to develop processes to exchange information about patient's prior treatment and to keep track of patients that move back and forth. Similarly, providers at these organizations with experience working together may develop processes for creating coordinated care plans through high quality verbal discussion and shared decision making (79). In consequence, networks made up of provider organizations that more frequently share patients, while still fragmented, distribute patients in a way that could lead to behaviors that more effectively mitigate the negative consequences fragmentation, relative to dispersed networks made up of relationships between many organizations that only rarely share patients.

Second, a centralized system, arranged in a hub and spoke manner around one or a few focal hospitals as opposed to a decentralized web of equally connected hospitals, may be beneficial because the often large and highly capable central organization has the capacity to support information sharing and coordination processes with many smaller partners, whereas in a decentralized network, peripheral and less capable organizations may be asked to coordinate with a large set of partners, stretching their organizational capacity to develop routines. Further, research on the volume-outcome relationship in health care has demonstrated that higher quality and lower costs might result from greater regionalization—that is, care for complex conditions should be centralized in large medical centers that others refer patients to, rather than fragmented throughout smaller organizations (80-82). Similarly, research on public health organizations indicates that the presence of a central organization may facilitate coordination between more peripheral actors and set expectations for the whole network (83). As a result of these interlinked phenomena, networks with high centralization might exhibit greater coordination and reduced fragmentation.

Prior studies that measure fragmentation have generally assessed the extent to which patients were seen by different providers and admitted to different hospitals (72-74). However, these approaches have done little to identify the characteristics of relationships between providers or the network as a whole. For instance, prior work has not distinguished between patients whose care is fragmented between many providers that rarely work together and those that frequently share in the care of the same patients. Because care fragmentation creates the need for interaction between multiple providers during the care of a patient, the tools of social network analysis can be leveraged to characterize the patient sharing relationships that might lessen the negative effects of dividing care between multiple providers and organizations. In this vein, prior studies have analyzed providers' patient network to identify a range of relationships between network characteristics and patient care (27-29) but have not used these tools to investigate fragmentation.

Using data derived from Medicare claims, I investigated how the structure of hospital networks of shared Medicare patients is related to the performance of hospitals in these networks on efficiency and patient outcomes. To do so, I measured two aspects of hospital networks associated with the structure of patient sharing: the extent of concentration and centralization of the network. I then related these network features to two measures of hospital performance, Medicare spending per beneficiary (MSPB) and hospital's 30-day all-cause readmission rate, a commonly used measure of hospital quality that may be particularly sensitive to differences in the quality of collaboration between hospitals.

CONCEPTUAL MODEL

This study specifically focuses on the relationship between the hospital network of shared patients and two outcomes, the level of Medicare spending and 30-day all-cause readmission rates. While the hospital network is only one piece of the overall healthcare delivery system, I focus on hospitals because a significant amount of prior research on care fragmentation has been based on patients seen at multiple hospitals (72, 84, 85). Further, the high cost and high acuity of this setting makes hospital outcomes an important driver of the overall performance of the healthcare system. I hypothesize that the structure of the inter-hospital network of shared patients will relate to both lower spending and lower readmission rates by increasing the sharing of information and improving the collaborative decision making processes between hospitals. Hospitals in networks that facilitate high levels of communication and collaboration are likely to have reduced levels of spending because this communication can decrease the need for redundant testing and the rate of costly medical errors. These hospitals are also likely to have lower rates of readmission because improved information sharing and collaboration may lead to improved outpatient and emergency care when a patient is seen at a new hospital and this improvement may reduce the need for a patient to be readmitted. In addition, having more information on patient history may reduce emergency department clinician's uncertainty about the status of their patient and make it less likely that they admit a patient in order to perform additional diagnostic procedures.

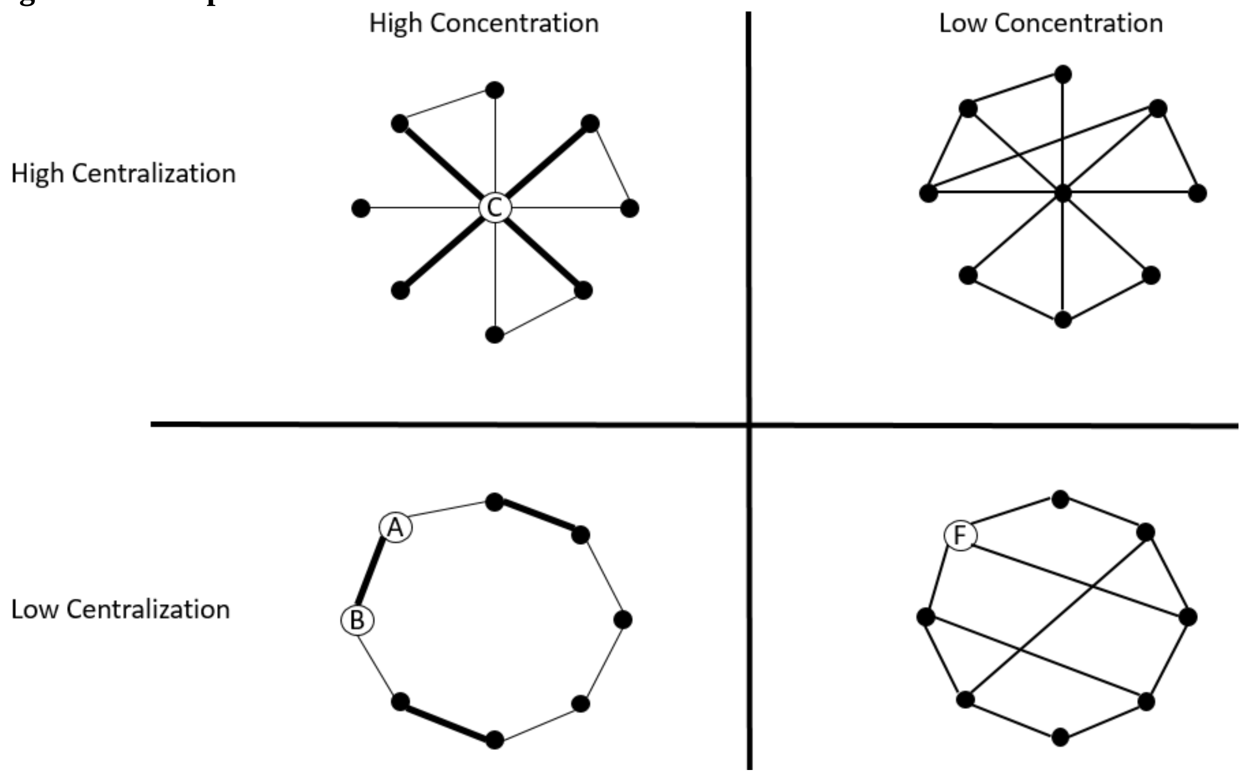
Two Levels of Networks

The two main network features characterized in this chapter, network concentration and centralization, can be conceptualized and measured at two distinct levels of analysis commonly used in the literature on social networks. The first level of analysis, often called the ‘ego-centric’ network, focuses on the characteristics of an individual entity—the ego—and its ties to others. A rich literature demonstrates that the structure of an ego’s direct relationship with others can influence its performance by providing access to information, easing coordination demands or placing the individual or organization in a position of influence (86-88).

The second level of analysis seeks to describe the network as a whole—that is, the collective network of linked hospitals—and identifies characteristics such as how centralized the network is around a primary actor or the level of interconnectivity in the network. The characteristics of the collective network—for instance, the relationship between members of a team, or networked R&D firms, have been used to predict the performance of that group (89, 90). The characteristics of the collective network can also determine the behavior of individual actors in the network by creating a structure within which the individual acts. As such, the structure of the collective network, unrelated to the individual ego-centric network, can relate to the performance of an individual or firm within that network (10, 91).

In this paper, I investigate the hypotheses that the concentration and centrality of a hospital’s ego-centric network, and the concentration and centralization of the broader network within which a hospital is embedded, have important consequences for the extent to which fragmentation inhibits hospital performance. Figure 7 provides a visual guide to the conceptual model, with each node representing a hospital, each line representing shared patients between hospitals and the thickness of the line representing the number of patients shared between the hospitals.

Figure 7. Conceptual Network Schematic



<u>Hospital-level Patient Sharing Concentration</u>

At the ego-centric level, low concentration occurs when a hospital shares a relatively small proportion of their patients with each of a large number of partners. For these hospitals, it may be challenging to develop robust information sharing routines with each of their partners. High functioning coordination requires experience and relationship-specific investment,(83, 92) and the ability for hospitals to make that investment in their partners in a way that covers a large proportion of shared patients may be a function of how many partners they have and the proportion of their shared patients covered by each partner. High proportions of patient sharing between partner hospitals may facilitate creation of processes that smooth the transfer of information and coordination of care. Achievement of high volumes of specific procedures at individual hospitals has been shown to be associated with superior health outcomes in individual hospitals, and it seems logical that the benefits of high volume in developing successful care processes should apply not only within a given hospital but also to how care is coordinated between hospitals (93). The ability to develop processes through repeated interactions with specific partners may be associated with more efficient and higher quality care. For instance, hospital A in Figure 7 can devote the majority of its attention to developing processes with their major partner, hospital B, with which they share most patients. In contrast, hospital F, with a less concentrated network and ties made up of an equal number of patients, must devote resources to all three of its partners, and may therefore either not do so or do so poorly.

Hypothesis 1a: Hospitals with more concentrated networks provide more efficient care.

Hypothesis 1b: Hospitals with more concentrated networks provide higher quality care.

Collective Network-level Patient Sharing Concentration

Even if an individual hospital's network is concentrated, the ability of a hospital to develop well-functioning coordination may depend on the collective network of its partners and their ability to commit a similar level of resources to coordinating with the focal hospital. As a result, hospitals in networks with low overall concentration may find it challenging to engage their partners in devoting resources to the development of information sharing processes because each of their partners have many other demands. Further, in networks with low concentration, poorly coordinated care may accumulate for patients as they move between hospitals with low concentration. Providers practicing at an individual hospital in that network may be challenged to identify all relevant patient information because they must seek out that information from multiple discrete sources as a result of low concentration at other hospitals and attendant challenges in coordination at those hospitals, which means that no one partner is certain to have all information.

Hypothesis 2a: Hospitals in more concentrated collective networks provide more efficient care.

Hypothesis 2b: Hospitals in more concentrated collective networks provide higher quality care.

<u>Hospital Patient Sharing Centrality</u>

In addition to concentration, hospital centrality and network centralization are likely to influence the extent to which patient sharing results in coordination challenges. An individual hospital's centrality within a network—that is, the extent to which the hospital occupies a central, coordinating position within the whole network or sits on the periphery of the network—may relate to how much work the hospital must do to overcome fragmentation. While the central hospital in a network, such as hospital C in figure 7, plays an important role in coordinating the network as a whole, that role may be costly for the hospital (6, 94). Like hospitals with networks that include many partners and low concentration, in order to reduce challenges faced through patient sharing, the central hospital will be required to expend effort developing relationships and coordinating with many partner hospitals, which will tax the organization's resources; further, the central hospital is likely to face a coordinating burden in organizing the peripheral hospitals and coordinating concordant decision making in the network that may not communicate directly and are predominately connected through the central hospital. However, central hospitals are also likely to serve as referral centers and to concentrate the treatment of complex patients in a single location, and therefore achieve the benefits observed in the volume-outcome literature (93). In sum, highly central hospitals may provide less efficient care than their peers due to the coordinating role they must play; however, central hospitals may provide higher quality care through their ability to function as high volume referral centers. For instance, hospital C in figure

7 likely plays a coordinating role for the network as a whole and serves as the primary referral center.

Hypothesis 3a: More central hospitals provide less efficient care.

Hypothesis 3b: More central hospitals provide higher quality care.

Collective Network Patient Sharing Centralization

The centralization of the network, defined as the extent to which the network as a whole is centralized around a focal hospital, may have important implications for the network's ability to manage fragmentation in the network. In highly centralized networks, hospitals are grouped around a single central hospital. In more decentralized networks, no hospital occupies a central position and instead hospitals are more equal and the network is more evenly distributed. Highly centralized networks look like a 'hub-and-spoke' model and resemble notions of regionalization of care with community hospitals grouped around a centralized quaternary care hospital, whereas decentralized hospitals more closely resemble a web. Centralization may lead to improved care by concentrating the provision of advanced procedures in the central hospital rather than allowing provision of this type of care to be fragmented throughout the system. Furthermore, in centralized networks, the central hospital serves an important coordinating and influencing function, and a great deal of information passes through the central hospital, while the coordination demands may be lessened for non-central hospitals that can rely on a central coordinating organization (95-97). Because hospitals are different sizes and offer complementary levels of service, ranging from a small critical access hospital to large medical centers, organizing hospitals into a centralized network may reduce coordination burdens on peripheral hospitals while allowing a centralized hospital to set ground rules and coordinate effectively with a large number of smaller hospitals. Finally, in the broader research on networks, centralization has been shown to positively affect performance when centralized control or coordination is beneficial and work is distributed and negatively affect performance when smaller subunits should be provided greater autonomy—therefore, centralization may provide a means to organize and control the network of hospitals that is beneficial to the extent that key collaboration needs to happen between central and peripheral hospitals, not between poorly connected peripheral hospitals (83, 98, 99). This seems likely given the differentiation in services provided by advanced hospitals likely to occupy the core and small community hospitals likely to occupy the periphery. In total, highly centralized networks may feature greater concentration of care into central hospitals and a greater degree of coordination between hospitals, resulting in more efficient and higher quality care.

Hypothesis 4a: Hospitals in more centralized collective networks provide more efficient care.

Hypothesis 4b: Hospitals in more centralized collective networks provide higher quality care.

DATA AND METHODS

As in chapter 2, I used the 2014 "Physician Shared Patient Patterns" network data file derived from Medicare claims housed in the Integrated Data Repository to identify hospital networks (57). The file contains information on all healthcare providers appearing on Medicare claims, including hospitals and other institutional providers. Hospital National Provider Identifiers (NPIs) were primarily identified using the NPIs listed in the American Hospital Association's Annual Survey. When no NPI was listed in the AHA survey, the hospital Medicare provider number was identified and mapped to the associated NPI in claims data. Finally, when no Medicare provider number was present, the NPI associated with a hospital was identified using the hospital address. Each observation in these data consists of three variables: the two providers that share patients, identified by their NPIs and the number of patients for whom both providers appeared on a Medicare claim within 30 days, aggregated over the course of the year. This claims based approach captures patients treated at the hospital as both inpatients and outpatients, including patients seen in the emergency department. However, these claims are unlikely to reliably include patients seen in an outpatient clinic associated with the hospital if they do not receive care associated with a facility or technical fee. Pairs of providers that shared fewer than 11 patients are not included in these files. The population under study includes all non-federal, acute care hospitals located within the 50 states and Washington DC as listed in the 2014 American Hospital Association Annual Survey. I identified these hospitals in the network file as described in Chapter 2.

Network Measures

In order to characterize the network of hospitals, I first had to define the boundaries of each network. To do so I used a hierarchical community detection algorithm designed to identify closely linked groups of actors in a network. I chose to identify 150 communities because, as described in Chapter 2, this number of communities appeared to perform well in terms of reliability over time, validity in relation to other methods of grouping hospitals, and in predictive power of outcomes that should be similar among related hospitals. In addition, 150 communities is close to the average number of communities identified when using different community detection algorithms with different underlying assumptions. Once these networks were identified, I defined the characteristics of each network.

Network Concentration

I defined network concentration at both the hospital and network levels. To define hospital-level network concentration, I first calculated the number of patients the hospital shares with each partner hospital in their network and divided by the total number of patients the hospital shared with other hospitals in their network. I then took the sum of squares, generating a measure similar to the Herfindahl-Hirschman Index (HHI) commonly used to measure the competition of a market. This produced a zero to one scale on which a hospital that shared all patients with a single other hospital would be a one while a hospital with many hospital partners each comprising a small portion of their total patient population would be closer to zero.

Following a similar logic, to measure the concentration of each whole network, I calculated the fraction of the network accounted for by each tie between hospitals and took the sum of the squares. Like the hospital-level measure, in a concentrated network with few strong ties, this number would approach one while in dispersed networks with many weaker ties this number would be closer to zero. I censored one network that was an extreme outlier and replaced its concentration score with the concentration of the next highest network.

Hospital Centrality and Network Centralization

I characterized the centrality of each hospital using closeness centrality, which is defined for each hospital as the number of steps required to access every other hospital in the network from the given hospital. A hospital that is very high on closeness centrality is few steps away from all other hospitals in the graph, even if they do not directly share patients with all other hospitals. I normalized the centrality for each network by dividing the total number of hospitals in the network minus one by the measure of closeness. This produced a measure of centrality with a theoretical minimum of 0 and maximum of 1 for each hospital.

To generate a measure of the centralization of the network, I summed the difference between the centrality of the hospital with the highest centrality and each other hospital in the network and divided by the difference between a theoretical hospital with the highest possible centrality and each other hospital (100). This creates a zero to one index in which a highly decentralized network in which no single point is much more central than any other would be near zero and a very centralized network in which there is a single, central point would be a one.

Outcome Measures

I drew MSPB and 30-day all cause readmission rates from Medicare's Hospital Compare data files and matched these to the hospitals identified in the network data. The MSPB measure is adjusted to account for differences in prices by geography, add-on payments to hospitals, for beneficiary age and severity of illness. The readmission measure is similarly adjusted for patient characteristics. The MSPB measure was created from hospital data from January 1, 2014-December 31, 2014 while the readmission measure was created from hospital data from July 1, 2014-June 30, 2015.

Control Variables

Network Controls

I controlled for the level of competition in the market by creating a HHI of market concentration, based on the number of beds within distinct hospital systems, for each of the 150 networks. This measure captures the extent to which the network features many hospital systems with relatively few beds in each or is more concentrated in fewer systems, which may reflect greater market power. I also controlled for the number of hospitals in each network and the number of shared patients in each network since these were likely to be correlated with the focal network measures.

Hospital Controls

I controlled for several hospital-related characteristics that might bias the relationship between the characteristics of the network surrounding the hospital and MSPB and readmissions rate. First, I controlled for the average strength of ties at a hospital and the variation in tie strength to control for the absolute number of patients that they share with others and variation in that measure in order to isolate the effect of sharing different proportions of patients with others. In addition, I included the ownership of the hospital (government, non-profit, for-profit), the teaching status of the hospital, the hospital's bed size (<100 beds, 100-399 beds, or 400+ beds), the hospital's membership in a multihospital system or network, whether the hospital was a general acute care hospital or some other specialty, and whether the hospital was in an urban area or a critical access hospital. Finally, I calculated the proportion of all hospital beds in the network comprised by each hospital.

County Controls

For each hospital in the data set, I included measures related to the demographics and supply of healthcare in the county surrounding the hospital using the Area Health Resource File. I controlled for the percentage of the population over 25 without a high school diploma, the income per capita, the unemployment rate, the percent of the county that was non-Hispanic white, female, and over 65, and the population density. The controls related to the supply of healthcare in the county included the number of physicians, primary care providers and specialists per 1,000 residents, and the number of hospital beds per 1,000 residents. These characteristics are likely to be related to the characteristics of the hospital network and to hospital performance.

