MULTI-STATE MARKOV MODELS FOR THE ANALYSIS OF EMRS DIFFUSION IN HEALTHCARE

by

Meng-Hao Li

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DEDICATION

This is dedicated to my parents, Chin-Shu Lee, Hsiu-Chun Tung, Yao-Huei Wei and Ming-Hsueh Chen, and my brother, Shang-Ju Lee. Thanks for your encouragement and the many ways you helped me make this happen. My heartfelt thank you goes to my wife, Wan-Chu, who provided steadfast support and faith in my ability to persevere through this journey.

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ABSTRACT

MULTI-STATE MARKOV MODELS FOR THE ANALYSIS OF EMRS DIFFUSION IN HEALTHCARE

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Prior studies on diffusion of innovations typically research the same units of analysis, top-down diffusion, bottom-up diffusion, spatial proximity or network analysis, paying little or no attention to the effect of bottom-up networks on the multilevel diffusion process. The adoption decision is formed at the organizational level, but the factors that formulate the decision possibly result from either inter- or intra-organizational networks, or mixed effects of inter- and intra-organizational networks. It remains unclear how individuals and organizations respectively are exposed to adoption information in their networks and collectively form an adoption decision at the organizational level. Using data (2009-2015) from the hospital's adoption of Electronic Medical Records (EMRs), individual healthcare provider referral networks, and hospital system networks, this study applies multi-state Markov models to examine how the mixed effect of intra- and inter-hospital networks influences the process of bottom-up EMRs diffusion. The findings suggest that hospital

system networks, individual provider networks within and between hospitals, and proximity of hospital locations play different roles in the transitions between EMRs states (i.e., non-adopters, basic adopters, intermediate adopters, and comprehensive adopters). The results enrich our understanding of how individuals (bottom) in an organization interact with internal and external environments to influence the organization's decisions (up) collectively. This study further offers four network-based policy intervention strategies for facilitating the adoption of advanced EMRs and suggests devising an EMRs incentive scheme based on hospital EMRs states.

CHAPTER 1 INTRODUCTION

According to a 2006 report by the Agency for Healthcare Research and Quality, health information technology (HIT) is defined as the application of information technology to support healthcare system processes that improve cost-effectiveness, efficiency, quality, and safety of healthcare delivery (Shekelle, Morton & Keeler, 2006). The implementation of HIT in hospitals is expected to automate labor-intensive tasks, reduce human errors, accelerate the delivery of laboratory reports, facilitate the exchange of health information, and support diagnosis. Among the various HITs, the deployment of electronic medical records (EMRs) or electronic health records (EHRs) systems has been demonstrated as the most significant step in the computerization of the healthcare environment.[1] The core components of basic EMRs provide structured data input for scheduling, medication administration, diagnosis, orders, and results viewing. Advanced versions of the EMRs encompass more functionality related to EMR integration with billing systems and dashboard tools, diagnostic decision support, and simultaneous access to health records for multiple users and locations. However, prior to 2009, the adoption

[1] HIMMS used electronic medical records (EMRs) to describe the adoption of health information systems. In practice, EHRs and EMRs are used interchangeably, but EHRs are a broader concept including all information systems implemented in the hospital and commonly used in government documents. Please see more discussion about the difference between EMRs and EMRs via https://www.healthit.gov/buzz-blog/electronic-health-and-medical-records/emr-vs-ehr-difference

rate of the EMRs was less than 48 percent.[2] The most common barriers to the adoption of EMRs by individual healthcare providers or hospitals include misaligned incentives, limited purchasing power among healthcare providers, variability in the viability of EMRs products and companies, and inadequate demonstrated value of EMRs in practice (Middleton et al., 2005).

1.1 Barriers to the Adoption of EMRs

From a hospital administration perspective, the barriers to the adoption of EMRs can be attributable to the transaction costs of the search process, EMRs management and learning.