Analysis

I first described the characteristics of the network and hospital characteristics to provide a sense of the average and range of each measure. I then assessed the correlation between key network measures to better understand how these network features interrelate and whether any suppression effects or collinearity issues may be present in the model. To further characterize these network measures, I selected four networks from the data and created example network diagrams, one high in concentration and centralization, one low in one and high in the other network characteristic, and one low in both. I then examined the relationship between hospital concentration and centrality as well as network concentration and centralization and the MSPB and readmission outcomes in a multivariate framework. I included network, hospital and county controls in multivariate regression models to account for observed factors that may bias the relationship between network characteristics and these outcomes. Because the outcomes were continuous and at the hospital level while some of the key independent variables were at the network level, I used a multilevel mixed effects linear regression model with network-level random intercepts to estimate the relationship between the key network measures and outcomes, and clustered standard errors at the network level.

Because both of the outcome measures have been processed by CMS, it is challenging to infer the size of any observed association in these values. Similarly, several of the network measures do not have intuitive scales. To facilitate interpretation, I standardized both the outcome variables and the network measures such that the coefficients on the variables of interest in all models represent the proportion of a standard deviation change in the outcome variable created by a one standard deviation change in the network measure.

Finally, because the MSPB measure is a composite of many types of claims, in a robustness test I investigated the relationship between network characteristics and three specific types of claims: inpatient spending occurring within 30 days after discharge from the index hospital, outpatient spending after discharge, and inpatient spending during the admission. I would expect to observe that both inpatient and outpatient spending after the visit follows the hypotheses I identified for overall spending because the hospital's ability to coordinate with outside hospitals may influence those costs. Similarly, inpatient spending at the focal hospital may be sensitive to coordination if the hospital is better able to gather information.

RESULTS

All identified hospitals were divided into 150 networks using a community detection algorithm; however, 6 hospitals were placed into single-hospital networks for which collective network characteristics could not be defined and so were subsequently dropped. The resulting final analytic sample included 4,294 hospitals for which CMS reported either readmissions or MSPB data and were identified in the Medicare network data, and these were divided into 144 total networks. Summary statistics for these networks and hospitals are reported in Table 6. Collective network concentration was generally low with a long right tail, with an average concentration of 0.05 and a range from 0 to 0.28. On average individual hospital's ego-centric networks were more concentrated than were collective networks, with a mean of 0.28, but the range of concentrations was very wide, covering 0.029 to 0.84. The average network contained 32 hospitals and nearly 300,000 shared patients.

Table 6. Characteristics of the Network and Hospital Sample

Network-level Variables (144 Networks)	mean	sd	min	max
Network Concentration	0.05	0.065	0	0.28
Network Centralization	0.33	0.075	0	0.53
# of Hospitals	32	20	3	102
# of Shared Patients	289,952	383,346	429	2,890,529
Herfindahl Index	0.19	0.13	0.042	1
Hospital-Level Variables (4,294)				
Hospital Concentration	0.28	0.17	0.03	0.84
Hospital Centrality	0.62	0.12	0.29	1
Adjusted Readmission Rate*	15.23	0.85	11.3	19.8
Medicare Spending Per Beneficiary*	0.98	0.084	0.62	1.63
Average Tie Strength	551.7	606.7	20.8	9,898
Tie Strength Variation	937.5	1362	0	20,481
Physicians per 1,000	2.24	2.11	0	35.9
PCPs per 1,000	0.70	0.32	0	4.67
Specialists per 1,000	0.71	0.75	0	13.8
Hospital Beds per 1,000	3.66	3.63	0	78.80
Proportion Female	0.50	0.015	0.36	0.57
Proportion over 65	0.16	0.041	0.048	0.377
Proportion White	0.78	0.17	0.11	0.99
Population Density	8.45	31.62	0.001	487.1
Proportion adults w/o high school diploma	0.14	0.060	0.026	0.533
Income per Capita ($)	42,899	12374	21,696	194485
Unemployment Rate	0.062	0.020	0.012	0.236
Critical Access Hospital	27%			
System Member	62%			
Teaching Major	5.3%			
Teaching Minor	24%			
No Teaching	61%			
Government Owned	21%			
Not For Profit	60%			
For Profit	19%			
Urban Location	60%			
Small (<100 beds)	50%			
Medium (100-399 beds)	40%			
Large (400+ beds)	10%			

***** Medicare Spending Per Beneficiary was not available for all hospitals; N=3,120
* Readmission Rate not available for all hospitals; N=4,313

To better understand the relationship between these collective network measures and other features of the network, I identified several important correlations between network features (Table 7). Collective network concentration was weakly and positively correlated with collective network centralization, modestly and negatively correlated with markers of network size including the number of hospitals and total number of shared patients in the network, and positively but weakly correlated with hospital market concentration. The degree of network centralization was only weakly associated with the number of hospitals, shared patients and market competition. The correlation between hospital-level concentration and collective network concentration was low, and the correlation between hospital centrality and network centralization was negative.

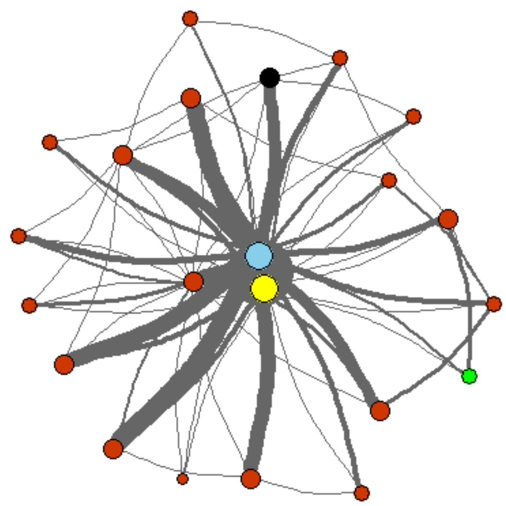
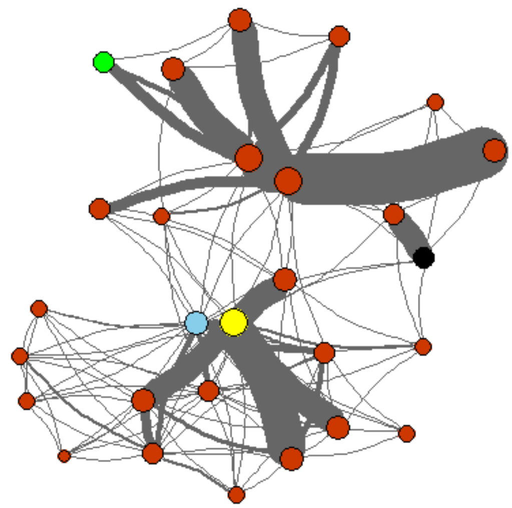
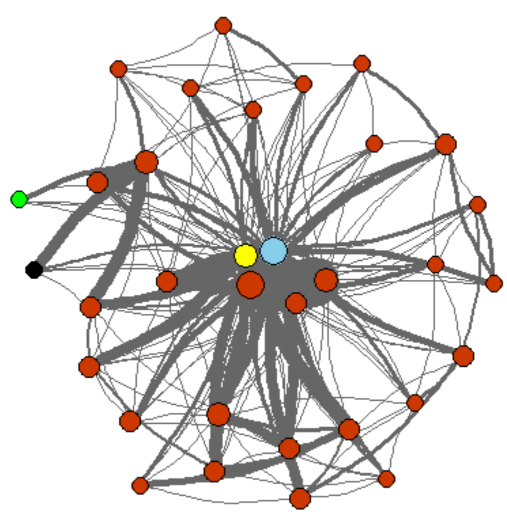
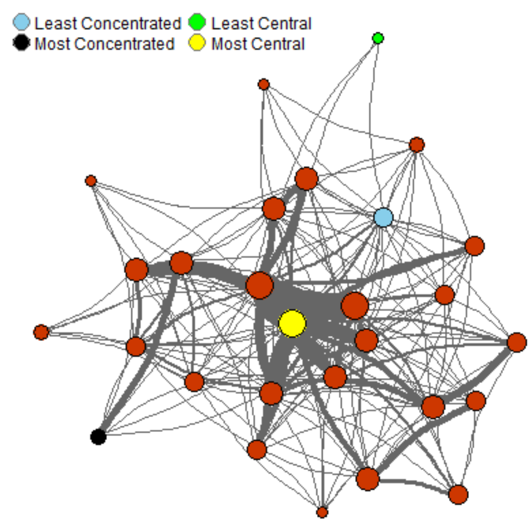
Table 7. The Correlation between Network Characteristics and Key Community Characteristics

	Network Concentration	Network Centralization	# Hosps	# Patients	Market Conc.	Hosp. Cent.
Network Concentration	1					
Network Centralization	0.11	1				
# of Hospitals	-0.37	0.28	1			
# of Shared Patients	-0.22	0.17	0.74	1		
Market Concentration	0.41	-0.05	-0.51	-0.38	1	
Hospital Concentration†	0.13	-0.04	-0.32	-0.19	0.28	1
Hospital Centrality†	0.09	-0.18	-0.24	-0.09	0.05	-0.36

N=144 unique communities
† Correlations for these variables use 4,294 hospitals in the sample, not unique communities.

Figure 8 depicts four hospital networks drawn from the data to provide a visual sense of how these networks differ on concentration and centralization. The top-left network features a few hub hospitals occupying a central position in the graph connected to several smaller hospitals through concentrated ties. The top-right network contains highly concentrated ties between hospitals but seems to be comprised of two components and therefore has low centralization. The bottom-left network has high centralization—i.e., several hub hospitals that are closely tied to one another—and many ties comprising relatively few patients. Finally, the bottom right network has both low concentration—i.e., many moderate and weak ties—and low centralization created because many hospitals seem to occupy relatively central positions creating a less clear hub and spoke system. In each network, the hospitals with the lowest and highest concentration and centrality are highlighted.

Figure 8. Four Example Network Graphs Drawn From Medicare Data

	High Centralization	**Low Centralization**
High Concentration		
Low Concentration		

Efficiency

When I analyzed the relationship between network structure variables and outcomes in a multivariate framework, I found a statistically significant association between greater hospital-level network concentration and lower MSPB, supporting hypothesis 1a. A one standard deviation increase in concentration at the hospital-level was associated with 6.7% of a standard deviation lower MSPB ($p=0.040$) (Table 8 column 1). When I tested hypothesis 2a, I observed a stronger association between collective network-level concentration and lower MSPB, such that a one standard deviation increase in concentration was associated with 18.0% lower MSPB ($p<0.001$). These two findings indicate that greater concentration is related to more efficient care.

Table 8. Multi-Level Regression Models of the Effect of Network Characteristics on MSPB and Readmissions

	Standardized Medicare Spending Per Beneficiary		Standardized 30-day All Cause Readmissions	
Network Concentration	-0.180***	(0.038)	-0.127***	(0.024)
Hospital Concentration	-0.067**	(0.033)	-0.030	(0.024)
Network Centralization	0.076**	(0.030)	-0.137***	(0.031)
Hospital Centrality	-0.090***	(0.034)	-0.048*	(0.025)
# Hospitals	0.010**	(0.004)	0.000	(0.003)
# Shared Patients	-0.000	(0.000)	0.000***	(0.000)
Market Concentration	-0.095	(0.291)	0.491**	(0.220)
Average Tie Strength/1000	0.146**	(0.074)	-0.073	(0.094)
Tie Strength Variation/1000	-0.042	(0.034)	0.024	(0.047)
Ownership (Ref: Government)				
Not-For Profit	0.044	(0.051)	-0.158***	(0.041)
For Profit	0.319***	(0.071)	0.195***	(0.067)
Teaching Status (Ref: None)				
Major Teaching	-0.231**	(0.113)	0.617***	(0.116)
Minor Teaching	-0.064	(0.070)	0.074*	(0.040)
Size (Ref<100 Beds)				
Medium (100-399 Beds)	0.202***	(0.042)	0.125***	(0.043)
Large (400+ Beds)	0.230***	(0.062)	0.255***	(0.096)
System Member	0.016	(0.055)	-0.039	(0.043)
Network Member	-0.028	(0.035)	-0.055*	(0.031)
General Acute Care Hospital	0.211	(0.163)	0.734***	(0.129)
Urban Location	0.234***	(0.048)	-0.024	(0.050)
Critical Access Hospital			0.196***	(0.045)
Hospital System Market Share	-0.206	(0.167)	-0.087	(0.116)
Proportion w/o High School Diploma	0.001	(0.001)	0.000	(0.000)
Income Per Capita	0.000	(0.000)	-0.000***	(0.000)
Unemployment Rate	-0.003*	(0.002)	0.002*	(0.001)
PCPs per 1,000	-0.154	(0.101)	-0.148*	(0.083)
Beds per 1,000	-0.013	(0.011)	0.006	(0.004)
Proportion Female	3.480**	(1.609)	0.233	(1.103)
Proportion over 65	-0.542	(0.787)	-0.079	(0.532)
Proportion White	-0.000	(0.000)	-0.001**	(0.000)
Population Density	-0.002***	(0.000)	0.001**	(0.001)
Specialist per 1,000	0.275**	(0.118)	0.544***	(0.137)
Physicians per 1,000	-0.063	(0.041)	-0.159***	(0.047)
Constant	-2.380**	-0.837***	-0.468	-1.234***
Observations	3,119		4,269	
Number of groups	144		144	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

When I tested hypothesis 3a, that hospital centrality was associated with higher spending, I found support for my hypothesis: greater hospital centrality was associated with *higher* MSPB, consistent with the idea that centrality imposed a burden on the central hospital (7.6% of a SD higher, p=0.012). Finally, when I examined network centralization, I found that higher levels of centralization were associated with lower MSPB (9.0% of a SD lower, p=0.008), which supports hypothesis 4a, which stated that centralization led to greater efficiency of the hospitals in the network.

Readmissions

The pattern of results was somewhat different when examining the relationship between these network characteristics and readmissions. I did not find support for hypothesis 1b: concentration at the hospital level was not associated with reduced readmission rates (p=0.22 Table 8 column 2). However, greater collective network concentration was associated with lower readmission rates (12.7% of an SD, p<0.001) supporting hypothesis 2b. Hospital centrality was associated with lower readmissions (13.6% of an SD, p<0.001), the inverse of the relationship observed for MSPB but in line with hypothesis 3b that centrality can improve patient outcomes by focusing care in large hospitals. Finally, network level centralization was marginally associated with lower readmission rates (4.8% of an SD, p=0.058), indicating marginal support for hypothesis 4d.

Robustness

When I investigated specific types of spending I found results that were generally consistent with my primary finding. As in the main results, greater network concentration was associated with reduced inpatient spending after discharge (Table 9); however, network concentration was also associated with higher inpatient spending during the visit. Greater hospital concentration was associated with reduced inpatient spending during the visit. Greater hospital centrality was associated with higher spending in all three categories. Centralization was marginally associated with lower inpatient spending after discharge but not outpatient spending or inpatient spending during the visit. In sum, with one exception all of the statistically significant relationships were consistent with the main MSPB finding; however, not all categories were statistically significant. These findings begin to clarify where the hospital network is associated with cost savings; however, since these measures are not adjusted by patient severity or other factors it is possible that those factors are influencing the observed relationships.

Table 9. Association Between Network Measures and Specific Spending Types

VARIABLES	Inpatient post-discharge	Outpatient post-discharge	Inpatient during admission
Network Concentration	-100.495**	5.972	132.684***
	(39.167)	(5.904)	(48.381)
Hospital Concentration	-16.484	1.742	-126.824**
	(35.309)	(10.493)	(53.407)
Centrality	78.220***	33.817***	386.833***
	(28.847)	(7.420)	(56.447)
Centralization	-84.490*	9.288	-21.700
	(47.078)	(7.362)	(38.942)
Observations	3,123	3,123	3,123
Number of groups	144	144	144

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
All Control variables in the main regression models were included in these robustness tests but omitted from this table for parsimony.

DISCUSSION

This study represents one of the first efforts to understand the relationship between the structure of the inter-hospital network of shared patient and coordination of care that influences hospital performance. I found that the structure of the inter-hospital network of shared patients was associated with two important measures of hospital performance: Medicare spending per beneficiary and 30-day all cause readmissions. At the network level, both the extent to which hospital patient sharing relationships were concentrated and the degree to which the network was centralized were associated with lower Medicare spending and readmissions. At the hospital level, greater network concentration was associated with lower spending but not readmissions, and this effect was smaller than the effect associated with the network-level measure. Finally, hospital centrality was associated with higher costs but lower readmissions, while the centralization of the collective network was associated both with lower spending and readmissions. The effect on readmissions is consistent with the volume-outcomes literature, while the finding that high centrality was associated with higher costs indicates that central hospitals may be taking on more of the coordination burden than hospitals in the periphery. In combination, these findings signify the importance of understanding not just an individual hospital's structure and capabilities but also the features of their partners, which make up their healthcare delivery network.

Prior studies have measured health care fragmentation either as patient movement between hospitals or as the extent to which individual patients are seen by multiple providers or organizations (71, 72, 84, 101). While important, those approaches do not capture information about the relationship between organizations that might facilitate successful coordination across organizations. Other work on the beneficial effects of relational coordination focused only on individual provider's perceived relationships and do not explain the inter-organizational level or capture structures that facilitate improved relational coordination (92, 102). My findings indicate that the characteristics of the relationship between hospitals matters, and that measures of these characteristics should account for both individual hospitals and the whole network. Specifically, greater concentration in a network facilitates coordination, perhaps because concentration allows for the development of experience and relationship specific investments in well-functioning processes. Centralization also appears to allow for better coordination of care throughout a network of shared patients by allowing large hospitals with greater organizational resources to coordinate the network as a whole.

This study also represents a contribution to our understanding of the relationship between provider networks and the performance of the healthcare system. A growing body of work has identified links between physician networks of shared patients and patient outcomes (27, 28, 103) as well as other behavior (104). While some work has been done to characterize the inter-organizational network of shared patients, that work has not explicitly associated these networks with outcomes (13, 34, 36, 39). As such, this study extends work focused on the impact of network structure on performance by focusing on a different unit of analysis—hospitals instead of individual physicians—and extends work on the inter-hospital network by investigating its relationship with performance. Specifically, I find that greater concentration in the network is associated with more efficient and higher quality hospital care.

These findings suggest that efforts that drive towards greater concentration and centralization will result in improved hospital outcomes. Several trends in the hospital market, including consolidation of hospital systems and the rise of Accountable Care Organizations, are likely to lead to greater concentration and may therefore result in improved performance through changes in the underlying network of hospitals. In addition, the finding that centralization is associated with greater performance indicates that regionalization may be associated with improved performance through a mechanism beyond the volume-outcome relationship, lending additional support to the body of research indicating the potential benefits of regionalization. Regionalization could be increased by altering financial incentives for hospitals to provide care that may be better provided at other organizations and by increasing the incentive to refer patients out, especially to the highest quality centers. However, as policy changes or private initiatives are implemented that implicitly alter the network of inter-linked providers, it is important to measure how those policies affect the collective network—that is, the network of both hospitals participating in these initiatives and the network of non-participating hospitals linked to those that participate through network ties. It could be that well-meaning policies disrupt functioning networks in unintended ways.

Finally, as trends towards organized networks progress, it will be important to ensure that central hospitals have the support they need to coordinate other hospitals in the network. Efforts to improve relational coordination, such as use of designated care coordinators, support for administrative staff working together, and support for clinicians collaborating across organizations may be easier to accomplish in well-structured networks; however, these efforts remain costly regardless of network structure. In particular, support of health information exchange between hospitals will be essential to facilitate greater availability of information throughout the network. Policy efforts aimed at rewarding hospitals that engage in coordination efforts and continued support for the development of robust health information exchange may lead to continued improvements in the quality of care for patients moving between organizations.

Limitations

This study is subject to several important limitations. First, it is cross-sectional and associational. While I attempted to control for many potential confounders of the relationship between network structure and MSPB and readmissions, it is possible that unobserved covariates biased the ability to measure the relationships of interest. Second, in this study I only measured the inter-hospital network of shared patients. I chose this focus to complement the growing literature on the inter-physician network; however, there are many important network sharing relationships and this study does not observe the effect of the physician-to-physician, physician-to-hospital network, or the many other pieces of the full healthcare delivery system network. Future research should work towards a fuller understanding of the important features of this complex network. Third, I theorized that the relationships observed between network structure and hospital performance are related to communication and coordination practices; however, I do not directly examine the relationship between networks and these practices. Further research might empirically investigate the idea that certain network structures corresponded to reported improvements in coordination. Finally, the publicly available network data contains very little information about the conditions for which patients are treated or the treatment received. In consequence, this study represents a very high level view of the hospital network and may not capture features of the network important for specific conditions, treatments or patient populations. However, prior research has focused more closely on specific groups so that this work represents a complement to that more focused work which may omit the broader network studied here.

Conclusion

By focusing on shared Medicare patients between hospital, I identified and measured salient characteristics of inter-hospital networks. Most importantly, I found that the *network level* is a more important contributor to hospital performance than individual hospital relationships with key partners, and that a concentrated and centralized network may allow for highest performance. These findings point to the important role network structure plays in the performance of the healthcare delivery system. Organizational leaders and policy makers should more closely consider the likely impact of new initiatives on the network of shared patients. Initiatives that are likely to push the structure of networks towards greater concentration and centralization, such as acquisition of new organizations and implementation of policy like ACOs and bundled payment initiatives, appear more likely to improve performance by strengthening relationships that mitigate the negative consequences of fragmentation.

CHAPTER IV

The Implications and Impact of Three Approaches to Health Information Exchange: Community, Enterprise and Vendor-Mediated HIE

INTRODUCTION

Policy makers in the United States (U.S.) have long pursued the goal of increasing electronic patient health information exchange (HIE) between healthcare organizations, believing that increased availability of such information is an essential foundation to facilitate a learning health system to improve the quality and efficiency of patient care (105). Despite continued support for HIE, growth in its adoption and use by healthcare organizations has been relatively slow (106, 107).Traditionally, policy efforts have aimed to support the development of third party entities, often known as regional healthcare information organizations (RHIOs) or more recently as Community HIEs (used hereafter), to coordinate HIE between multiple stakeholders in an area (105, 108, 109). However, Community HIEs have struggled to engage healthcare organizations and other relevant entities, to create a sustainable business model and to develop a technical architecture (106, 110-112). This has led to slow growth among many Community HIEs and to the closure of others (108, 113-115).

These challenges, combined with a shift in policy towards supporting HIE in varied form, created the opportunity for new approaches to HIE to emerge. Specifically, large healthcare organizations support health information exchange with other organizations via Enterprise HIE, and electronic health records (EHR) vendors have begun to develop HIE for their customers within the EHR (116-118). These different approaches to HIE vary along several dimensions, such as their openness to participation by competitive providers and their ability to establish rich data exchanges that are integrated with providers' EHRs. Enterprise and Vendor-based HIE provide the underpinning for newer initiatives to expand the reach of HIE, such as the CommonWell Health Alliance, and the Sequoia Project's Carequality and eHealthExchange, such that future developments may be imbued with the strengths and weaknesses of each type (119, 120). Because the differences characteristic of each type of HIE can impact the ability to develop a learning health system and improve patient care (121), it is critical to assess the impact that each type of HIE has had on patients and providers to help guide investment decisions by healthcare organizations and policy makers as they navigate and try to support the continually changing HIE landscape. Further, these differences in types of HIE may have important implications for the value of HIE to hospitals with different types of patient sharing networks.

RESEARCH INTERESTS

In this study, I build from existing definitions of different types of HIE (116, 122) to better characterize types of HIE both conceptually and empirically. Specifically, I address three research objectives. First, I define three forms of HIE and identify their key characteristics, including who facilitates sharing of data, the rationale of participation in each form, and the particular costs and benefits offered by each approach. Second, I identify the current prevalence, use and impact on cost and patient outcomes of each type of HIE. Finally, I propose future directions for research on HIE that will allow for better assessment of the relative benefits to patients and providers from each approach.

Methods

To develop a conceptual understanding of the types of HIE currently in use, I revisited articles cited in two recent systematic reviews that summarized the empirical literature on HIE (123, 124) and surveyed additional works that either cited or were cited in those articles to develop a conceptual overview of the available HIE types. Drawing from this literature, I first sought to describe HIE types based on core characteristics, including the rationale for participation, role of competition, technical barriers, expectation for patient benefit and prospects for growth that influence participation, use and success of each HIE tool.

Next, I categorized the empirical literature by HIE type to capture the extent of the evidence, prevalence, usage, usability and impact on utilization and patient outcomes of each type of HIE. Because of the varied methods used and results presented in the reviewed studies, I qualitatively summarized the literature to describe each facet of HIE. To estimate prevalence, I used the most recently available studies on each type of HIE. I summarized the frequency of use by drawing on 21 studies from recent reviews and citing publications that described use. To summarize usability issues, I synthesized the key conceptual issues from these studies and additional articles. Finally, to assess the impact of each type of HIE, I included 25 of the 28 studies on impact cited in recent reviews as well as one additional study published after these reviews. I excluded three studies because I could not categorize them by type of HIE used. 84% of included studies focused on HIE efforts in the U.S. while 16% of studies were set outside of the U.S. Unless otherwise noted, cited findings come from studies of the U.S.

RESULTS

A Taxonomy of Health Information Exchange

HIE is the process of electronically sharing health data between healthcare organizations (125, 126). To occur, HIE requires technological and governance structures between unaffiliated organizations, both of which require a facilitating convener. Experts believe that HIE will reduce the frequency of medical errors—such as adverse drug events—associated with missing information, will improve medical decision making and efficiency, and will reduce redundant diagnostic tests.(127-129)

Despite sharing an overarching definition and set of goals, existing HIE efforts vary along several technical and social dimensions. I follow Vest, Campion and Kaushal's (2013) division of HIE into types based on the entity providing the convening role for the HIE effort (116). The convening dimension of HIE is essential because each convener establishes the rules and rationale for participation by outside organizations in different ways, which may drive participation from specific groups, and participation is particularly salient since adoption of HIE remains far from complete (106, 130).

The most studied type of HIE, **Community HIEs,** are third-party organizations created specifically to provide the infrastructure to connect healthcare organizations (131). These organizations are expected to build consensus and participation among healthcare organizations (113). The Mid-South eHealth Alliance (MSeHA), which covers the metropolitan Memphis area and connects 16 of the 17 hospitals in the area, is a frequently studied example of a Community HIE. **Enterprise HIE** is convened by a large healthcare organization like a multihospital system to create connections with select providers with whom sharing information is in the convening organizations' interest (116). Enterprise HIE can involve 'rolling out' the convener's EHR system to unaffiliated healthcare organizations, creating an interface between different EHRs, or sharing a portal that allows others to view their information. Finally, EHR **Vendor-Mediated HIE** is convened by an EHR vendor that offers technical and networking support to establish connections between their customers. For instance, Epic Systems' Care Everywhere platform is included as part of their EHR and facilitates information sharing between all of their customers.

Along with differing convener, each type of HIE is characterized by varying levels of seven key characteristics related to participation and growth. (1) **Openness**, the extent to which the HIE form is designed to allow for participation from a broad group of health care organizations (2) The **Logic of Participation**, the reasons why a healthcare organization might be interested in joining each type of HIE, (3) the role of **Competitive Motivation** in spurring or slowing each form of HIE, (4) The **Apparent Difficulty** of establishing and sustaining each form of HIE, (5) The level of **Expected Patient Benefit** from each form of HIE, which is based on the likelihood that the HIE connects necessary organizations in valuable ways, (6) The prospects for **Growth** of each form of HIE in the future and (7) the **Scalability** of each form of HIE into a single unified network.

The characteristics of each type of HIE are briefly summarized in Table 10. In general, Community HIEs are appealing due to their openness and the possibility that they will lead to a nationwide, inclusive system of HIE; however, other options may be more appealing to key stakeholders, fulfill different needs and face fewer technical barriers.

Table 10. Key Characteristics and Differences Between Community HIEs, Enterprise HIE and Vendor-Mediated HIE

	Convener
Community	Neutral Third Party Organization
Enterprise	Large Healthcare Organizations
Vendor	EHR Vendor
	Openness
Community	Open view of HIE available to all participants, regardless of affiliation, or competitive interests (110, 132).
Enterprise	More closed-system HIE than Community HIEs (132). Specifically include key partners of convening organizations and may exclude competitors (116, 133).
Vendor	Designed to facilitate exchange within a vendors' customers. Few incentives encourage HIE across vendors.
	Logic of Participation
Community	Driven by geographic proximity and shared patients.
Enterprise	Gathers participants from healthcare organizations that are either already officially affiliated, such as physician offices and hospitals owned by the same healthcare system, or are close informal partners that privately agree to collaborate.
Vendor	Driven in large part by provider choice of vendor, which may not relate strongly to vendor HIE capability or other participating organizations. Vendors may be effective conveners because they hold the technical expertise to support infrastructure development, and build close relationships with multiple healthcare organizations as part of the implementation process (134).
	Competitive Motivation
Community	Due to the high level of openness, Community HIEs have struggled to deal with healthcare organizations' reluctance to share information with their competitors.
Enterprise	Development may be a competitive advantage because it can provide efficiency gains to providers within a large organization or can tie loosely affiliated outside healthcare organizations closer to the organization (117, 135).
Vendor	EHR vendors may find it in their competitive interest to facilitate HIE within their customer base, the vendors may also block information sharing with healthcare organizations using other vendors to increase the appeal of selecting their system (136).
	Apparent Difficulty
Community	In part due to their openness and intended wide participation, Community HIEs have faced many challenges including cost to join; technical and usability issues; security, privacy and liability issues ; and concerns about loss of market competitiveness (110, 132, 137).

Enterprise	Because enterprise HIE usually involves a participants with a history of collaboration, increasing participation among collaborators may be easier than other HIE approaches which may connect competitors or unaffiliated organizations.
Vendor	Simplified because each implementation of the same vendor's EHR system share similar—though not necessarily identical—data structures.
	Expected Patient Benefit
Community	Could logically extend to all healthcare organizations in an area, offering relatively high potential value to patients. However, many community HIEs share a limited set of data.
Enterprise	May provide lower benefit to the local community as a whole because it can exclude some healthcare organizations, limiting the extent to which patient data is shared. However, it may connect the most frequent healthcare provider partners together, supporting the sharing of information necessary for collaboration-based initiatives like bundled payments and accountable care organizations.
Vendor	May provide less value to the community of patients than a more open approach to the extent that vendors block information sharing across organizations that use different vendors. Relative to Enterprise HIE, vendor HIE may connect providers that happen to share vendors, but may not connect the most frequent collaborators. Vendors may provide highly functional systems.
	Growth
Community	Given the difficulties encountered by many Community HIEs, their future growth seems in doubt.
Enterprise	Likely to grow as more organizations gain sophistication in IT support through their own EHR implementation.
Vendor	An increasing number of vendors offer easily implemented vendor-mediated HIE, and many vendors are developing these tools (138, 139).
	Scalability
Community	As Community HIEs grow they may be logically combined into a single network (125).
Enterprise	Growth may be driven by increases in the *number* of enterprise HIEs, rather than growth towards an interlinked network.
Vendor	Vendor networks may result in silos of information unless vendors and healthcare organizations can overcome important competitive barriers to cross-vendor HIE, and transfer technical benefits from enabling HIE on a single vendor system towards sharing across vendors. Several cross-vendor initiatives are being developed but not yet widely used (119, 120).

Does HIE Type Matter?

Although the evidence on vendor-mediated and enterprise HIE is relatively limited, it is clear that each form of HIE is used by a substantial group of providers and offers key differences in usability and impact.

Community HIE

Extent of Evidence

Community HIEs are the most frequently studied form of HIE with two sources of national data on Community HIE participation (the American Hospital Association's (AHA) Information Technology survey and annual surveys of Community HIEs), and many studies on their usage and impact. However, most existing studies on the impact of HIE have focused on a few large Community HIE efforts, including several efforts in New York State, the Integrated Care Collaborative (ICC), in the Austin Texas area, and the MSeHA, in the Memphis Tennessee metropolitan area. As a result, the generalizability of these studies may be questionable.

Prevalence

Since 2008 the AHA Information Technology Supplement has asked hospitals whether they actively share data through a Community HIE, and about one third of hospitals reported exchanging data and participating in a Community HIE in 2013 (140). In addition, an annual survey of Community HIE entities identified 119 active in 2012 and estimated that 30% of hospitals and 10% of ambulatory providers participated (106). However, case studies have reported the failure of several Community HIEs, and the overall number of community HIEs declined in 2014 (108, 114, 115).

Usage and Usability

Several studies have reported on the usage and usability of Community HIEs. Five studies on the use of Community HIEs found that data from the HIE was used in 2-4% of all visits (141-145).

Community HIEs were found to be more frequently used for certain types of visits, and in particular repeated ED visits, especially for back pain and headache, have been found to be associated with much higher rates of HIE use, ranging from 12.5-21.9% (145-147) A different study reported much higher overall rates of HIE use, at 21%,(148) indicating that many implementation and social factors including integration with the EHR and success convincing providers of the value of HIE, might influence the rate of use of HIE.

Other studies assessed usage at the physician or patient level. A Study of the ICC indicated that 57% of patients had their exchanged information accessed at some point over the course of two years (148). In two Community HIEs in New York, 80% of physicians reported using the Community HIE (149). Yet again, there is a great deal of variation in use. Within the same Community HIE usage rates varied enormously at three sites depending on local implementations and policies: 1% of patients at one community and 5% of patients at another had their information accessed, while at the third over 50% did (150).

The low use of Community HIE may be due to several factors related to usability. Community HIE systems often relied on web-based portals or read-only documents and rarely provided structured data that was integrated with providers' EHR. As a result, providers report that the systems were often slow, disrupted their workflows, needed a separate log-in and password from the EHR, and required providers to look up patient' information in a separate system (149, 151, 152). In general, systems lacked advanced functionality like automated querying of the HIE from the EHR that might ameliorate these challenges and raise usage rates (152). Community HIEs may be unlikely to offer integration with EHRs because they sought to function similarly when used by stakeholders using many different EHRs, making investment in integration with any one system unlikely (137, 151). Several studies noted providers' frustration with missing data and that failed attempts to look up patients discouraged future use of the HIE (145, 151, 153). Community HIEs may be particularly susceptible to missing data because organization participation is voluntary and usually relatively low in an area, so that their coverage of the history of any given patient may contain gaps (151, 154). Finally, and somewhat paradoxically, when patient data was present, it was often of overwhelming quantity, coming from all visits to all organizations, and relevant information was not extracted for easy review (149).

Impact

Taken together, recent empirical studies have generated ambiguous results. Early estimates of the savings generated by MSeHA pointed towards large financial benefits (128) and a later study indicated lower, but substantial, benefits from it (155). Several studies have demonstrated that Community HIEs can reduce the rate of imaging (146, 147, 156). Community HIE participation in Wisconsin that linked 5 competitive systems was shown to save $29 per visit (157). A Colorado based Community HIE demonstrated that Community HIE adoption was associated with reduced lab testing, but the benefits were smaller than anticipated, and another examination of lab testing showed no effect (158, 159). On the other hand, use of the Texas based Community HIE was associated with a higher likelihood of admission and little financial benefit (143). Use of an HIE in Finland had similarly mixed effects (160). Finally, patient benefit was found in one of two studies of similar public-health driven Community HIEs, illustrating the challenge in identifying consistent effects in the available literature (161, 162).

Enterprise HIE

Extent of Evidence

In contrast to Community HIEs, there is no clear, national data on the extent of Enterprise HIE participation. A few studies using qualitative data or small-group surveys focus on the usability of physician portals and other forms of inter-organizational Enterprise HIE. Most of what is known about the impact of Enterprise HIE comes from studying a few specific hospitals or systems, most notably the Clarit HMO in Israel (163-165).

Prevalence

While there are no clear national assessments of the extent of Enterprise HIE participation, available evidence points towards wide prevalence. Unlike Community HIEs, which are specifically focused on linking disparate healthcare organizations, Enterprise HIE is used to connect both affiliated and unaffiliated organizations, and links between affiliated healthcare organizations appear to be more common. For instance, in 2013, 39% of physicians indicated that they shared information with other groups within their organization and 15% said they shared with outside organizations (107). Many large, multi-hospital systems engage in HIE, including Clarit in Israel and Kaiser Permanente, one of the largest healthcare organizations in the United States. Both of these systems use HIE tools to exchange data across multiple instances of their EHR, and in large part led development of these interfacing tools.

Enterprise HIE between unaffiliated organizations also appears to be widespread. In 2012, 58% of US hospitals reported on the AHA IT survey that they exchanged some information with outside organizations—approximately twice the percentage that reported participating in a Community HIE (166). Similarly, 15% of physician offices reported sharing information with outside organizations—50% more than participated in Community HIEs (107). It is therefore likely that current studies that only focus on Community HIEs may have underestimated the number of organizations engaged in HIE.

Usage and Usability

Studies of Clarit's within-system HIE showed that information generated outside of the site where the patient was being seen was viewed 4.3% of the time for the entire referral population, and 7% of the time among patients who received a specific lab test (163-165). A study in Sweden found that a hospital-based HIE there was used 7% of the time (167). Finally, a study in the US examining use of a physician portal focused on three separate six-month time periods and found that only 29% of physicians used the portal in all three periods (168).

Usability appears to vary across enterprise HIE systems. In cases like Clarit or Kaiser Permanente, enterprise HIE is integrated into providers' EHR, allowing for fewer obstacles than Community HIEs. In other cases, because providers have access to multiple different enterprise HIEs, any given hospital-provided portal requires yet another password and time consuming patient lookup process, likely limiting use (132). Access to multiple enterprise HIEs could be challenging because each system contained different information, making it hard to find specific information (117, 154). This has the potential to exacerbate problems accessing information or logging into systems reported in studies of Community HIEs (169). Enterprise EHRs were also sometimes designed using proprietary data structures, making them challenging to scale (170).

Impact

Many of the assessments of Enterprise HIE come from international studies. Four studies on Clarit's HIE demonstrated that using HIE was associated with positive outcomes (163-165, 171). One randomized control study in the Netherlands showed that use of an HIE was associated with improved diabetes care (170). U.S.-based studies showed that an HIE link between two affiliated academic hospitals reduced redundant imaging, and that use of a physician portal was associated with closer adherence to clinical guidelines (172, 173). Use of the HIE within the VA system of hospitals is associated with reduced redundant tests and other utilization (174). However, a randomly assigned control study of a link between an ED and associated physicians demonstrated no benefit, despite physician's perception of value (168) and another randomized trial, undertaken in Sweden, showed no benefit from a hospital sending information from their

ED to outpatient care(167). In general, observational studies of large integrated systems seem to point towards benefits from enterprise HIE; however, smaller scale studies using more randomized designs did not find evidence of benefit.

Vendor Mediated HIE

Extent of Evidence

In part because HIE mediated by a shared EHR vendor is relatively new, there are few studies on the prevalence, usage or impact of this form of HIE, and no national estimates.