More EMRs offerings on the market are expected to provide hospitals with better services and comparative pricing. Nevertheless, the various types of EMRs greatly increase the search costs and external data exchange costs for hospitals. According to a report by the Office of the National Coordinator for Health Information Technology (ONC), there are over 70 different types of EMRs nationwide.[3] The diversity of EMR systems increases the cost of search, learning and data exchange for healthcare organizations. For example, hospitals may be concerned about how to choose EMRs to make their data useful and secure. In a small or medium-sized hospital, healthcare providers need to find ideal EMRs to store clinical data in a secure place. If a small or medium-sized hospital decides to deploy its own servers to store data, the risk of patient privacy invasion is minimized. However,

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[2] The Office of the National Coordinator for Health Information Technology (ONC), Retrieved December 16, 2021, from https://dashboard.healthit.gov/quickstats/quickstats.php

[3] ONC EHR Products Used for Meaningful Use Attestation, Retrieved December 16, 2021, from https://www.healthit.gov/data/datasets/ehr-products-used-meaningful-use-attestation

the maintenance costs of running a server can be expensive for a small or medium-sized hospital. Conversely, if a small or medium-sized hospital decided to store its data in cloud storage managed by an external organization, the potential issues would be how to protect patient privacy and how to ensure that data management complies with the Health Insurance Portability and Accountability Act of 1996 (Dargin, 2017).

The second issue is who is responsible for managing and overseeing the EMRs. In a paper-based healthcare delivery process, hospitals do not need professional IT personnel to manage EMRs. As hospitals implement EMRs systems, they may consider whether there is value in creating a new position for IT personnel or whether it is more cost-effective to contract out the operation of EMRs (McBride, 2012). The cost consideration between contracting out of EMRs and employment costs is difficult for hospitals to make.

Introducing a new system in hospitals inevitably requires convincing healthcare workers to change their established workflow and spend additional time learning record entry and how to convert paper records to electronic records. The learning curve for younger healthcare providers may be smoother (faster learning) than for more experienced healthcare providers. Hospitals could design training programs that facilitate the adaptation of healthcare providers to the new EMRs system, but the training programs require hospitals to allocate more budget to the implementation of EMRs (Green, 2021). This is particularly challenging for small and medium-sized hospitals with limited budgets, and the benefits of using EMRs cannot be immediately foreseen.

1.2 Interoperability Issues

The high cost of external data exchange leads to interoperability issues. Central to interoperability is ensuring that electronic laboratory results, electronic prescriptions, or summaries of care records can be exchanged, integrated and shared across different EMRs systems. However, the process of achieving interoperability between different EMRs systems remains cumbersome (DesRoches, Painter& Jha, 2015; US Department of Health and Human Services, 2016). Only a few EMRs vendors offer user-friendly functionality for the extraction of health records, and there is no certified software that allows hospitals to convert different formats of health records into a standardized format.

From a data exchange perspective, all certified EMRs should allow clients to extract Continuity of Care Documents (CCDs) or Continuity of Care Records (CCRs) for use or exchange (i.e., interoperability). Nevertheless, only a few allow clients to use the most efficient way of extracting CCDs/CCRs in batch format. Most EMRs vendors do not offer user-friendly interfaces for the extraction of CCDs/CCRs. Some only allow clients to download one patient's CCDs/CCRs at a time. If clients plan to migrate from their EMRs to another, they will need to extract all single CCDs/CCRs from the EMRs, which is a time-consuming process. In the worst-case scenario, the EMRs systems are not designed to generate CCDs/CCRs. Those EMRs provide functionality for clients to query the entire database, but the extraction of CCDs/CCRs is prohibited.[4]

[4] Author's field experience

The fundamental challenge of interoperability is to standardize the format of data exchange. Health Level Seven International [5] (HL7) is a not-for-profit standards development organization accredited by the American National Standards Institute (ANSI). HL7 creates standards to facilitate the exchange, management, and integration of electronic healthcare information standards for clinical and regulatory objectives. The standards for CCDs/CCRs contain mandatory and non-mandatory sections for EMRs vendors to customize their requirements, resulting in different versions of CCDs/CCRs and barriers to interoperability. Besides, there is no certified software that allows end-users to convert different versions of CCDs/CCRs into a standardized version.