Prevalence

While there are no good measures of how much HIE occurs through EHR-vendor based solutions, Epic Systems alone reports including 293 healthcare organizations in their Care Everywhere Network including many very large healthcare organizations, like Kaiser Permanente, Geisinger, and Sisters of Saint Mary(175). In 2013, six other EHR vendors announced their commitment to working together to launch a collaboration to foster HIE(120).

Usage and Usability

Two studies have evaluated the use of a vendor mediated HIE, and both focused on Epic Systems. In one study in the ED, Epic's HIE was used in 1.46% of patient encounters (134). In a second study, the rate of use was measured for multiple types of encounters and ranged from less than one half of a percent for specialty care encounters to 3.5% for ED encounters (118). These rates are notably lower than those reported for either enterprise or Community HIEs in comparable encounters. On the other hand, Epic's HIE uses the Consolidated Clinical Document Architecture, which should provide structured data in a commonly used format (176), and usability and perceived value were reported to be quite high in both studies, and appear to be higher than for Community HIEs or Enterprise HIE.

Impact

Only one study has examined Vendor-Mediated HIE (Epic Systems') (134). This study focused on the 1,488 patient encounters in the EDs of four hospitals in an integrated delivery system. Through chart review, the investigators found that use of the HIE was associated with 560 avoided duplicative diagnostic tests and 28 fewer cases of drug seeking behavior within those patient encounters.

The evidence for each type of HIE is summarized in Table 11. As noted in the discussion above, much more evidence exists on the prevalence and use of Community HIE, but some initial findings are available for the other two types of HIE.

Table 11. Evidence of Prevalence, Use and Impact of Each Type of HIE

	Community HIEs	Enterprise HIE	Vendor Mediated HIE
Prevalence	Estimated 119 Community HIEs nationwide. 30% of hospitals participated in 2012. 10% of ambulatory providers participated in 2012.	No direct national quantitative estimates. Physician portals appear widely used. Estimates of overall HIE participation is over 50% higher than Community HIE estimates alone.	Leading Vendor attests to having 293 participating organizations.
Use	Evidence drawn from 14 available studies. Access ranged from 1-5% overall, much higher for ED visits and visits with existing information. Up to 50% of patients had their data accessed at least once. Most physicians used the HIE at least once, though use was infrequent and inconsistent over time.	Evidence drawn from six available studies. Patient data accessed in 2-8% of visits.	Used in only 1.5 and 3.5% of ED encounters in only two studies available.
Impact	Evidence drawn from 15 available studies. Mixed evidence of decreased utilization. Mixed evidence of patient benefit.	Evidence drawn from nine available studies. Evidence for reduced utilization and readmissions from studies on large systems. No benefits from RCTs of individual linkages.	Evidence from only available study reports reduced use of diagnostic tests.

Evidence drawn from all studies included in prior systematic reviews or citing included studies.

FUTURE DIRECTIONS

A focused research agenda will help guide organization leaders to the choices that might facilitate transformation into part of a learning health system and provide the most benefit for their patients and organization. Research may also inform policy developments to encourage adoption of HIE that most benefits patients. Such an agenda must start with a better understanding of the current prevalence of each type of HIE and the reasons for that prevalence to provide a better sense of the prospects for. Research should continue on to issues of usage, usability and impact of each type of HIE to provide a comprehensive assessment of the value of each type of HIE.

It may be relatively straightforward to obtain better quantitative estimates of the prevalence of vendor-mediated and enterprise HIE. Much of this work might be completed by modifying existing surveys, including the AHA IT supplement and National Ambulatory Medical Care Survey, to account for adoption of these types of HIE by hospitals and ambulatory providers, respectively. Both surveys already include questions related to HIE that could be expanded.

It is likely that the prevalence of each type of HIE is not uniform across organization types, and some research has identified organizational characteristics associated with adoption of Community HIEs (140). Future research into the prevalence of each type of HIE might focus on factors that determine the fit of each type with organizational strategies and goals, which may be related to observable hospital characteristic such as ownership, market position, and the network of other healthcare organizations surrounding the organization. Identifying trends in engagement in each type of HIE would help in understanding the appeal and scalability of each approach.

A key piece of the prevalence of HIE will be to identify with whom healthcare organizations are being connected and where gaps in the emerging network are likely to persist.

As HIE becomes more widespread it is likely that some organizations will be well connected and others left behind; however, identification of those requiring assistance to connect to the HIE network may be challenging because approaches to HIE continue to evolve. For instance, both the CommonWell and Carequality collaborative projects offer an opportunity for vendor-mediated HIE to cross silos created by HIE tools designed to connect providers on the same EHR platform. Monitoring the success of programs like this will be essential to evaluating the prevalence and connectivity achieved by each type of HIE and the gaps where they occur (119, 120).

The first step towards understanding the value offered by HIE is to conduct additional research on the relative frequency of use of each type. With the current evidence, it is challenging to assess how often systems are used and the drivers of use across studies because of differing definitions of use, different units of observation (encounters, providers, patients) and different encounter types. Despite these limitations, existing research on vendor-mediated HIE indicates that it may be used least frequently, and additional work may provide valuable insight into the reasons for this and whether low use significantly limits its patient benefit. A key challenge for such analysis is to determine when there is a “need” for HIE. Focusing on care transitions as the common denominator would be consistent with the ONC approach and might provide a useful baseline.

Healthcare organizations are likely adopting multiple types of HIE to meet different needs, and use these tools to different extents. Research into both the prevalence and use of each type of HIE may benefit from understanding when and why healthcare organizations adopt a mix of HIE types, which partner organizations each type connects them to, and the frequency with which each type of HIE is used when adopted alongside others. Key to this will be recognizing that different types of provider organizations have different networks of exchange partners and therefore different needs for HIE connectivity. Researchers may also be able to leverage sites that use multiple types of HIE to compare the benefits offered by each HIE network and how they do (or do not) complement one another.

The next step to understanding the value of different types of HIE is assessing usability of each type of HIE. The technical sophistication of each type of HIE may lead to differing levels of interoperability, usability and workflow integration. For instance, vendor-mediated HIE is likely to be embedded in the provider's EHR in a familiar format and to use standardized structured data, whereas provision of data to providers through community HIE and enterprise HIE often occurred through portals, free text and other tools that may provide lower value. Higher quality data sharing may offer greater benefits than simpler free text or portal based systems, but empirical evidence on this question remains limited. Relatedly, providers have complained about the sheer amount of information provided through HIEs. By utilizing better structured information, different types of HIE may be successful in allowing easy navigation or display of the most relevant items.

An additional key usability issue may arise when organizations participate in multiple HIE networks. Because each HIE network connects the organization to a different set of partners, it may be necessary for clinicians and their staff to search through multiple systems to find the information that they need. This level of effort may strain providers, discouraging use. As HIE approaches become more widespread, the obstacles presented by access to multiple systems are likely to be more widely felt unless they are well integrated.

Existing evidence on the impact of HIE remains ambiguous. In particular, research on enterprise HIE and vendor-mediated HIE is underdeveloped. It seems clear that more attention must be paid to the type of HIE being used and the context of its use. Different types of HIE may be particularly well suited for supporting different use cases—for instance, enterprise HIE may easily connect providers who frequently participate in episodes of care for a patient or who form an ACO and want to monitor shared care, while community HIE may be better suited to monitor population health among more disparately connected providers. Future research should leverage the availability of national and longitudinal data on HIE adoption, allowing for large-scale quasi-experimental studies that can identify effects with reduced risk of bias relative to purely observational studies, and without the sample size and power constraints that may reduce the likelihood of finding an effect in purely experimental settings. In addition, continued development of more micro-level studies should strive to understand the mechanisms through which HIE is having a beneficial impact on care, and the barriers slowing realization of benefits from HIE.

DISCUSSION

Existing HIE efforts can be divided into three different types based on the convener of the effort: Community HIE, Enterprise HIE and vendor-mediated HIE. Each type provides different benefits and challenges, including the openness of each effort to broad participation, the challenges impeding sustainability, and prospects for the future. Although Community HIEs appear best designed to include the most participants and thereby provide the most potential to benefit the public, the numerous challenges aligned against their development may make investment in other options more appealing.

This study is subject to a number of limitations. Most importantly, the review aimed to synthesize current research into the prevalence, use and impact of each type of HIE and as such the conclusions drawn are limited by the studies conducted, which have focused on Community HIEs. In addition, I focused on the types of HIE that appear most prevalent based on available information; however, other types of HIE may emerge and gain high use. One key omitted type of HIE is Direct Exchange, which is designed to limit the need for a convener (125); however, current apparent low use rates, and the changing regulatory environment that de-emphasizes use of Direct (177), may limit the importance of this model. It will also be important to monitor growth in other types of HIE convened by different entities than those identified here.

It appears that only about one half of HIE occurs through Community HIEs, with the remaining intra- and inter-organizational HIE occurring through enterprise HIE and vendor-mediated HIE. Based on the current evidence, it is unclear which of the alternatives – alone or in combination– will facilitate improved sharing of data necessary to provide opportunities for real-time learning and care improvement in a learning health system and other collaboration-based initiatives. It seems likely that different approaches to HIE will work better for different organizations, and the best HIE may depend on the type of patient sharing network that organization has. Therefore, continued and increased research focused on understanding which entities use each type of HIE, and how well these approaches are working for them, remains critically important. Without attention to the presence of these different types of HIE, researchers and policymakers will be poorly positioned to guide continued initiatives to increase HIE use that build upon these types of HIE. This work may provide the most benefit if it focuses on key components of HIE that are likely to influence its use, usability, and ultimately, impact on patients and by apply more consistent methodology to allow for clearer inference across studies.

CHAPTER V

Does Health Information Exchange Meet Hospitals' Patient Information Needs?

INTRODUCTION

Following significant public and private investment over the past decade, adoption of health information technology in general and health information exchange (HIE) in particular has increased greatly (128, 178, 179). However, there are concerns that use of HIE remains low relative to other forms of health IT, and it is not clear that the increase in engagement in HIE is leading to the expected improvement in patient care (123, 124). One reason for the slow start to HIE benefits may be that, while other types of health IT, such as computerized provider order entry, can be implemented and used by an individual organization, HIE is specifically designed to foster an inter-organizational network of information. Development of HIE that allows information to follow patients across healthcare organizations therefore depends on cooperation between organizations. This may not occur because there are multiple available approaches to HIE and organizations have to weigh their decision on internal and external factors including their need for patient information, desire to share information and develop connectivity with outside healthcare organizations, and competition in the local market. This dynamic was highlighted in a recent report to Congress that discussed 'information blocking'—that is, healthcare organizations and IT vendors choosing not to share patient information with others because of competitive concerns (136). Researchers have found that organizations may not be motivated to engage in the approach to HIE that provides the most information on their patients because competitive considerations can shape the groups with which each organization would like to share information (180, 181). Because of this ongoing concern, and because public policy has provided funding to support HIE without dictating the approach that hospitals take to HIE, it is important to assess the extent to which hospitals' approaches to HIE are sensitive to their information needs and the needs of other organizations with which they share patients, rather than driven by competitive interests.

For HIE to provide value, the developing HIE network must match the existing inter-organizational network formed by the movement of patients between organizations because the need for information is defined by sharing in the clinical care of patients. A key dimension on which the network of shared patients varies is the extent of dispersion or concentration of the network—that is, whether organizations share few patients with each of many partners or share many patients with just a few key partners. This dimension relates closely to a key difference between two of the prominent types of HIE discussed in chapter four: community and enterprise HIE. As third-party organizations, community HIEs are created with the goal of facilitating HIE between all providers in a geographic area, thereby providing a wide breadth of connectivity to many patients that may be appealing to organizations with dispersed patient sharing networks; however, community HIEs often offer limited technological functionality and sophistication (182). Enterprise HIE, defined as HIE led by a healthcare organization, is designed to support connectivity between the lead organization and the subset of providers with which the organization is already formally or informally affiliated, and given this more narrow focus, often supports greater functionality (116). In consequence, if organizations select the HIE approach that matches their information needs, community HIE may be more appealing to organizations with dispersed patient sharing networks and enterprise HIE may be more appealing to organizations with concentrated patient sharing networks.

An individual organization's choice of HIE has important repercussions for the collective network of organizations in which they are embedded because the decision of an individual organization can impact the value of a given HIE approach for its partners (183-185). It is therefore likely that the members of the network of organizations surrounding any individual organization will exert pressure to conform to their needs. This influence process is likely to result in HIE that matches the structure of the collective network as network members as a whole push member organizations towards HIE solutions that are best for the majority of members. Network members could influence HIE decisions by reinforcing organizational motivation when the organization's network is similar to the network of its partners' or could lead organizations to choose a type of HIE that is not in their individual interest – that is, network members could influence HIE by conflicting with the motivation derived from the structure of the organization's own network when that network does not resemble its partners'. However, the level of influence that the network exerts on the organization may depend on the extent to which the network is structured to support high social capital or alternatively the organization is isolated from its network through adversarial competition. Therefore, two key questions are when organizations in the whole network are able to sway an individual organization's decision, and whether this depends on contextual factors that alter their ability to apply normative pressure.

In this study, I combine Medicare data on the network of shared patients between hospitals with survey data on hospital HIE approaches to examine the relationship between hospitals' patient information needs and the choice of HIE approach. While many healthcare organizations interact to provide patient care, I focus on the relationship between hospital patient sharing patterns and hospital choice of HIE approach because hospitals serve as large, influential hubs in the overall healthcare delivery system, and information sharing between hospitals promises to positively impact patients during high acuity visits. While the relationship between hospitals and their ambulatory providers is also likely to influence hospital HIE decisions, the complex relationship between hospitals as both competitors and complementary collaborators is likely to be highly influential in driving hospitals' choice of HIE approach.

I assess the relationship between patient sharing networks and hospitals approach to HIE in multivariate regression models adjusting for factors with the potential to influence hospital selection of a particular HIE approach. Specifically, I seek to answer three related research questions. First, to what extent do hospitals choose an HIE approach (community HIE versus enterprise HIE) that matches their hospital's patient information needs, defined by their patient sharing network structure? Second, are hospitals responsive to the information needs of partner hospitals represented by the collective shared patient network? Third, do contextual factors that increase or decrease normative pressure to adopt the HIE approach preferred by hospitals in their network influence the extent to which hospitals adopt that HIE approach?

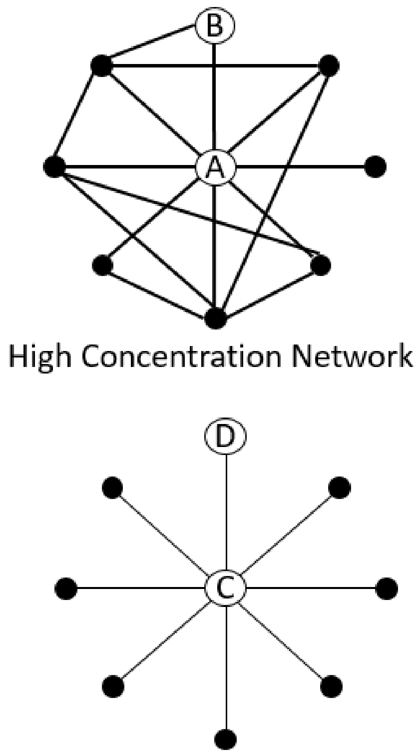
Ultimately, when organizations select the approach to HIE that matches their network of shared patients, they may have access to salient health information for their population of patients, and this access should increase their ability to make informed clinical decisions. It follows that organizations with well-fitting HIE would provide more efficient and effective patient care. However, the degree of fit between the patient sharing network and HIE operates on two levels: (1) the fit between the hospital's network of shared patients and choice of HIE, and (2) the fit between the collective network of shared patients within which the hospital is embedded and the hospital's choice of HIE. Therefore, in a supplementary analysis, I assess whether hospitals that adopt an HIE approach that matches their patient information needs, or the overall needs of the network, have better care processes and outcomes than hospitals that adopt an approach that does not match their individual information needs.

BACKGROUND AND HYPOTHESES

The fundamental decision I analyze in this study is hospitals' choice between two approaches to HIE: community and enterprise. In interviews of health system leaders, Vest et al. (5) report that community HIE is perceived as helpful to connect the hospital to a wide array of providers that may be loosely connected to the hospital, so that the hospital has access to patient information regardless of where that patient has been previously seen. However, community HIEs also have important limitations: because they are outside the control of a single health system they demand cooperation and consensus among multiple stakeholders and cannot be designed to the specification of any one participant. To minimize complexity, they typically focus on sharing only a subset of clinical data and shared data is usually not seamlessly integrated into providers' electronic health records (EHRs) (110, 186). In other words, community HIE may feature a wide breadth of connectivity but with some tradeoff in the form of lower functionality and usability. Rather than participate in a community HIE, hospitals might develop enterprise HIE. Because it features fewer stakeholders and a clear "lead" organization, enterprise HIEs have greater ability to customize to best meet the needs of participants;(116) however, it is unlikely that enterprise HIE can be expanded to provide the breadth of coverage that community HIE offers. In Vest et al.'s interviews, respondents often viewed enterprise HIE as more central to their core strategy than community HIE because it created or reinforced strategic links to key partners (5).

If I therefore conceptualize community HIE as broad connectivity with limited functionality, and enterprise HIE as limited connectivity with deep functionality, the value of each approach should be determined by the structure of the hospital's patient sharing network

Figure 9. Simple Network Schematic



(i.e., the providers with which the hospital needs to be able to exchange patient information) (187). Depending on their size, market position and other factors, hospitals may have dispersed patient sharing networks such that they share a small proportion of their patients with many partners or they may have more concentrated networks in which the majority of their patients are shared with a few key partners. When choosing among HIE approaches, the appeal of community HIE is likely to be higher for hospitals with more dispersed patient sharing relationships and the appeal of enterprise HIE is likely to be higher for hospitals with more concentrated relationships. For instance, in Figure 9, a simple network schematic, hospitals A and C both have relatively dispersed networks in that they share patients with six partners (and, for illustrative purposes, assume they share equal numbers of patients with each partner). For these hospitals, community HIE may be more attractive than enterprise HIE because it promises to provide a single link to each of their partners, whereas engaging in enterprise HIE with each of these partners may be costly. In contrast, hospitals B and D have relatively concentrated networks made up of one and two partners, respectively. For these hospitals, enterprise HIE may be more attractive than community HIE because it could easily cover their few partners and is likely to be more customized and to feature greater functionality.

The apparent value of each HIE approach is not the only consideration driving hospitals' decisions about which type of HIE approach to select. Evidence suggests that higher levels of competition and strategic interests in forming partnerships may inform engagement in HIE, and concerns about this strategic interest imply that providers may be actively slowing the sharing of information with some partners (136, 140, 153, 188). While it is possible that these factors are sufficiently compelling to drive HIE decision making, when hospitals are deciding which approach to HIE to select, I hypothesize that hospitals will be responsive to their network structure and need for patient information.

Hypothesis 1a: Hospitals with dispersed patient sharing networks are more likely to adopt community HIE than enterprise HIE relative to hospitals with more concentrated networks, which are more likely to select enterprise HIE.

While the hospital's individual network may influence their HIE approach, the decision to select a specific approach to HIE is also a social process likely influenced by peers (189, 190). The importance of the social aspect of HIE adoption is particularly high because one hospital's choice of HIE approach has implications for the value each HIE approach offers to other hospitals with which a given hospital shares patients, collaborates or competes (191). Recent research points towards the influence of peers' adoption of HIE on their neighbors in the network and finds that the adoption of certain HIE vendors does influence hospital choice of HIE (192). It is therefore likely that, overall, the collective hospital network will work to influence members of the network to adopt the type of HIE that is in the interest of most members. Returning to Figure 9, hospitals in the top network may exert pressure on one another to join a community HIE because this form can facilitate electronic connections between the many hospitals sharing patients with one another; while hospitals in the bottom network will exert pressure to collaborate in enterprise HIE with key partners.

Hypothesis 1b: Hospitals in networks with dispersed overall patient sharing networks are more likely to adopt community HIE than enterprise HIE, relative to hospitals in networks in more concentrated overall patient sharing networks.

Contextual Factors

While individual hospitals may experience normative and social pressure from their surrounding network, it is not obvious how effective that pressure will be. An influential idea in network research is that some network structures influence the degree of social capital in a group and therefore the group's ability to influence member behavior. One of the structures commonly associated with a greater ability to exert pressure on individuals is the *Network Density* of the group (193, 194). Density is defined as the extent to which all actors are tied to one another, and reflects the extent of interconnectivity and intertwined sharing of information. Note that while in Figure 9, the extent of overall network dispersion and density are identical, in practice that would only be true if hospitals shared an identical proportion of their patients with each of their partner hospitals, which is very unlikely. In networks with higher density, group norms are more easily communicated and shared, and the ability of the group to exert collective action is higher because everyone knows everyone else and therefore non-normative actions are easily observed and reported throughout the network (195-197). Therefore, the pressure to adopt the approach to HIE that matches the information needs of the overall network may be greatest in networks with high density.

Hypothesis 2: The association between network-level concentration and hospital adoption of community HIE in dispersed networks and enterprise HIE in concentrated networks is stronger in networks with low density.

Competition Between Hospitals in the network is also likely to play a role in the extent to which the overall network influences hospitals choice of HIE. Hospitals in highly competitive environments may be less interested in cooperating with their competitors than hospitals in markets that feature lower overall competition. As a result, pressure from their competitors to join an enterprise HIE or community HIE may not be effective at swaying hospital decisions. Instead, hospitals in these markets may be primarily self-interested so that they select the HIE that appears most useful to their network to achieve a competitive advantage, rather than acting in the best interest of hospitals with which they are closely competitive. This may be one reason why prior research has found that competition is associated with lower rates of engagement in community HIE (180, 188).

Hypothesis 3: The association between network-level concentration and hospital adoption of community HIE in dispersed networks and enterprise HIE in concentrated networks is stronger in networks with low competition.

<u>Reinforcing and Conflicting Collective Networks</u>

The role that the collective network plays in influencing hospitals decision to engage in HIE depends on the extent of similarity between the structure of the hospital's network and the collective network. The influence of the collective network may alter the focal hospital's approach to HIE by reinforcing their initial motivation to select an approach to HIE ("reinforced fit"). For instance, hospitals in a dispersed network, such as the top network in Figure 9, are likely to view participating in a community HIE system as more appealing than engaging in multiple enterprise HIEs. For hospital A in this Figure, which has a dispersed network that matches the overall network, their preference for community HIE may be reinforced by their network partners because the extent to which community HIE fits their network is reinforced by the collective network level. Similarly, hospitals in more concentrated overall networks may feel additional pressure to engage in enterprise HIE to connect with partners if their partners are interested in developing enterprise HIE capabilities because not doing so may lead to being excluded from those developing networks. Hospitals may also develop enterprise HIE if their competitors have begun to develop that capability to avoid losing referrals to a system with better information systems. For hospital D, the preferences of the collective network are likely to reinforce the hospital's preferences based on its shared patient network—but in contrast to hospital A for which both the hospital and collective network dispersion reinforce motivation to engage in a community HIE, in this instance both networks motivate engagement in enterprise HIE.

Hypothesis 4a: Hospitals with dispersed networks that are embedded in reinforcing (i.e. dispersed) collective networks are more likely to engage in community HIE than hospitals with concentrated networks overall.

Hypothesis 4b: Hospitals with concentrated networks that are embedded in reinforcing (i.e. concentrated) collective networks are more likely to engage in enterprise HIE than hospitals with concentrated networks overall.

In contrast, for some hospitals the collective network of partner hospitals creates pressure to adopt an HIE approach that conflicts with what is preferred by the individual hospital ("conflicting fit"). For instance, hospitals may feel pressured to participate in a community HIE by normative forces—because of their grassroots, local, community-oriented mission, community HIEs are viewed as a societal good and hospitals that choose not to participate may be viewed as shirking their responsibility to the community of patients and providers (105, 180).

In consequence, hospitals with focused patient sharing networks (that would lead them to pursue enterprise HIE) may participate in a community HIE due to pressure from their collaborators to join the community HIE. Returning to the example in Figure 9, Hospital B is likely to prefer enterprise HIE because it has only two ties that can easily be covered by an enterprise system; however, the dispersed nature of the collective network may make community HIE more appealing to its partners, and they may exert pressure on Hospital B to 'go along' with the community HIE for their benefit and the benefit of shared patients. Similarly, hospital C is likely to prefer a community HIE; however, each of its partners may prefer adopting enterprise HIE because their networks--and the collective network as a whole—are concentrated and therefore enterprise HIE better fits their information needs. As a result, hospital C in network 2 may experience pressure to adopt an enterprise system even if that system covers only part of its direct patient sharing network. In sum, the collective network in which a hospital is embedded is likely to influence their choice of HIE approach, but it is not clear if this mechanism will be more or less effective at reinforcing or contradicting motivation from the hospital's individual network.

Hypothesis 4c: Hospitals with dispersed networks that are embedded in conflicting (i.e. concentrated) collective networks are less likely to engage in community HIE than hospitals with dispersed networks overall.

Hypothesis 4d: Hospitals with concentrated networks that are embedded in conflicting (i.e. dispersed) collective networks are less likely to engage in enterprise HIE than hospitals with concentrated networks overall.

DATA & METHODS

<u>Hospital Network of Shared Patients</u>

As described in Chapter 2, I used publicly available data on hospital's shared Medicare patients to define the inter-hospital network of shared patients in 2014. The final network includes 4,602 hospitals with 91,120 patient sharing links. In order to calculate the network features of each hospital, I identified 150 hospital networks using the Walktrap algorithm further described in Chapter 2.

Independent Variables

Hospital Direct Patient Sharing Concentration

Network concentration measures the extent to which a hospital has a broad or limited set of exchange partners. To define network concentration, I first calculated the number of patients the hospital shares with each partner hospital in their network and divided by the total number of patients the hospital shares with other hospitals in their network. I then took the sum of squares, generating a measure similar to the Herfindahl-Hirschman Index (HHI) commonly used to measure the competition of a market. This produced a zero to one scale on which a hospital that shared all patients with a single other hospital would be a one while a hospital with many hospital partners each comprising a small portion of their total patient population would be closer to zero.

To facilitate interpretation of results, and because the distribution of patient sharing concentration was irregular and the relationship between concentration and HIE choice may not be linear, I sorted hospitals into three equal-sized tertiles made up of hospitals with dispersed networks, moderately concentrated networks, and highly concentrated networks.

Collective Network Patient Sharing Concentration

As with measuring an individual hospital's network concentration, I measured the concentration of the collective hospital network by first calculating the fraction of the network accounted for by each tie between hospitals—with the denominator set to the number of patients shared in the entire network—and took the sum of the squares. In a concentrated network with few strong ties, this number would approach one while in dispersed networks with many weaker ties this number would be closer to zero. Like the measure for hospital concentration, I divided this measure into tertiles.

<u>Dependent Variables: Choice of HIE Approach</u>

I sought to measure whether hospitals that were engaged in HIE chose to participate in community or enterprise HIE using the 2014 AHA IT Supplement Survey. Hospitals were defined as participating in community HIE if they reported actively sharing data in a regional HIE and indicated that they shared one of five types of data with outside providers. I defined all hospitals that responded to these two questions about HIE but did not indicate actively participating in a community HIE as participating in enterprise HIE. By doing so, in the main analysis I consider any hospital engaged in community HIE *and* some other form of HIE as engaged in community HIE because this choice indicates an open, pro-social approach to HIE. Meanwhile, I define engagement in enterprise HIE as engagement in *only* enterprise HIE because this indicates a limited and more strategic approach to HIE.

However, it is possible that hospitals that did *not* participate in community HIE also did not have an enterprise HIE and instead engaged in HIE through their EHR vendor. I created an alternative measure of HIE choice to account for this possibility and included it in a robustness test: I modified the definition of enterprise HIE in my primary HIE choice variable to exclude hospitals that used their EHR vendor as their primary HIE vendor.

Finally, the choice between community and enterprise HIE is only relevant in places where a community HIE exists. Since some hospitals are located in areas where no community HIE is active, I created an additional measure of HIE choice that excluded hospitals located in networks where no hospitals participated in a community HIE, since these hospitals could not have chosen a community HIE. I limited this variable to secondary analyses because the process by which a community HIE becomes available in a network may depend on hospital interest, competitive forces and other factors analyzed here—in other words, availability might be considered a part of the choice to participate in community HIE.

Contextual Factors

Network Density

I measured the network density for each hospital network by counting the number of ties between networks and dividing by the total possible ties between hospitals in the network. This creates a 0-1, normalized scale where a very sparse network is close to zero and a very dense network approaches 1. Like the measures of concentration, I divided this measure into tertiles for easier interpretation.

Network Competition

To measure the level of competition in each hospital network, I generated a HHI measure of market share based on the number of hospital beds in each hospital in the market. This measure is commonly used to measure the extent to which a market resembles conditions of perfect competition (at very low levels) or is a monopoly (when the HHI reaches 1). The HHI is empirically distinct from the measures of network concentration described above because it does not take into account links between patients but only considers the aggregate number of hospital beds. As a result, a network that is very competitive (i.e. has many equally sized hospitals) could be very concentrated if each of those hospitals only shares patients with a small number of other hospitals. I also divided this measure into low, medium and high tertiles.

Control Variables

I included two network-level measures intended to account for the differing size of the identified networks: the number of hospitals in each network and the number of shared patients in each network. I included these because a network with more hospitals and equal concentration per hospital would appear to be less concentrated in my measure of network concentration and networks with fewer patients may on average appear more concentrated. I also controlled for hospital-level characteristics that might be related to HIE participation and network characteristics including the total number of physicians with privileges at each hospital (for which I replaced missing data with the predicted value generated from regressing the total number of physicians on hospital size), general acute care, critical access, teaching status (major or minor teaching hospital), system membership, network membership, rural or urban location, size (small, medium or large), ownership (for-profit omitted, government-owned, not for profit). I also included variables associated with the county the hospital is located in, including measures of the supply of healthcare (Physicians per 1000 residents, PCPs per 1000, Specialists per 1000, and Hospital Beds per 1000). Finally, I controlled for other area demographics: income per capita, unemployment rate, population density, proportion female, proportion over 65, proportion white, and proportion without high school.

Analysis

I defined a sample of hospitals that indicated on the AHA IT survey that they shared information without outside organizations and were identified in the network data. I then compared the analytic sample to the overall population of hospitals in key demographic characteristics to assess the extent to which the sample resembled the population. Within the analytic sample, I examined the distribution of the concentration measures and identified tertiles in histograms to provide a sense of the empirical effect of my categorization of hospitals into tertiles. Next, I produced correlation matrices between key variables of interest first using Pearson's correlation and then using Spearman's rank correlation to assess the extent to which these variables are related. I then categorized hospitals by their patient sharing network and choice of HIE approach to identify fit, reinforced fit and conflicted fit. Table 12 displays the resulting categories of hospitals with the HIE that 'fits' the hospital identified by the hospital-level network concentration and the presence of reinforcing or conflicting fit determined by whether or not the network-level concentration matches the hospital level.

Because the outcome of interest is a binary choice for hospitals, I used multivariate logistic regression models with clustered standard errors to account for the association between, and shared network-level properties of, hospitals in the same network. To address hypotheses 1a and 1b, I predicted hospital participation in a community HIE as opposed to an enterprise HIE based on whether the hospital had a dispersed, moderately concentrated or concentrated network of shared patients and was *in* a dispersed, moderately concentrated or concentrated collective network. I then generated predicted probabilities and tested if these probabilities differed. I would find evidence supporting hypothesis 1a if overall hospitals with dispersed networks were more likely to engage in community HIE than enterprise HIE, relative to hospitals with concentrated networks. I would find evidence for hypothesis 1b if overall hospitals *in* a more dispersed network were more likely to engage in community HIE than enterprise HIE, relative to hospitals in a concentrated network. To address hypotheses 2 and 3 about whether network and market factors increase the influence of collective network concentration on HIE choice, I interacted the whole network concentration with density and competition. I would find evidence that social factors are guiding hospital decisions if the relationship between the whole network concentration and HIE choice was stronger in networks with high network density and weaker in networks with higher competition. To facilitate interpretation of results, I report these findings by comparing predicted probabilities of participating in a community HIE as opposed to enterprise HIE over the range of network concentration at high and low density and competition.

To address hypotheses 4a-d, I interacted the hospital-level network concentration variable with the collective network concentration variable. I generated adjusted probabilities for each category and tested whether these probabilities were statistically significantly different. To test hypothesis 4a and 4b, that the network can reinforce hospital preferences, I compared the extent to which hospitals that both have and are in a dispersed network are more likely to participate in a community HIE than the pooled average of all hospitals with dispersed network, regardless of whole network concentration, and I compared hospitals that both have and are in a concentrated network to the pooled average of all hospitals that have a concentrated network regardless of the collective network concentration. I next investigated hypothesis 4c and 4d, that the network can contradict hospital preferences and thereby reduce the extent to which hospitals engage in an HIE that fits their individual network. To do so, I tested whether hospitals with a dispersed network that are in concentrated collective networks are less likely to engage in community HIE than the pooled average of all hospitals with dispersed collective networks. Similarly, I tested whether hospitals with a concentrated network that are in dispersed collective networks are less likely to engage in enterprise HIE than the pooled average of hospitals that have more concentrated collective networks.

Table 12. Relationship between Hospital- and Network-level Network Concentration and HIE Fit

		Network-Level Concentration		
		Pooled	Dispersed	Concentrated
Hospital-Level Concentration	Pooled	(a) Pooled network, pooled hospitals hospital	(b) Network level supports community, all hospitals pooled	(c) Network level supports enterprise, all hospitals pooled
	Dispersed	(d) Hospital supports community, all networks pooled	(e) Hospital-level and network level support community HIE: Reinforced Community Fit	(f) Hospital-level supports community, network supports enterprise HIE: Conflicted Community Fit
	Concentrated	(g) Hospital supports enterprise, all networks pooled	(h) Hospital-level supports enterprise, network supports community HIE: Conflicted Enterprise Fit	(i) Hospital and network levels support enterprise HIE: Reinforced Enterprise Fit
Hypothesis 1a: cell d > cell g				
Hypothesis 1b: cell b > cell c				
Hypothesis 4a: cell e > cell d				
Hypothesis 4b: cell f < cell d				
Hypothesis 4c: cell i > cell g				
Hypothesis 4d: cell h < cell g				

In robustness tests, I re-examined the first two hypotheses in four different ways: First, I redefined enterprise HIE to exclude hospitals that report using their EHR vendor for their HIE solution and reran the initial model with this dependent variable. Second, I limited the sample to only hospitals in areas where community HIE is available. Third, I redefined the hospital-level and community-level networks using a linear concentration measure, and fourth, I used a binary measure split at the medians rather than tertiles.

I consider relationships statistically significant when the likelihood of observing these relationships under the null hypothesis is less than 10 percent and report p-values in the text.

RESULTS

Descriptive Statistics

Out of a total of 4,632 hospitals in the population, 2,764 hospitals responded to the AHA IT supplement and 2,092 indicated that they had some form of HIE. Nine of these hospitals were not identified in the network data, leaving a final analytic sample of 2,083 hospitals in 141 hospital networks nationwide. Relative to the hospitals not included in the final sample, included hospitals were more likely to be large hospitals, to be teaching hospitals and to have lower network concentration (Table 13). Despite statistically significant differences in many measures, the practical difference between hospitals in and out of the sample in concentration, density, and competition, as well as many control variables, was quite small.

Table 13. Descriptive Statistics Relative to Population

	In Sample (n=2,083)	Out of Sample (n=2,551)	p-value
Hospital-Level Concentration	0.272	0.301	p<0.0001
Network-Level Concentration	0.036	0.038	p=0.1578
Network Density	36.40%	36.10%	p=0.3609
Hospital Market Share	11.60%	9.10%	p<0.0001
Market Concentration	0.141	0.145	p=0.074
# of Hospitals in Network	43.4	46	p=0.0001
# of Shared Patients in Network	517,448	428,075	p<0.0001
Hospital Taype			
General Acute Care	98.2%	94.0%	p<0.0001
Critical Access	32.6%	23.0%	p<0.0001
Major Teaching	7.9%	3.0%	p<0.0001
Minor Teaching	27.5%	19.2%	p<0.0001
System Member	64.6%	58.2%	p<0.0001
Network Member	40.0%	29.3%	p<0.0001
Urban	64.2%	55.5%	p<0.0001
Size			
Small	40.8%	60.7%	p<0.0001
Medium	45.2%	33.0%	p<0.0001
Large	14.0%	6.3%	p<0.0001
Ownership			
Government-owned	19.7%	23.6%	p=0.0015
Not for Profit	68.5%	52.0%	p<0.0001
For Profit	11.8%	24.4%	p<0.0001
Healthcare Supply			
Physicians per 1000	2.44	2.04	p<0.0001
PCPs per 1000	0.73	0.67	p<0.0001
Specialists per 1000	0.79	0.64	p<0.0001
Hospital Beds per 1000	3.74	3.77	p=0.81
Area Demographics			
Income Per Capita	43,487	42,680	p=0.0285
Unemployment Rate	6.1%	6.3%	p=0.0004
Population Density	8.2%	9.0%	p=0.394
Proportion Female	50.5%	50.3%	p=0.004
Proportion over 65	15.8%	16.2%	p=0.0105
Proportion White	78.9%	76.9%	p=0.0001
Proportion without High School	13.4%	14.8%	p<0.0001

* n=2513 for Network Measures

The distribution of patient sharing concentration is right skewed, with most hospitals exhibiting relatively low concentration and a few hospitals exhibiting much higher concentration (Figure 10). Despite this skew, the data is relatively continuous: there are few large break points. The distribution of network patient sharing concentration is even more dramatically skewed, with most networks exhibiting low concentration and a few networks exhibiting much higher concentration (Figure 11).