1.3 Detrimental Effects

Problematic EMR design and interoperability issues can have a detrimental effect on innovative healthcare initiatives. Healthcare providers are more concerned about retrieving their patient information and making patient appointments but less concerned with whether EMRs capture critical information, such as smoking cessation or flu shot screenings, in a structured format. A poorly designed EMRs user interface will make it difficult for healthcare providers to search for patient information (Brandt, 2008; Zahabi, Kaber, & Swangnetr, 2015). For example, Accountable Care Organizations (ACOs) is innovative healthcare organizations designed to find patients with difficult medical conditions and provide coordinated care for patients from primary to acute. Without a user-friendly interface, ACOs will lack accurate and meaningful data to contact the right patients

[5] https://www.hl7.org/

(Royer, 2015). Furthermore, one way to facilitate data sharing among the AOC healthcare organizations is to ensure data exchange standards (i.e., CCDs/CCRs). As noted in the context of interoperability, there is currently no certified software that users can adopt to standardize different versions of CCDs/CCRs. ACO healthcare providers may struggle to find ways to extract patient records from various EMRs and organize the data in a meaningful way, which takes time and effort. Both the design and interoperability of EMRs are critical in determining whether an innovative ACO initiative can effectively achieve its goals.

1.4 Current Policy Efforts

Over the past decade, governments have mobilized significant efforts to address the low adoption rate of EMRs, interoperability, and coordination of healthcare delivery. In response to the slower-than-expected adoption of the EMRs systems, Congress enacted the Health Information Technology for Economic and Clinical Health (HITECH) Act as part of the American Recovery and Reinvestment Act of 2009, which set EMRs implementation standards for hospitals and physicians to meet (Balgrosky, 2019). In 2017, 86% of US hospitals had adopted at least a basic EMR system, up from 48% in 2009.[6] EMRs/EHRs incentive programs as a policy intervention have been identified as one of main factors in accelerating the growth of EMR adoption (Adler-Milstein & Jha, 2017). The implementation of the EMRs incentive programs (also known as Meaningful Use) consists

[6] See note 2. The definition of basic EMR by ONC is not the same as the definition used in Chapter 4 in this research.

of three phases. The first phase requires participants to establish an EMR environment for the electronic extraction of clinical data. The second phase requires participants to ensure care coordination and exchange of patient information. The final phase expects participants to produce better clinical outcomes and quality of care. Eligible participants in the program are Medicare or Medicaid healthcare providers and hospitals that meet the requirements. Participants who meet or do not meet the criteria for each phase are rewarded with monetary payments (beginning in 2009) or penalties (beginning in 2014). Each phase of the EMRs incentive programs is summarized below.

- Phase 1 laid the groundwork by establishing requirements for the electronic capture of clinical data, including providing electronic copies of health information to patients. Both CCDs and CCRs are acceptable formats for clinical care summaries.
- Phase 2 expanded on the Phase 1 criteria with a focus on advancing the clinical process and ensuring that the meaningful use of EHRs supports the goals and priorities of the National Quality Strategy. Phase 2 criteria encouraged the use of CEHRT for continuous quality improvement at the point of care and the exchange of information in the most structured format possible. In addition, CCDs were identified as the most appropriate format for clinical document exchange.
- In October 2015, CMS issued a final rule identifying Phase 3 for 2017 and beyond, which focuses on the use of CEHRT to improve health outcomes. In addition, the rule modified Phase 2 to ease reporting requirements and align with other CMS programs.

The Electronic Medical Documentation Interoperability (EMDI) program is another policy effort to 1) reduce the administrative burden on providers, 2) increase interoperability between systems and organizations in the public and private sectors, and 3) improve communication among providers.[7]

Despite significant efforts by governments to improve interoperability, the 2015 American Hospital Association Annual Survey revealed that only 30% of hospitals engaged in the four domains of interoperability, including finding information, sending information, receiving information, and integrating patient information (Holmgren, Patel & Adler-Milstein, 2017). Therefore, the successful implementation of the EMRs incentive programs and the EMDI program is expected to improve EMRs adoption and remove barriers to data exchange among healthcare organizations.

1.5 Research Questions

The EMRs incentive programs (i.e., Meaningful Use) have been demonstrated to be the most effective policy instrument for accelerating the adoption of EMRs and coordinating the health data exchange among healthcare organizations that participate in ACOs

Research has found that physicians' perceptions of the importance of the Meaningful Use policy were strongly associated with the adoption of EMRs in the first three years (2010–2012) of the policy implementation (Cohen, 2016). However, progress from Meaningful Use Phase 1 to Meaningful Use Phase 2 remains cumbersome. Only 5.8% of hospitals met all the requirements of Meaningful Use Phase 2, implying that hospitals

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[7] Electronic Medical Documentation Interoperability (EMDI) Program https://www.cms.gov/Research-Statistics-Data-and-Systems/Computer-Data-and-Systems/Electronic-Medical-Documentation-Interoperability/Overview

“haves” and “have-nots” are not valid measures of EMR adoption, and that the focus should be shifted from “haves” and “have-nots” to “basic haves” and “advanced haves” (Adler-Milstein et al., 2014).

Moreover, the EMRs incentive programs coordinate the collection of patient health records between ACOs and other healthcare organizations to improve the quality of care. Data sharing and exchange between ACOs and healthcare organizations require standardized data formats and EMRs support (Trotter & Uhlman, 2011). Of the performance measures for ACOs, 26 of the 65 quality measures were related to quality measures used by the EMRs incentive programs (Gruber, 2011). However, in a 2014 survey, 46 ACOs rated EMRs vendors as meeting the ACOs’ requirements with an average score of 6.3 out of 9.0 (Royer, 2015). Also, the CMS Innovation Center has developed several payment and service delivery models to help ACOs improve access to care. The Pioneer ACO Model is one of the innovative models “designed for organizations with experience providing coordinated, patient-centered care, and operating in ACO-like arrangements.” A CMS report shows that more than 50% of the Pioneer ACO’s primary care providers have met the requirements for Phase 1 of the EMRs Incentive Program.[8] However, for the second phase of the EMRs Incentive Programs, the performance of ACOs is still unknown and needs to be assessed with caution. Therefore, the study of EMRs should not be seen as a stand-alone technology. Instead, the EMRs consist of several components that support clients in customizing their needs and using them for various

[8] CMS, Pioneer ACO Model Fact Sheet, Retrieved December 16, 2021, from https://innovation.cms.gov/initiatives/Pioneer-ACO-Model/PioneerACO-FactSheet.html

purposes. If a hospital deploys only a basic version of EMRs, it can be expected that poor EMRs user interface design, interoperability issues and corresponding adverse effects have the potential to undermine innovative healthcare initiatives and lead to poor quality of care. Nevertheless, most prior research on the adoption of EMRs focused on whether or how fast the information system is adopted. Statistical methods used to estimate the binary adoption outcome and time-to-event adoption data are the logit regression and survival models respectively, yet the methods for approaching a time-to-transition outcome with different adoption levels of EMRs have not been widely discussed. Adoption levels of EMRs can be an upgrade from basic EMRs adopters to comprehensive EMRs adopters, or from EMRs non-adopters to intermediate EMRs adopters. Therefore, the first goal of this study is to use the multi-state Markov model to simultaneously estimate the factors that affect the transitions between different levels of EMRs adoption.