Figure 10. Distribution of Hospital-Level Patient Sharing Concentration

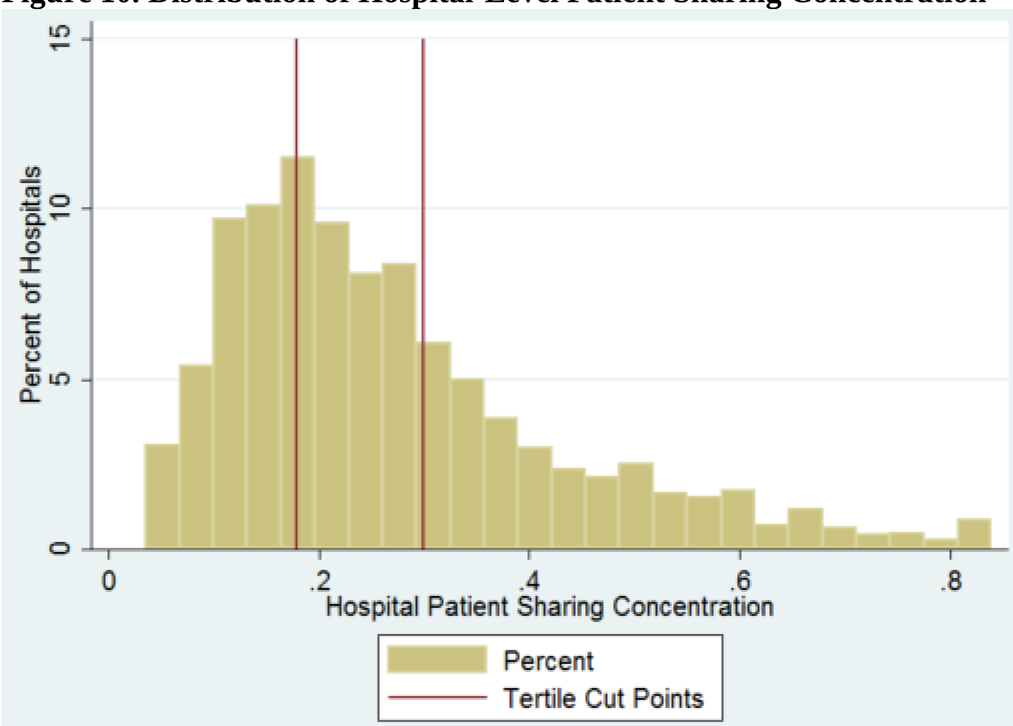
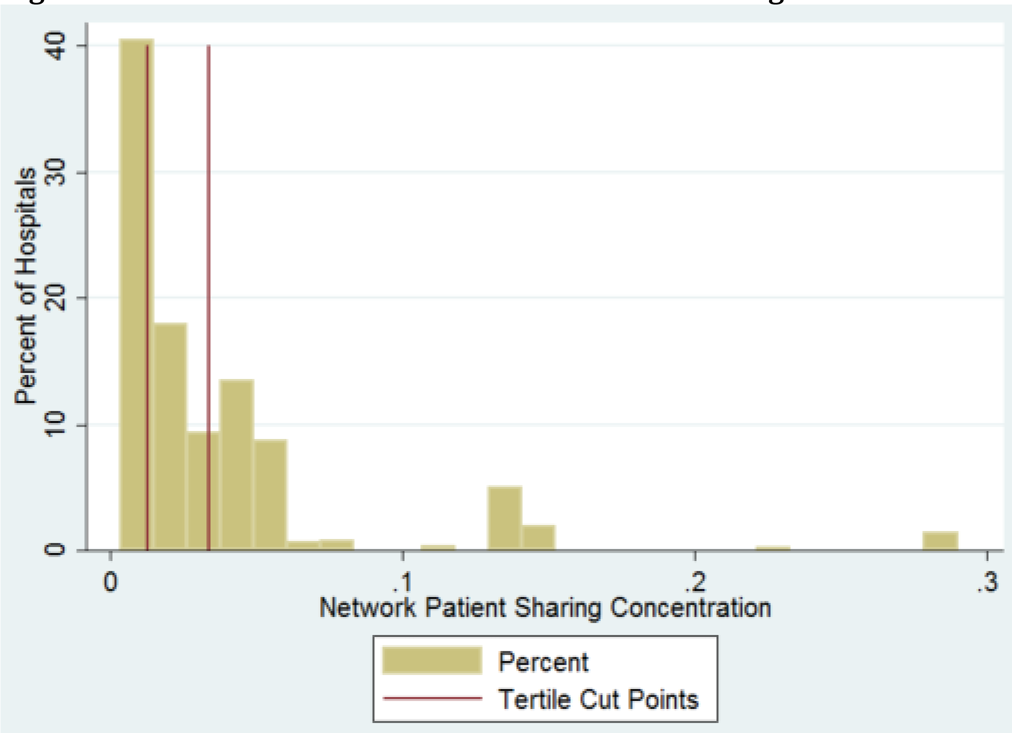


Figure 11. Distribution of Network-Level Patient Sharing Concentration



I next examined the bivariate correlation between key variables of interest (Tables 14a and 14b. I found relatively weak correlations between hospital-level concentration, network-level concentration, and density, and modest relationships between market concentration and each of these variables. The number of hospitals and patients in each network was moderately correlated with several variables, indicating the need to include them in regression models to ensure results are not biased simply by the size of the network. When I repeated this correlation matrix using Spearman's rank correlation I found modestly higher correlations reinforcing my choice to use a tertile-based measure of network characteristics rather than a linear approach.

Table 14a. Correlation Between Key Network Independent Variables

	Hosp Conc.	Net Conc.	Net Density	Hosp Mkt Share	Mkt Comp.	# Hosps	# Patients
Hospital-Level Concentration	1						
Network-Level Concentration	0.1633	1					
Network Density	0.0126	0.1348	1				
Hospital Market Share	0.0607	0.1107	0.2193	1			
Market Competition	-0.261	-0.2008	-0.3705	-0.5382	1		
# of Hospitals in Network	-0.3016	-0.2071	-0.5498	-0.2601	0.5738	1	
# of Shared Patients in Network	-0.185	-0.132	-0.211	-0.2219	0.457	0.7391	1

Table 14b. Correlation Between Key Network Independent Variables: Spearman

	Hosp Conc.	Net Conc.	Net Density	Hosp Mkt Share	Mkt Comp.	# Hosps	# Patients
Hospital-Level Concentration	1						
Network-Level Concentration	0.1835	1					
Network Density	-0.0162	0.1058	1				
Hospital Market Share	-0.0282	0.0416	0.1588	1			
Market Concentration	-0.2686	-0.1899	-0.3417	-0.3499	1		
# of Hospitals in Network	-0.3507	-0.3084	-0.5729	-0.2244	0.655	1	
# of Shared Patients in Network	-0.2841	-0.3371	-0.3394	-0.1965	0.597	0.8454	1

Descriptively, 68% of hospitals that engaged in HIE participated in community HIE, while 32% participated in enterprise HIE only. 73% of hospitals with dispersed networks participated in community HIE while 63% of hospitals with concentrated networks did so (Table 15). Very similar sorting is observed for hospitals in dispersed and concentrated collective networks.

Table 15. Hospital HIE Choice by the Patient Sharing Network Concentration

HIE Choice by Hospital Network Approach	Enterprise	Community
Dispersed	204 (27%)	552 (73%)
Moderately Concentrated	206 (32%)	432 (68%)
Concentrated	258 (37%)	431 (63%)
HIE Choice by Whole Network Approach	Enterprise	Community
Dispersed	185 (27%)	510 (73%)
Moderately Concentrated	226 (33%)	468 (67%)
Concentrated	257 (37%)	437 (63%)

Adjusted Associations with Community HIE Approach

In regression models accounting for all hospitals in the sample, I observed that hospitals with dispersed networks were more likely to engage in community HIE relative to hospitals with concentrated networks (71.5% versus 64.8%; p=0.052 Table 16). Hospitals in dispersed whole networks were also more likely to engage in community HIE than hospitals in concentrated networks (73.5% versus 63.7%, p=0.027). These findings support hypothesis 1a and 1b and are evidence that hospitals are selecting HIE strategies that match their patient networks and associated information needs.

I next tested whether the influence of the collective network on HIE choice was moderated by contextual factors using a related regression model (Table 17). I found that 77.1% of hospitals in dispersed networks with high density participated in a community HIE (with the complement engaging in enterprise HIE only) while only 58.6% of hospitals in concentrated network with high density participated in a community HIE, a difference of 18.5 percentage points (p=0.017). In contrast, 65.7% of hospitals in dispersed networks with low density participated in a community HIE while 70% of hospitals in concentrated networks with low density participated in community HIE (p=0.58). These results support hypothesis 2, that the influence of network concentration is greater at high density, where social norms are stronger.

When I investigated the mediating effect of competition, I observed that 76.6% of hospitals in dispersed networks with high competition participated in community HIE (again with the complement engaging in enterprise HIE) while only 57.8% of hospitals in concentrated networks with high competition did so (p=0.007). In contrast, 65.4% of hospitals in dispersed networks with low competition participated in a community HIE and 66.7% of hospitals in concentrated networks with low competition participated in community HIE (p=0.8791). This finding provides evidence against hypothesis 3, which argued that hospitals would be less responsive to pressure from the network of peers in highly competitive networks. Instead, it points towards hospital HIE decisions being more sensitive to pressure from the network of peers in networks with high competition.

Table 16. Adjusted Marginal Probability of Engagement in Community HIE

		Hospital-Level Concentration	
		Dispersed	Concentrated
	Pooled	(a) 71.5%	(b) 64.8
		Network-Level Concentration	
		Dispersed	Concentrated
	Pooled	(c) 73.5%	(d) 63.7%
Density	Low	(e) 65.7%	(f) 70.4%
	High	(g) 77.1%	(h) 58.6
Competition	Low	(i) 65.4%	(j) 66.7%
	High	(k) 76.6%	(l) 57.8%

Hypothesis 1a: cell a > cell b, supported p=0.052
Hypothesis 1b: cell c > cell d, supported p=0.027
Hypothesis 2: cell g - cell h > cell e- cell f, supported=0.042
Hypothesis 3: cell k - cell h > cell I – cell j, marginal support, p=0.103

Finally, I investigated how the whole network was influencing hospitals' approach to HIE. When I tested hypothesis 4a, I did not find support for the hypothesis that hospitals with dispersed networks were more likely to engage in community HIE when embedded in dispersed networks: hospitals with dispersed networks engaged in community HIE 74% of the time when in reinforced fit compared to 71.5% that selected that approach based on hospital fit only. However, I did find support for hypothesis 4b, that hospitals with concentrated networks embedded in concentrated networks were more likely to select enterprise HIE: 42.7% of hospitals engaged in enterprise HIE when they were in reinforced fit, whereas only 35.2% did so when they were in hospital-only fit (p=0.053).

When I tested hypotheses 4c and 4d, that the collective network could work to contradict hospital-only fit, I again found support only for hospitals with concentrated networks. When I tested hypothesis 4c, I found that overall 71.5% of hospitals with dispersed networks adopted community HIE while 70.2% of hospitals in conflicting fit adopted the fitting HIE (p=0.677). In contrast, when I tested hypothesis 4d, I found that 35.2% of hospitals engaged in enterprise HIE overall while only 28.8% engaged in enterprise HIE when in conflicted fit (p=0.065).

Table 17. Adjusted Marginal Probability of Engagement in Community HIE

		Network-Level Concentration		
		Pooled	Dispersed	Concentrated
Hospital-Level Concentration	Dispersed	(a) Hospital supports community, all networks pooled: **71.5%**	(b) Hospital-level and network level support community HIE: Reinforced Community Fit: **74.0%**	(c) Hospital-level supports community, network supports enterprise HIE: Conflicted Community Fit: **70. 2%**
	Concentrated	(d) Hospital supports enterprise, all networks pooled: **64.8%**	(e) Hospital-level supports enterprise, network supports community HIE: Conflicted Enterprise Fit: **71.2%**	(f) Hospital and network levels support enterprise HIE: Reinforced Enterprise Fit: **57.3%**

Hypothesis 2a: cell b > cell a, not supported p=0.37
Hypothesis 2b: cell f > cell d, supported p=0.053
Hypothesis 2c: cell c < cell a, not supported p=0.677
Hypothesis 2d: cell e < cell a, supported p=0.065

I conducted four robustness checks to evaluate the relationship between network concentration and three closely related HIE choices. My findings were robust to excluding hospitals that use their EHR vendor as their HIE vendor from my definition of enterprise HIE (Table A1, column 1). I also found effects for hospital and network concentration consistent with my main findings when I limited the sample to hospitals that are in networks in which a community HIE is available (Table A1, column 2).

When I replicated the first two hypotheses using linear or median-divided measures of hospital and network concentration, I found that higher levels of both hospital-level and network-level concentration were associated with a lower likelihood of selecting community HIE consistent with my hypotheses (OR=0.38, p=0.015 for hospital concentration and OR=0.02, p=0.04 for network concentration). When I used a median split I found that hospital-level concentration did not influence HIE selection but that network-level concentration was associated with fit (OR=0.80, p=0.19 for hospital concentration and OR=0.64, p=0.029 for network concentration). This suggests that hospitals with networks on the margin were less likely to select HIE based on the form that was slightly more appealing for their network and the network was more influential further from the median.

SUPPLEMENTARY ANALYSIS: NETWORK STRUCTURE MODERATES HIE EFFECTS

Embedded in the logic of this study is the idea that hospitals that adopt an HIE approach that matches their patient sharing network should produce better patient care quality. That is, for hospitals with a concentrated network, using an enterprise HIE system will provide greater benefits than using a community HIE because it can provide information for a large proportion of patients in a more customized and useable way, while for hospitals with a dispersed network, using a community HIE will provide greater benefits than using an enterprise HIE because it will cover a larger proportion of all patients. It is also possible that these same relationships may hold at the collective network level—that is, for hospitals with identical patient sharing networks, the hospitals in highly concentrated networks may benefit more from adoption of enterprise HIE while for hospitals in dispersed networks community HIE may provide more overall information.

This may occur because more partner hospitals in dispersed networks are likely to select the community HIE approach so that the community HIE offers more successful connections, while enterprise HIE may be easier to establish with key partners if those partners also have concentrated networks. Therefore, I conducted a supplementary analysis to investigate whether fit between HIE approach and the hospital-level and network-level concentration were associated with greater patient care quality.

To assess these relationships, I used three measures intended to capture diverse and important dimensions of hospital quality: hospital efficiency, hospital outcomes and hospital processes influenced by HIE. I measured hospital efficiency using Medicare Spending Per Beneficiary. Using an HIE approach that fits the hospital's information needs should result in fewer redundant tests and costly errors of omission relative to HIE that does not fit the hospital's information needs and again this may apply both to their direct partners and the accumulation of information in the network (126, 127, 164). I used hospital 30-day all cause readmission rates to capture hospital outcomes that may be sensitive to HIE. HIE should allow providers outside the hospital where the initial admission occurred access to better information, increasing the quality of follow-up outpatient care and reducing the likelihood of complications leading to readmissions (164). It should also provide clinicians at other hospitals with the information necessary to make proper readmission decisions—and potentially avoid unnecessary readmissions. To measure hospital processes, I focused on the rate of Mammogram follow-up. Hospitals with well-functioning HIE, both in terms of their information sharing with key partners and, in turn, their partners' sharing with their partners, should have easier access to the mammogram results from other locations, increasing the likelihood that proper follow-up action will be taken.

Data and Methods

I measured the quality of patient care provided by hospitals using publicly available data from Medicare's Hospital Compare program. The MSPB is derived from data created from hospital data from January 1, 2014-December 31, 2014 and is adjusted to account for differences in prices by geography, add-on payments to hospitals, for beneficiary age and severity of illness. The readmission measure was created from hospital data from July 1, 2013-June 30 2014 and is similarly adjusted for patient characteristics. The mammography follow-up rate is calculated from data gathered July 1, 2013-June 30, 2014.

I created three linear regression models, one each with MSPB, readmissions, and mammogram follow up rate as outcomes, and predicted the level of each outcome based on the interaction between the hospital's choice of HIE approach and the hospital's patient network concentration as well as the collective network's concentration, controlling for hospital, market and network characteristics described above. I then calculated marginal effects for hospital choice of community HIE relative to enterprise HIE with and in dispersed and concentrated networks. I would find support for the hypothesis that good fit between the hospital's network and HIE leads to improved performance if the effect of using a community HIE (relative to using an enterprise HIE) for hospitals with dispersed networks was *negative* for MSPB and readmissions and positive for Mammogram follow-up rate, such that hospitals with more dispersed networks achieved greater benefits from using community HIE than enterprise. I would find further support if the reverse were true: that using a community HIE resulted in lower hospital performance for hospitals with concentrated networks. In total, I would find support for the hypothesis that good fit between the collective network of shared patients and the hospital's choice of HIE is associated with improved outcomes if the effect of using a community HIE was associated with improved outcomes for hospitals in dispersed networks and worse outcomes for hospitals in concentrated networks.

Results

Costs. When I examined the association between HIE, hospital and network concentration and patient care costs (Table 18), I observed only one statistically significant relationship: hospitals *with* a dispersed network that participated in community HIE had 17.5% of a standard deviation higher MSPB (p=0.010).

Readmissions. When I tested the relationship with readmissions, hospitals *with* moderately concentrated networks that participated in community HIE had higher readmissions (29.0% of a SD higher). Meanwhile, hospitals *in* dispersed networks that participated in community HIE (i.e. hospitals engaged in community HIE when in fit with the overall network) and hospitals *in* moderately concentrated networks that engaged in community HIE both had higher readmissions (16.1% (p=0.084) of an SD higher for hospitals in dispersed networks and 16.5% of a SD higher for hospital in moderate networks (p=0.029).

Mammography Follow-Up. Hospitals *with* dispersed networks that engaged in community HIE had 11.9% (p=0.088) of a standard deviation higher mammography follow-up while hospitals *with* concentrated networks that participated in community HIE had 19.1% (p=0.036) of a standard deviation lower follow-up.

In combination these findings provide mixed support for the idea that better HIE fit will result in improved performance, but generally point towards greater benefit from use of enterprise HIE than community HIE, even for hospitals with and in dispersed networks.

Table 18. Adjusted Marginal Estimates of Difference in Standardized Outcomes Between Hospitals Choosing Community HIE Over Enterprise HIE

Hospital level	MSPB (lower is beneficial)	Readmissions (lower is beneficial)	Mammography F/U (higher is beneficial)
Concentrated Network (Expect less beneficial association)	8.9%	3.3%	-4.4%
Moderate Network	-14.8%	29.0%***	0.0%
Dispersed Network (Expect more beneficial association)	17.5%***	13.6%	-9.8%
Whole Network level			
Concentrated Network (Expect less beneficial association)	12.9%	12.0%	-19.1%**
Moderate Network	-3.8%	16.5%**	-10.8%
Dispersed Network (Expect more beneficial association)	7.0%	16.1%*	11.9%*

*** p<0.01, ** p<0.05, * p<0.1

DISCUSSION

In this chapter, I investigated the link between the structure of hospital patient sharing networks and the approach to health information exchange that they chose to adopt. In an additional analysis I also explored the resulting impact of their choice on patient care. Consistent with the hypothesis that hospitals would prefer an HIE approach that 'fit' their patient sharing network, I found that hospitals *with* more concentrated patient sharing networks were more likely to engage in enterprise HIE rather than community HIE relative to hospitals *with* more dispersed networks. Further, individual hospital choices were also sensitive to the concentration of the collective hospital network in which they are embedded. In particular, I found that hospitals with concentrated networks could be influenced by the network either through reinforcing fit (when the surrounding network was concentrated) or by conflicting fit (when the surrounding network was dispersed). Consistent with theories of social capital, the influence of the overall network on hospital HIE choice was strongest when network density was high—that is, when normative pressure from their peers was high. Contrary to my hypothesis, I also found that the influence of the overall network was strongest when competition was highest. Finally, in supplementary analyses, I did not find that hospitals engaging in the HIE approach that fit their network structure experienced the highest benefits. Instead, I found mixed results that overall might be interpreted as indicating that enterprise HIE provides more benefit than does community HIE, regardless of network structures.