Other important barriers to the adoption of EMRs vary considerably by individual healthcare provider specialty (Boland et al., 2013) and the individual healthcare provider network (Zheng et al., 2010), hospital size, hospital ownership, and hospital location (Adler-Milstein et al., 2014; Adler-Milstein & Jha, 2017). Traditional EMRs adoption has focused on the organizational level or the individual level. At the organizational level, hospitals search eligible vendors, allocate budgets, install EMRs systems, provide EMRs training and recruit EMRs professionals. A policy analysis of the adoption of EMRs at the organizational level seems appropriate, as the “organization” contracts and makes purchasing decisions with the EMRs vendor. However, the target users may not be ready for the new EMRs. At the individual level, physicians, nurses, administrative staff, and information technology personnel jointly decide whether to incorporate EMRs into daily work. Thus, the adoption of EMRs is related to hospitals and hospital employees: hospitals are more willing to invest in EMRs if their end users are willing to do so (Fonkych & Taylor, 2005). Furthermore, previous studies of innovation diffusion focused on the same unit of analysis (individual, organization, or government), top-down diffusion, bottom-up diffusion, spatial proximity, or network analysis, with little or no attention paid to the impact of bottom-up networks on the multilevel diffusion process (Berry & Berry, 2007; Fareed et al., 2015; Sherer et al., 2016; Shipan & Volden, 2006). The adoption decisions are formed at the organizational level, but the factors that shape the decisions may come from inter- or intra-organizational networks, or a mixture of inter- and intra-organizational network effects (Brass & Borgatti, 2019). It remains unclear how individuals and organizations are respectively exposed to adoption information in their networks and collectively form an adoption decision at the organizational level. Using data from hospital EMRs surveys, individual healthcare provider referral networks, and hospital system networks, the second goal of this study is to investigate how the mixed effect of intra- and inter-hospital networks plays a role in the bottom-up diffusion of EMRs. Through the lens of network mechanisms and bottom-up diffusion analysis, the results are expected to provide policymakers with network-based intervention strategies to improve current EMRs-related incentive policies, which is important for facilitating EMRs adoption, in turn improving patient safety and quality of care.

CHAPTER 2 ORIGINS OF DIFFUSION OF INNOVATIONS

The decision to adopt EMRs in hospitals is usually an incremental process and is seen as an innovation, as the adoption of a new technology introduces risks and uncertainties of costs and benefits to the hospital, leading to organizational change. Previous studies describing the diffusion or adoption of innovations have been extensively researched in various fields, from epidemiology, sociology to public policy. These theories are rooted in different theoretical foundations, units of analysis and the nature of innovation, but the diffusion processes observed by these theories do not differ significantly. In the following sections, this study will summarize and discuss the diffusion of innovations in epidemiology, sociology and public policy, respectively.

2.1 Epidemiology View of Diffusion

Epidemiology has developed several mathematical models to explain how an infectious disease spreads through the direct contact of individuals with those infected. The simplest model to explain the process of diffusion is the Susceptible-Infectious-Recovery (SIR) model in epidemiology (Kermack et al., 1927). The SIR model is used to predict the theoretical number of people infected with an infectious disease over time in a closed and homogeneous population. 'S' represents susceptible individuals, 'I' represents infected individuals and 'R' represents recovered individuals. The SIR model assumes that the total population is fixed, which means that no one will be added to the susceptible group, as the model ignores mortality, birth rates and migration. The model also ignores characteristics of the disease, such as incubation period or the age at which infection is most likely. When individuals do not carry lifelong immunity to the disease after recovery and return to a susceptible state, the estimation of the SIR model can be extended to a susceptible-exposed-infected-recovered (SEIR) or susceptible-infected-recovered-susceptible (SIRS) model (Vynnycky & White, 2010). Current research in this field has relaxed several previous assumptions to improve the performance of the models. Taking the COVID-19 diffusion study as an example, Yang et al. (2020) extended the SEIR model by including data on domestic migration before and after travel restrictions in Wuhan, China. The modified SEIR model introduced move-in and move-out parameters to account for dynamic susceptible and exposed population status. Chen et al. (2020) also argued that the SEIR model requires an accurate reproduction number (R0) to estimate the spread of disease. However, COVID-19 is a new disease. It is difficult for researchers to obtain a precise reproduction number and accurately estimate the spread of COVID-19 in the early or mid-epidemic outbreak. Thus, discrete-time Markov chain models relying on the transition probabilities between COVID-19 states were introduced to overcome the sensitivity problem of the SEIR parameters. In short, the disease-based diffusion models have developed several useful tools for researchers to study the diffusion of innovations.