The finding that hospitals pursue HIE solutions that fit their network of shared patients indicates that hospitals may be working to select HIE that appears the most beneficial for their performance, patients and peers. In particular, the ability of the collective network to influence hospitals to engage in community HIE, both when it reinforces the motivation from the hospital's network and when it conflicts with that motivation, indicates that hospitals are responsive to the needs of their patients and to the needs of other hospitals in the community. This finding contrasts with concerns about strategic information blocking in which hospitals are perceived to work to avoid sharing information with others. As a result, the finding that hospitals are attempting to select an HIE approach that both meets their needs and reflects the networks' needs supports the current policy approach of facilitating HIE in many forms.

While hospitals appear responsive to the needs of their peers, the degree of responsivity depends on key characteristics of the network. As expected, I found that density was associated with a stronger influence of the collective network on the HIE approach that hospitals selected. This finding supports the idea that the network of hospitals is working to influence one another to select HIE that benefits the group. However, it also indicates that some networks may be less successful at influencing the behavior of member hospitals because low network density results in reduced normative pressure to adopt HIE that is of benefit to peers. I was surprised to find that competition also increased the strength of the association between the collective patient sharing network and hospital HIE decisions—I hypothesized that competition would have an insulating effect. This hypothesis was informed by prior work that indicated that competition dissuaded hospitals from engaging in community HIE (188). It may be that competition increases the influence of the community through a mechanism similar to greater density—that is, the cost of acting outside the norm may be higher in areas of greater competition because the hospital's partners may more easily work with a different hospital. Competition may also compel hospitals to attend more closely to the behavior of other hospitals in the local market in pursuit of a strategic advantage.

While I did find that hospitals engaged in an HIE approach that fit their patient sharing pattern, when I attempted to identify the relationship between fit and outcomes I could not make strong conclusions. Instead, I found mixed results and several null associations between choice of HIE approach and outcomes at differing levels of network concentration. Still, five of the six statistically significant results showed that hospitals engaging in community HIE had worse outcomes than hospitals that engaged in enterprise HIE. One of these relationships occurred when hospitals had dispersed networks—that is, when I hypothesized that community HIE will provide the most benefit. This provides suggestive but inconclusive evidence that community HIE may not provide the same degree of patient benefit as other approaches to HIE. As discussed in Chapter 4, prior work investigating the benefit associated with HIE has primarily focused on community HIE and has generally found an inconsistent relationship between the adoption and patient outcomes (123, 124). The inconsistent results of this work may be due to particular features of community HIE and suggest that even if it covers more shared patients, the downsides to engaging in community HIE, such as worse functionality, may make the technology ineffective in its current form.

Contribution to the Literature

Prior research on hospital engagement in HIE has primarily evaluated factors that influenced whether hospitals engaged in any approach to HIE, or defined engagement solely as participation in community HIE (130, 140, 153, 188). Studies on community HIE participation found that hospital competition and for-profit status was associated with lower participation,(140, 188) but that hospitals with larger market shares were more likely to participate (130). Another study showed that hospitals in larger systems were less likely to engage in any HIE (153). This chapter extends that work by focusing on the *choice of HIE approach*, not whether or not they chose to engage in HIE at all, and adds important nuance to the role that social factors, including competition, play in selecting an approach. As more hospitals begin to engage in HIE, it is increasingly important to better understand their choices, why they select specific approaches, and the benefit their choices have for their patients. However, this analysis does not generalize to explain the reasons why some hospitals have not yet decided to engage in any HIE approach.

This work also extends prior work on social influence in networks to a new empirical context. When evaluating the approach to HIE adoption, it is essential to remember that technology adoption is a social process and that this social aspect may be particularly important for network technologies like HIE. In particular, hospitals with concentrated networks were most likely to be influenced by the degree of concentration of the whole network. These hospitals are likely to be smaller and less central to the network as a whole than hospitals with more dispersed networks, and literature on social networks has found that these types of actors are often influenced by their larger, more central peers (100, 198, 199). Similarly, network density functioned in a way consistent with the social network literature: it increased social pressure and therefore the influence of the needs of the community on individual hospital's HIE decisions.

Finally, this chapter represents a contribution to the literature on inter-organization networks in healthcare. While prior work has explored the role of formal relationships in driving the diffusion of innovation and of organizational behavior,(20, 200) little work has explored the role of informal relationships such as the network of shared patients. I demonstrated that the structure of the hospital network of shared patients was an important factor associated with organizations' strategic decisions. Similar network structures may guide other hospital decisions, such as mergers and acquisitions, expansions, choice of specialization and other behavior, and further work might explore these contexts. I also demonstrated the important role of network structure in influencing the ability of the organizations in the network to self-govern and support engagement in the approach to HIE that benefited most hospitals in the network. While the role of interconnectivity in enforcing norms is one of the best known ideas in network analysis,(201) it has not been deeply studied in the inter-organizational context (97). Therefore, the finding that density magnified the influence of the network indicates that a phenomenon conceptualized for networks of individuals is useful to understand networks of organizations.

<u>Limitations</u>

This chapter is subject to several limitations. First, I observe only the hospital network of shared patients. The structure of many other networks, most notably the physician network of shared patients and the physician-hospital network of shared patients is not observed. These networks are likely influential in the HIE decision-making process. While I control for the number of affiliated physicians, this represents only a rough measure of this network. However, it does indicate that the physician network is likely to act in a similar way to the hospital network—hospitals with more affiliated physicians appear marginally more likely to engage in community HIE in my model. Future work might explore the role of ambulatory networks in more detail. Second, this study is associational and cross-sectional. Like most network analysis, I have limited ability to develop a causal or exogenous model and I do not identify change over time. Part of this challenge is that, globally, hospital networks change slowly over time, such that an analytic model focused only on change is likely to be underpowered. I have done my best to limit the influence of confounders by controlling for a wide range of likely confounders to attempt to eliminate sources of bias. Third, the measure of HIE used here represents the best currently available national data on hospital HIE engagement; however, it does not capture all approaches to HIE. To address this concern, I altered the outcome variable to exclude hospitals engaging in vendor-medicated HIE, and my findings were generally robust to this variation. However, I was not able to identify hospitals that engaged in both community and enterprise HIE and therefore conceptualized enterprise engagement as *only* enterprise HIE. Finally, while the patient outcomes used here are likely to be influenced by well-functioning HIE, these are aggregate measures that include the experience of patients that do not move between hospitals. In consequence, the associations with outcomes identified should be interpreted with caution.

Conclusion

Hospital choice of HIE approach is associated with the structure of their patient sharing network as well as with the structure of the collective inter-hospital network of shared patients that surrounds them. These findings indicate that hospitals are pursuing HIE approaches that are most useful for their patient networks, and that the collective network appears to exert pressure on their peers. The latter dynamics serve to regulate the approach to HIE taken in the network by pushing members towards adoption of an HIE approach that fits the structure of the collective network (by reinforcing aligned choices or pushing against conflicting choices). The pressure from the network is most effective when the network has high social capital, as measured by the density of the network. These findings support the US policy approach to let multiple types of HIE emerge in the market, rather than preferentially supporting specific approaches to HIE.

However, they raise concern that in certain networks—those with low social capital and competition—the network may not regulate itself to achieve the best choice of HIE approach. Finally, the association between HIE and outcomes was inconsistent—reflecting a broader and concerning trend in recent research—and it is not clear that network structure moderates this relationship. It is therefore important to prioritize efforts that seek to ensure consistent benefit from all forms of HIE.

CHAPTER VI

Conclusion

I argued in the introduction that the work to understand the healthcare delivery system as a network is both very old—dating back at least to Coleman et al.'s studies in the 1960s—and very new. That is to say that while the basic insight that healthcare delivery is a network, and studies on the diffusion of medical innovations inspired by Coleman, are reasonably commonplace, the broader implications of the network features of healthcare delivery system have not been very widely explored. This absence marks a missed opportunity. Perhaps a comparison makes the point. Coleman's study, among the first to consider the network implications of the healthcare delivery system, is a contemporary of another famous paradigm shift in our understanding of the healthcare delivery system: Kenneth Arrow's "Uncertainty and the Welfare Economics of Medical Care". While the field of health economics is today well developed, rapidly growing and successfully applying the methodological tools and theoretical insights from the field of economics to inform policy decisions, a field of health network analysis remains scattered and limited in scope. And yet the basic insight remains: healthcare is an intrinsically networked field. The currently limited investigation into the implications of this network prevents the development of insights that might shape practitioners', organization leaders', and policy makers' approach to health care in a way that could meaningfully improve human health. With that said, the network approach is more widespread than it first appears because many efforts that are at their core concerned with the healthcare system as a network do not directly invoke a network perspective or set of tools. For instance, it seems obvious to conceptualize the identification of hospital referral regions, and the specialty care based plurality rule used by researchers to identify those regions, as a type of network partitioning. However, by not directly identifying with a network approach, work that continues in the vein of network-based approaches is not able to capitalize on the tools and insights gathered in the enormous multi-disciplinary field of network analysis.

In this dissertation, I have sought to expand the use of network analysis in healthcare in two key ways. First, I examine the inter-hospital network of shared patients, while the clear majority of existing work focuses on inter-physician networks. Second, I have applied a network-based perspective to three areas of ongoing inquiry that have intrinsically network-based characteristics that have so far not been thoroughly understood: identifying groups of hospitals, healthcare fragmentation, and health information exchange (HIE).

In chapter 2 I identified dense networks of interconnected hospitals using a community detection algorithm designed to group hospitals into sub-communities of the overall network of shared patients. While many rules have been used to identify hospitals that are related through either collaboration or competition, none of these past methods have explicitly invoked a network framework. By using tools developed in other fields to identify groups of hospitals, I was able to create communities of closely connected hospitals, to test their reliability (both over time and to varying underlying assumptions), to test their validity in relation to other methods of group identification and to the extent to which the groups combined hospitals with similar outcomes, an important goal because these grouping methods are commonly used to characterize the performance of regions of hospitals. In total, I have presented a method that is more verifiably reliable and valid than past methods while also demonstrating that the existing HRR method performs reasonably well on certain key metrics.

In chapter 3, I applied network analytic tools to better understand health care fragmentation. Fragmentation—the extent to which a patient's care is divided between multiple providers—has been found to be associated with higher spending and worse outcomes. However, the implications of the way patient sharing between providers is structured and how that structure relates to their success in caring for patients has not been explored. I found that two network structures, concentration and centralization, are associated with lower spending and better patient outcomes—in other words, that the deleterious effects of fragmentation may be less pronounced in areas where the sharing of patient care is concentrated and centralized. Importantly, I found that the structure of the collective network of hospitals was more strongly associated with outcomes than the structure of individual hospital's networks. This points to the importance of considering the hospital's environment and peers when considering their quality and ability to optimize treatment for their patients.

Finally, I used network analysis to better understand hospitals engagement in HIE. HIE is at core a network phenomenon because the goal of developing well-functioning HIE is to form a network of shared information between provider organizations. Therefore, much remains to be learned about how well this exchange network is being built to cover the sharing of patients between organizations. In chapter 4 I laid out the conceptual distinction between three types of HIE and reviewed the available literature on each type of network. I found that far more studies have been published on community HIEs than enterprise HIE and vendor-mediated HIE, despite these other forms appearing to be relatively wide spread. Then in chapter 5 I investigated whether hospitals were choosing the type of HIE that best fit their network of shared patients. I found that hospitals with more concentrated networks were more likely to engage in enterprise HIE—which is designed to facilitate exchange between relatively few key partners– while hospitals with more dispersed patient sharing networks were more likely to engage in community HIE, which is designed to connect a broader array of providers. Further, I found that the collective network of hospitals surrounding each individual hospital was influential in driving hospital's HIE decisions, a finding that echoes the importance of the collective network found in the study of fragmentation.

Two important limitations shape the contribution of this study. First, the data source used to define networks includes data on all Medicare patients shared by providers; however, it contains very limited data on those patients. Importantly, the data does not indicate what conditions they are treated for, their co-morbid conditions, socio-demographic characteristics, or the extent of their treatment. This limitation shaped the nature of the inquiry throughout this dissertation, driving a high-level perspective on all patients shared between hospitals. This low level of fidelity led to the choice of associated performance measures in the third chapter, which include spending and readmissions due to all causes. The focus on all patients also facilitated association of the network with health information exchange in the fifth chapter because HIE is conceptually useful to a very wide breadth of shared patients. Future research might usefully complement this high-level view by focusing on the shared patients for specific conditions or between certain types of clinical departments, where much information sharing and coordination occurs. As a corollary to this limitation, the data does not indicate why the patients were shared: by coincidence, by referral or by direct transfer. More detail on why the patients were shared may influence the type of interventions that appear most useful or how we conceptualize shared patients. Again, this limitation shaped the focus of inquiry: regardless of the reason for sharing patients, structures that facilitate coordination and engagement in HIE are important to ensure that patients receive optimal care such that the research questions pursued in this dissertation could be well addressed with this level of observation.

The second fundamental limitation to this work is the cross-sectional, associational approach taken to assessing the relationship between network structure, performance and HIE. It is possible that the causal direction discussed in chapters three and five—that network structure leads to coordination and HIE choices—is reversed: successful coordination may lead to network structure and HIE choices may also influence network structure. However, as demonstrated in Appendix 1, the overall structure of the hospital patient sharing network is reasonably stable over time—on average it exhibits little change from year to year. This consistency argues for the causal direction described through this dissertation because performance and especially HIE likely change faster than network structure. However, this consistency also limits the empirical methods that can be adopted because a (short-duration) panel based approach is unlikely to identify sufficient variation to drive statistically significant relationships. Similarly, the effect of policies are likely to shape the overall network slowly, making identification of clear discontinuities unlikely. In consequence, the results of this study should be interpreted with care. In particular, it is plausible that the association between network structure and performance identified in chapter 3 is representative of a feedback loop in which causation flows in both directions. That is, network structure facilitates coordination and coordination reinforces helpful network structure. As such, the magnitude of the associations identified in that study should be interpreted with caution. However, the identification of a relationship indicates that this feedback loop or direct effect may be occurring, and the strong observed association is particularly remarkable because the outcomes used include not only patients seen by multiple hospitals (for whom network structure and coordination are both highly salient) but also patients seen at a single hospital for whom these features may be less important. Therefore, it is reasonable to believe that for the individuals for whom the network structure and associated ability to coordinate is particularly important, its effect is substantial and perhaps larger than estimated here. Future research should endeavor to more precisely estimate the causal effect of network structure on patients that move through the network. Doing so would require a different data resource with information on specific patients and different methods that moved away from the global analysis of all hospitals and focused on hospitals for whom policy change or new market entrants may have caused an exogenous shock to the network or who are geographically proximate to hospitals in other communities that are across state lines, such that their assignment to a specific community with network characteristics is plausibly exogenous.

Notwithstanding these limitations, the findings in this dissertation have important implications for organizational leaders and policymakers. Many organizational and policy initiatives relate to hospital relationships with one another and other providers outside of the hospital's walls. When dividing hospitals into communities based on the pattern of shared Medicare patients, I identified substantially larger hospital groups than found using prior methods. For organizational leaders, this highlights the importance of considering the broader environment of providers that influence the care that their patients receive—to consider not only their partners but also their partners' partners, and how their strategic decisions will be received by the system as a whole collective. For policy makers, this highlights the importance of considering broad patterns of interaction when devising policies intended to influence coordination and alter variation in the quality of care. These broader patterns may influence individual hospital's ability to react in response to policy initiatives. However, because this approach is hierarchical, smaller sub-groups of hospitals can be identified and these sub-groups may be important when organizational leaders and policy makers are interested in identifying the most closely tied organizations for targeted strategic action or policy change.

Several ongoing policy initiatives, such as bundled payments, accountable care organizations, patient centered medical homes, readmission reduction programs, and others, are implicitly concerned with the way in which hospitals and other providers inter-relate through network structures. Despite this, we do not measure how policy efforts change networks, though it is likely that these changes will shape the trajectory of the patient sharing network. The finding that certain network structures are associated with better performance points towards the importance of measuring the effect that policy initiatives—and market change and consolidation more generally—have on the inter-organizational network of shared patients. The potential that the association between network structure and performance represents a feedback loop highlights the potential power of influencing the structure of the network to set off improvements of coordination that further reshape the network. However, while it is possible that these changes are facilitating improved networks, prescribed policy changes may also be disrupting well-functioning networks or otherwise negatively impacting organizations that do not participate in the program but are closely linked to participating organizations. However, because we do not measure these changes—or know which network structures facilitate better care—we are blind to how policy change may be causing unintended consequences.

In combination, the work to identify communities of hospitals and to identify network characteristics of these communities has important implications for measuring and explaining geographic variation in the cost and quality of care. Because these network structures are related to the efficiency and quality of hospital care, variation in these structures by geographic area could form part of the explanation of previously unexplained variation in quality and efficiency of care. For instance, hospital service areas primarily served by hospitals on the periphery of their network may be associated with lower quality care than hospital service areas primarily served by central hospitals, especially when patients on the periphery are not well funneled to central hospitals. The usefulness of these structures in explaining variation in quality does not depend on a strictly causal relationship, though to the extent that the causal mechanism theorized in this study form a plausible accounting of the observed effect, they may motive action aimed to alter certain networks.

The positive association between network concentration, centralization and the efficiency and performance of hospital care points towards a potential renewed interest in considering the regionalization of care. That is, while the volume-outcome relationship argues for the benefits of focusing care of some procedures in certain high volume centers, a broader focus on network structure considers the effect of this policy not only on the outcomes offered by individual hospitals but also the effect of directing patients to these hospitals on the average performance of all participants in a network. In so doing, it strengthens the case that helping to shape the network towards a concentrated, centralized structure appears to have benefits for the system overall, not just the high-volume hospitals that are the ‘winners’ in traditional studies on the volume-outcome relationship. For organizational leaders, this points towards specific designs of multihospital systems and for ways in which to design efficient care delivery systems: by creating well-functioning community hospitals that funnel patients effectively to large centers of excellence rather than attempting to provide treatment for patients beyond their core competencies. For policymakers, this finding points towards the logic of incentivizing regionalization of care, efforts that have been undertaken more aggressively outside of the

United States but may be considered as ways to improve the quality and efficiency of care without reducing the overall provision of services.

The final key policy implication of this work is that hospitals appear to be selecting HIE approaches that fit both their own network of shared patients and the collective network of hospitals in which they are embedded. This finding is important because of recent concern that organizations may be engaging in information blocking—that is, that they may be purposefully engaging in HIE approaches that match their strategic priorities and competitive incentives by *not* sharing information with other hospitals with which they compete. The fact that hospitals are not only reactive to their own network but also respond to pressure from the collective network to adopt a certain type of HIE should mitigate these concerns to some extent. However, the insight that hospitals might select an approach to HIE that benefits the network but does not best fit their own network of direct shared patients may point towards a need to further support these hospitals and ensure that they can both meet their individual needs and the needs of the collective network. In the sociologic literature, the idea of social capital as a force that can shape behavior by increasing the salience of norms held by the community is widely acknowledge. The relationship between the needs of the network and hospitals' HIE decisions points towards the important role that pressure from peers, partners and competitors in the delivery system play in driving organizational decisions, and this insight may extend beyond engagement in HIE towards adoption of practices that could lead to approval or censure from important sources of reputation and revenue.

In sum, this dissertation represents a substantial step forward in our understanding of the implication of network structure for the functioning of the healthcare system. I have demonstrated that network analysis can contribute policy- and practice-relevant understanding of the health care delivery and hope to continue to build our understanding of these important features of the way care is delivered in order to work towards a high-performing healthcare system.

APPENDIX A

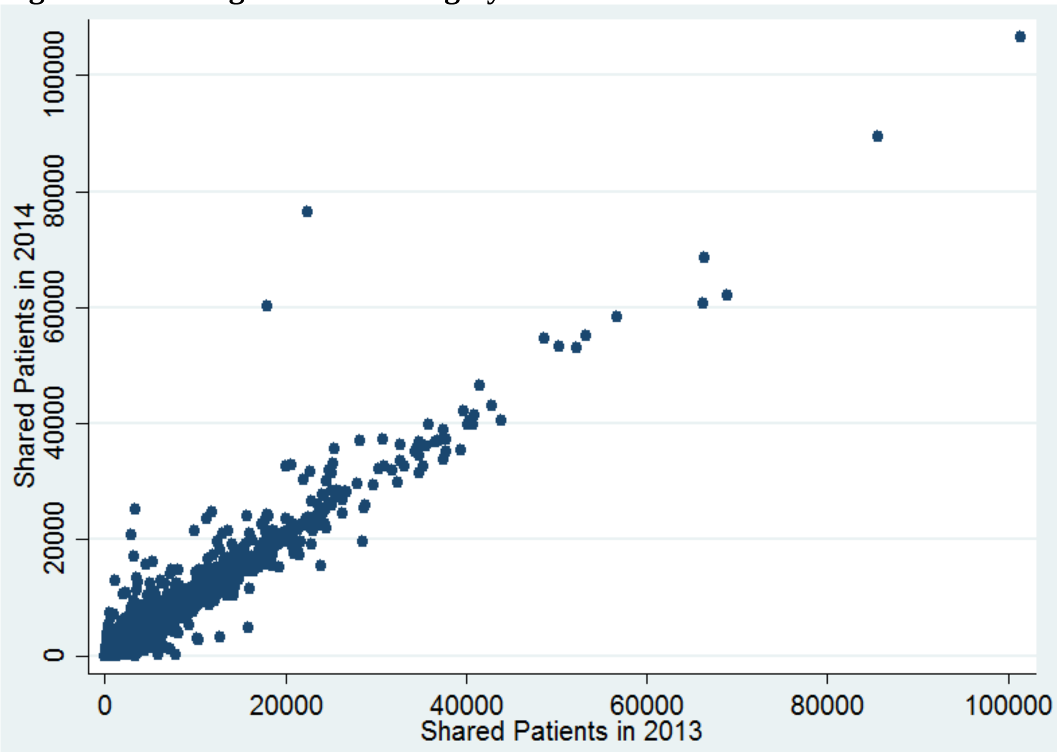
Network Data Validity

Over Time Reliability of Data

To demonstrate that this data was generating reliable measurement, I compared the 2014 network to the 2013 network. Even though the primary analysis conducted throughout this dissertation, the reliability of the data is an important measure of the degree to which measurement error may be distorting results. Of the 91,120 inter-hospital patient sharing ties in 2014, 81,709 (90%) were also present in 2013. The persistence of ties over these two years was strongly associated with the strength of the tie: the median tie that was present in 2014 but not 2013 was comprised of 32 shared patients while the median persistent tie in was comprised of 141 patients.

For ties that persisted, the correlation between the strength of the time in 2014 and 2013 was very high, at 0.97 (Figure A1).

Figure A1. Strength of Ties is Highly Persistent Over Time



Validity of Hospital Graph Strength

To test the validity of the network data I used data from the AHA Annual Survey that was likely to be associated with a larger number of shared patients in the network: the number of Medicare discharges reported and teaching status. Hospitals with more Medicare discharges are likely to have more shared patients, while teaching hospitals are likely to serve as referral centers and therefore have more shared patients. Because the number of shared patients is highly skewed, I modeled both the raw total number of patients shared and the natural log of patients shared. I found that the number of discharges and teaching status were each very strongly associated with the total number of shared patients, validating that the data is capturing the quantity of patients treated at this hospital.

Table A1. Predictors of Total Number of Patients Shared

	Total Patients Shared	Log Total Patients Shared
Medicare Discharges	1.9	
	(0.06)	
Log Medicare Discharges		0.48
		(0.0085)
Major Teaching Hospital	21,576	0.91
	(1,068)	(0.061)
Constant	3,442	5.07
	(270)	(0.061)
R-Squared	0.36	0.48
N	4,602	4,602

Validity of Pair Tie Strength

To further test the validity of the data, I predicted the strength of ties between pairs of hospitals that were observed to share at least 11 patients using ordinary least squares regression. I predicted these ties based on simple characteristics of the hospitals in the network. Larger hospitals, closer hospitals, and hospitals that are members of the same system should logically be associated with stronger ties. Because the number of shared patients is highly skewed, I modeled both the raw total number of patients shared and the natural log of patients shared. I found that larger hospitals shared more patients, farther away hospitals shared fewer patients and hospitals that were members of the same system shared many more patients than hospitals that were not. Each of these findings points towards the validity of the measurement of the strength of these ties.

Table A2. Predictors of the Strength of Hospital Ties

	Patients Shared Between Hospitals	Log Patients Shared Between Hospitals
Log Medicare Discharges Hospital 1	95.5	0.093
	(4.17)	(0.033)
Log Medicare Discharges Hospital 2	87.1	0.08
	(4.14)	(0.033)
Distance Between Hospitals	-1.12	-0.002
	(0.045)	(0.00004)
Same System Membership	1,029	0.84
	(21.2)	(0.017)
Constant	-938.5	3.68
	(45.2)	(0.036)
R-Squared	0.04	0.07
N	90,688	90,688

APPENDIX B

Full Results and Robustness Checks for Chapter 5

Table B1. Full Regression Results for Effect of Hospital and Network Concentration, Density and Competition on HIE Approach

	Fit, Reinforcement and Conflicting Fit		Moderating Effect of Density and Competition	
Hospital-Level Concentration				
Dispersed Network (Omitted: Concentrated)	1.861**	(0.026)	1.387*	(0.058)
Moderately Concentrated Network	1.355	(0.167)	1.196	(0.208)
Whole Network-Level Concentration				
Dispersed Network (Omitted: Concentrated)	1.968**	(0.037)	0.468	(0.202)
Moderately Concentrated Network	1.451	(0.207)	0.915	(0.881)
1.concTert#1.concTertComm	0.625	(0.135)		
1.concTert#2.concTertComm	0.672	(0.283)		
2.concTert#1.concTertComm	0.923	(0.805)		
2.concTert#2.concTertComm	0.710	(0.278)		
Network Density				
Moderate Density (Omitted: Low Density)	1.132	(0.579)	0.724	(0.405)
High Density	1.005	(0.984)	0.555	(0.242)
Dispersed Whole Network*Moderate Density			2.541*	(0.083)
Dispersed Whole Network*High Density			3.371**	(0.043)
Moderately Concentrated Whole Network*Moderate Density			0.980	(0.969)
Moderately Concentrated Whole Network*High Density			1.354	(0.614)
Competition				
Moderate Competition (Omitted: Low Competition)		(0.538)	1.112	(0.810)
High Competition		(0.378)	0.650	(0.423)

Dispersed Whole Network*Moderate Competition			1.555	(0.446)
Dispersed Whole Network*High Competition			2.882*	(0.086)
Moderately Concentrated Whole Network*Moderate Competition			0.662	(0.415)
Moderately Concentrated Whole Network*High Competition			1.936	(0.303)
# of Hospitals in Network	0.985*	(0.052)	0.987*	(0.064)
# of Shared Patients in Network	1.000***	(0.006)	1.000***	(0.006)
Hospital Type				
# Affiliated Physicians	1.000*	(0.090)	1.000*	(0.092)
Hospital System Market Share	31.572***	(0.000)	29.459***	(0.000)
General Acute Care	1.827	(0.115)	1.850	(0.113)
Critical Access	1.034	(0.859)	0.996	(0.981)
Major Teaching	0.954	(0.865)	0.970	(0.913)
Minor Teaching	0.952	(0.772)	0.927	(0.658)
System Member	1.025	(0.886)	1.018	(0.916)
Network Member	1.273*	(0.064)	1.243*	(0.092)
Urban	0.927	(0.664)	0.921	(0.623)
Size (Large Omitted)				
Small	1.194	(0.481)	1.147	(0.593)
Medium	1.254	(0.239)	1.248	(0.262)
Ownership (For-Profit Omitted)				
Government-owned	0.971	(0.912)	0.974	(0.920)
Not for Profit	1.507*	(0.065)	1.522*	(0.059)
Healthcare Supply				
Physicians per 1000	1.158	(0.358)	1.152	(0.345)
PCPs per 1000	0.764	(0.360)	0.683	(0.194)
Specialists per 1000	0.756	(0.538)	0.811	(0.623)
Hospital Beds per 1000	1.009	(0.655)	1.007	(0.726)
Area Demographics				
Income Per Capita	1.000	(0.253)	1.000*	(0.069)
Unemployment Rate	25.093	(0.501)	38.788	(0.428)
Population Density	1.013**	(0.039)	1.010*	(0.086)
Proportion Female	0.103	(0.555)	0.217	(0.679)
Proportion over 65	0.252	(0.485)	0.349	(0.590)
Proportion White	2.739	(0.106)	2.472	(0.153)
Proportion without High School	0.046**	(0.042)	0.027**	(0.021)
Constant	0.858	(0.943)	1.541	(0.841)

Observations	2,083	2,083

Robust pval in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table B2. Robustness Tests for Community HIE exists, Omitting EHR vendor and Including Additional HIE Types

VARIABLES	Community HIE Exists odds ratios	Omit EHR Vendor odds ratios
Hospital-Level Concentration		
Dispersed Network (Omitted: Concentrated)	1.364*	1.414
	(0.082)	(0.131)
Moderately Concentrated Network	1.174	1.111
Whole Network-Level Concentration	(0.265)	(0.512)
Dispersed Network (Omitted:	1.596**	1.620**
Concentrated)	(0.035)	(0.035)
Moderately Concentrated Network	1.113	1.125
	(0.623)	(0.638)
Network Density		
Moderate Density (Omitted: Low Density)	1.256	1.363
	(0.306)	(0.234)
High Density	0.965	1.010
	(0.893)	(0.977)
Competition		
Moderate Competition (Omitted: Low Competition)	1.125	0.916
	(0.613)	(0.749)
High Competition	1.252	1.207
	(0.426)	(0.531)
# of Hospitals in Network	0.983**	0.988
	(0.025)	(0.105)
# of Shared Patients in Network	1.000***	1.000**
	(0.004)	(0.019)
Hospital Type		
# Affiliated Physicians	1.000	1.000
	(0.122)	(0.668)
Hospital System Market Share	33.437***	80.427***
	(0.000)	(0.001)
General Acute Care	1.869	2.695**
	(0.104)	(0.015)
Critical Access	1.019	1.250

	(0.921)	(0.312)
Major Teaching	0.954	1.255
	(0.865)	(0.601)
Minor Teaching	0.961	0.848
	(0.819)	(0.425)
System Member	0.982	0.968
	(0.917)	(0.872)
Network Member	1.248*	1.131
	(0.089)	(0.460)
Urban	0.906	1.104
	(0.569)	(0.626)
Size (Large Omitted)		
Small	1.104	0.807
	(0.698)	(0.571)
Medium	1.178	0.995
	(0.399)	(0.986)
Ownership (For-Profit Omitted)		
Government-owned	0.904	0.776
	(0.711)	(0.423)
Not for Profit	1.475*	1.382
	(0.085)	(0.246)
Healthcare Supply		
Physicians per 1000	1.135	1.308
	(0.434)	(0.153)
PCPs per 1000	0.772	0.702
	(0.371)	(0.358)
Specialists per 1000	0.802	0.534
	(0.634)	(0.273)
Hospital Beds per 1000	1.007	1.020
	(0.716)	(0.363)
Area Demographics		
Income Per Capita	1.000	1.000
	(0.174)	(0.442)
Unemployment Rate	5.531	9.732
	(0.729)	(0.650)
Population Density	1.013**	1.011
	(0.037)	(0.113)
Proportion Female	0.009	0.001
	(0.298)	(0.269)
Proportion over 65	0.446	0.073
	(0.696)	(0.230)
Proportion White	2.560	2.704
	(0.132)	(0.182)
Proportion without High School	0.061*	0.053*
	(0.065)	(0.064)
Constant	4.650	22.442

	(0.533)	(0.355)
Observations	2,056	1,747

Robust pval in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table B3. Robustness Tests Using Alternative Definitions of Concentration

VARIABLES	Linear Concentration odds ratios	Median Concentration odds ratios
Hospital-Level Concentration		
Linear Network Concentration	0.385**	
	(0.015)	
High Concentration (Median Split)		0.799
		(0.188)
Whole Network-Level Concentration		
Linear Network Concentration	0.023**	
	(0.042)	
High Network Concentration (Median Split)		0.643**
		(0.029)
Network Density		
Moderate Density (Omitted: Low Density)	1.106	1.143
	(0.661)	(0.591)
High Density	0.950	0.876
	(0.850)	(0.642)
Competition		
Moderate Competition (Omitted: Low Competition)	1.154	1.213
	(0.543)	(0.438)
High Competition	1.275	1.343
	(0.363)	(0.284)
# of Hospitals in Network	0.986*	0.982***
	(0.054)	(0.009)
# of Shared Patients in Network	1.000***	1.000***
	(0.008)	(0.004)
Hospital Type		
# Affiliated Physicians	1.000*	1.000*
	(0.083)	(0.073)
Hospital System Market Share	32.700***	27.419***
	(0.000)	(0.000)
General Acute Care	1.822	1.389
	(0.123)	(0.415)
Critical Access	1.026	1.055
	(0.889)	(0.784)
Major Teaching	0.937	1.039
	(0.812)	(0.902)

Minor Teaching	0.946	1.079
	(0.744)	(0.691)
System Member	1.037	0.989
	(0.832)	(0.952)
Network Member	1.262*	1.277*
	(0.068)	(0.063)
Urban	0.916	0.931
	(0.604)	(0.712)
Size (Large Omitted)		
Small	1.207	1.206
	(0.457)	(0.490)
Medium	1.262	1.244
	(0.231)	(0.311)
Ownership (For-Profit Omitted)		
Government-owned	1.014	1.598*
	(0.956)	(0.097)
Not for Profit	1.551**	2.352***
	(0.048)	(0.000)
Healthcare Supply		
Physicians per 1000	1.155	1.102
	(0.375)	(0.568)
PCPs per 1000	0.742	0.704
	(0.313)	(0.289)
Specialists per 1000	0.776	0.805
	(0.580)	(0.673)
Hospital Beds per 1000	1.005	1.018
	(0.805)	(0.477)
Area Demographics		
Income Per Capita	1.000	1.000
	(0.214)	(0.329)
Unemployment Rate	40.929	63.649
	(0.437)	(0.419)
Population Density	1.012**	1.014***
	(0.046)	(0.009)
Proportion Female	0.094	0.024
	(0.552)	(0.399)
Proportion over 65	0.162	0.127
	(0.376)	(0.430)
Proportion White	2.591	3.110
	(0.153)	(0.106)
Proportion without High School	0.034**	0.034**
	(0.025)	(0.044)
Constant	2.604	7.886
	(0.676)	(0.412)
Observations	2,083	1,709

Robust pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B4. Multivariate Regression Testing the Moderating Effect of Network Concentration on Relationship Between HIE and Outcomes

	(1) MSPB	(2) Readmissions	(3) Mammography Follow Up
Community HIE	0.169	0.004	-0.182*
	(0.120)	(0.109)	(0.098)
Whole Network-Level Concentration			
Dispersed Network (Omitted: Concentrated)	0.198	0.079	0.006
	(0.128)	(0.085)	(0.126)
Moderately Concentrated Network	0.451***	0.096	0.225
	(0.135)	(0.095)	(0.194)
Dispersed Network*Community HIE	0.086	0.103	-0.054
	(0.116)	(0.117)	(0.105)
Moderately Concentrated Network*Community HIE	-0.237*	0.257**	0.041
	(0.140)	(0.125)	(0.120)
Hospital-Level Concentration			
Dispersed Network (Omitted: Concentrated)	0.183*	0.043	-0.305***
	(0.104)	(0.104)	(0.107)
Moderately Concentrated Network	0.172*	-0.066	-0.053
	(0.103)	(0.087)	(0.118)
Dispersed Network*Community HIE	-0.059	0.041	0.310***
	(0.123)	(0.121)	(0.109)
Moderately Concentrated Network*Community HIE	-0.167	0.046	0.083
	(0.127)	(0.112)	(0.138)
Network Density			
Moderate Density (Omitted: Low Density)	0.289**	-0.027	0.263*
	(0.123)	(0.103)	(0.155)
High Density	0.322**	0.207*	0.208
	(0.129)	(0.112)	(0.131)
Competition			
Moderate Competition (Omitted: Low Competition)	-0.111	0.140*	0.055
	(0.124)	(0.083)	(0.097)
High Competition	-0.046	0.367***	0.272***
	(0.155)	(0.089)	(0.099)
# of Hospitals in Network	0.007*	0.004	0.007
	(0.004)	(0.004)	(0.006)
# of Shared Patients in Network	-0.000	-0.000	-0.000*
	(0.000)	(0.000)	(0.000)
Hospital Type			
Hospital System Market Share	-0.189	-0.168	-0.272
	(0.266)	(0.249)	(0.277)
General Acute Care	0.178	1.283***	0.347
	(0.206)	(0.240)	(0.254)

Critical Access		0.264***	-0.045
		(0.067)	(0.071)
Major Teaching	-0.041	0.701***	0.257**
	(0.076)	(0.110)	(0.105)
Minor Teaching	-0.003	0.046	0.177*
	(0.050)	(0.062)	(0.096)
System Member	0.000	-0.021	-0.123
	(0.051)	(0.057)	(0.119)
Network Member	0.015	-0.068	0.089
	(0.041)	(0.051)	(0.089)
Urban	0.365***	0.015	-0.035
	(0.068)	(0.058)	(0.068)
Size (Large Omitted)			
Small	-0.295***	-0.032	0.187*
	(0.068)	(0.119)	(0.112)
Medium	-0.094*	-0.086	0.277***
	(0.050)	(0.096)	(0.103)
Ownership (For-Profit Omitted)			
Government-owned	-0.450***	-0.312***	-0.082
	(0.088)	(0.111)	(0.103)
Not for Profit	-0.400***	-0.402***	-0.052
	(0.072)	(0.094)	(0.081)
Healthcare Supply			
Physicians per 1000	-0.115*	-0.231**	-0.329**
	(0.060)	(0.098)	(0.155)
PCPs per 1000	-0.405***	-0.255*	-0.052
	(0.142)	(0.137)	(0.154)
Specialists per 1000	0.457**	0.832***	1.119**
	(0.179)	(0.280)	(0.488)
Hospital Beds per 1000	-0.001	0.020**	-0.013
	(0.014)	(0.008)	(0.009)
Area Demographics			
Income Per Capita	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)
Unemployment Rate	-7.035***	6.446***	4.646**
	(2.065)	(2.323)	(2.173)
Population Density	-0.001	0.002	-0.002***
	(0.001)	(0.001)	(0.001)
Proportion Female	7.907***	-0.214	-0.012
	(2.378)	(1.585)	(1.989)
Proportion over 65	0.728	1.340	0.048
	(1.101)	(0.871)	(0.880)
Proportion White	0.114	-0.221	0.773***
	(0.280)	(0.373)	(0.290)
Proportion without High School	1.779***	0.490	-0.488
	(0.668)	(0.703)	(0.607)

Constant	-4.648***	-1.625	-1.898
	(1.254)	(0.995)	(1.447)
Observations	1,544	2,009	1,641
R-squared	0.280	0.233	0.140

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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