2.2 Sociology View of Diffusion - Organizations

Sociology and organizational science share a common theoretical framework for the diffusion of innovations at the organizational and individual levels. At the organizational level, the central issue is to understand why organizations appear to be increasingly homogenized. For example, the organizational structures of different universities or different hospitals are very similar. One possible reason that explains the homogenization of organizational structures is that organizations are under normative, coercive or mimetic pressures to compete for long-term survival and to gain legitimacy in their environments. Normative pressure states that the norms of a professional organization act as peer pressure to influence member organizations to conform to a new body, for example, to obtain a non-solicitation certificate. Coercive pressure usually occurs when one organization exercises legitimate authority to force another organization to adopt a new regime. Mimetic pressure occurs when one organization imitates the structure of another in an ambiguous situation where learning from another organization is an advantageous way of reducing risk (DiMaggio & Powell, 1983).

The adoption of technology as an institutionalization process has been extensively studied in information systems research, such as enterprise resource planning systems or electronic trading systems (Mignerat & Rivard, 2009). For example, Sherer et al. (2016) used country representative data from 2008 to 2012 to examine how institutional pressures affect the diffusion of EMRs. The findings suggest that the mimetic pressure was a key predictor of EMRs adoption in the high uncertainty environment of 2008. After the enactment of HITECH in 2009, the coercive pressure became a significant predictor of the adoption of EMRs in 2012. Normative pressure continued to influence EMR adoption from 2008 to 2012. Another study, which surveyed 191 US healthcare employees participating in an online healthcare MBA program, showed that mimetic and coercive pressures did not have a direct and significant impact on EMR adoption levels. Normative and mimetic pressures had an indirect effect (i.e., mediation effect) on EMR adoption levels through the involvement of top management (Gopalakrishna-Remani et al., 2019). The inconclusive results of institutional pressure on EMR adoption may be attributable to different research designs, sampling methods, target populations, and measures of institutional pressures.

2.3 Sociology View of Diffusion - Individuals

At the individual level, social contagion theory is one of the fundamental theories that elucidate how the diffusion of new ideas or practices is contingent on the way in which social proximity brings adopters and non-adopters together. The social proximity of innovations is illustrated in two ways of managing uncertainty about costs and benefits: cohesion and structural equivalence (Burt, 1987; Marsden & Friedkin, 1993). The cohesion approach sees direct contact and more frequent communication between adopters and non-adopters as a socialization process in which adopters and non-adopters establish a normative understanding of the costs and benefits of adopting an innovation. When non-adopters are confronted with the need to make decisions in ambiguous situations, non-adopters seek advice from those with whom they have established trusting relationships to discuss the innovation (Friedkin, 2004). This theme continues to be researched on the spread of choices, attitudes, or behaviors in communication networks (Christakis & Fowler, 2013).

The structural equivalence model holds a contradictory view, stating that people will compete for "survival" and imitate or learn from each other when they occupy similar positions in the social structure but do not have to be connected directly. Examples include two primary care physicians competing to serve as consultants on new drugs in the medical marketplace, or two graduate students trained by the same academic advisor competing to publish articles for a degree. The structural equivalence model describes the innovation that can be observed in non-adopters when they maintain a social status similar to that of the adopters (Burt, 1987). The concept of structural equivalence has been extended to different measures of structural proximity. For example, Angst et al. (2010) investigated how prior adopters, social proximity and spatial proximity affect EMR adoption. Social proximity was operationalized as hospitals within the same health system, while spatial proximity is calculated based on the Euclidean distance between the postal codes of two hospitals.

2.4 Public Policy View of Diffusion

Public policy research on diffusion follows the concepts from the fields mentioned above and uses them to explain the reasons that governments or countries choose similar policies (institutions) over time. Policy diffusion occurs when a government's or state's decision on choosing a particular policy is influenced by the decisions of other governments or states (Elkins & Simmons, 2005). Similar to the sociological perspective on diffusion, the analyses of policy diffusion investigate either at the individual level (e.g., public officials) or at the organizational level (e.g., national, state, or local governments), but policy adoption at the organizational level is usually operationalized as a measure at the individual level. For example, LeRoux, Brandenburger, & Pandey (2010) examined public managers and their affiliations in a two-mode network to examine factors that influence interlocal cooperation. Drawing data from the National Administrative Studies Project in the US, the study operationalized the decision of local governments as public manager behavior and found that public managers who frequently participate in regional associations or councils of governments are more likely to increase interlocal service cooperation. Additionally, most governments are inertial to change, and the decisions made by them are normally an incremental process. Thus, the public policy perspective on diffusion views policy adoption as an institutional innovation process (Berry & Berry, 2018).

Walker's (1969) seminal work depicted that state governments learn and adopt new programs or policies through two phases. In the first phase, regional pioneers or leaders adopt programs or policies more readily than others, and in the second phase, the rest of the states mimic those leaders' adoption decisions and decide whether they want to implement the same program or policy. The speed of the state policy adoption process is determined by socio-economic factors (e.g., population density, income, urbanization, industry, and education) and political factors (e.g., party competitiveness, turnover of officials, legislative services, and misallocation). Following Walker's work, Berry and Berry (1990) proposed internal determinants and diffusion models to explain the policy adoption process and applied event history analysis to estimate the models and diffusion rates. The internal determinants of policy adoption include political, social and economic factors, while the diffusion model assumes that policy adoption by one government is influenced by previous adoption by other governments.

Specifically, the process of policy decision-making can be elucidated in three ways: similarity of economic shocks, culture and institutions, coordination, and diffusion. The similarity perspective is similar to the aforementioned structural proximity or internal determinants of policy adoption, emphasizing that governments' similar economic shocks, cultures and institutions cause them to act independently and similarly, regardless of the behavior of other governments. The coordination perspective suggests that if governments are affiliated with the same international or domestic organization, or are bound by the same international or domestic agreement, they will be forced to adopt the same policies. The diffusion perspective, however, exploits the advantages of similarity and coordination by emphasizing that the adoption of new policies is an interdependent process. Under this concept, governments make their own decisions independently without cooperation or coercion but estimate the costs and benefits of adopting new policies interdependently by observing or imitating the choices of other governments (Elkins & Simmons, 2005). Research in this area is therefore interested in exploring how the timing of policy adoption by one government is influenced by the choices of other governments; why some governments are early adopters of policy and others are late adopters. Mechanisms of policy diffusion may arise from imitation (Shipan & Volden, 2008), learning (Volden, 2006), spatial proximity (Berry & Berry, 1990) or economic competition (Berry & Baybeck, 2005) (see Berry & Berry, 2018 for a thorough review).

2.5 Limitations of Diffusion Research

The diffusion of innovations has been described differently in different contexts by epidemiology, sociology and public policy, but the processes described by these theories are not largely different. The classical epidemiological approach of SIR and its extensions aims to understand how an infectious disease spreads from one person to another person. The sociological approach emphasizes how network proximity and direct contact affect the diffusion of innovations. The public policy approach concentrates on how structural proximity and external pressures accelerate the diffusion of policies or programs in government. Recent research in those fields has acknowledged their limitations and introduced new directions of research.

In epidemiological research, recent studies have focused more on how interdependence and actions between people affect the spread of infectious diseases. For example, there are robust findings on the short-term increase in mortality due to the loss of a spouse. The hospitalization of one spouse also increases the risk of death for the other (Christakis & Allison, 2006). In addition, peer effects in friendship networks or siblings in the family can contribute significantly to individual behaviors such as smoking, alcohol consumption, weight control and food preferences (Smith & Christakis, 2008). However, less recent research has focused on how the coupling of organizational or institutional factors with individual networks affects the transmission of infectious diseases. For example, hand hygiene behaviors can be effective in reducing the probability of transmission of infectious diseases from one individual to another, but organizational culture and social norms may influence whether individuals adhere to this practice (Wilson et al., 2011). Failure to carefully consider cultural or organizational predictors can be a barrier to researchers' understanding of the disease transmission process.

In terms of sociological approaches, most previous studies analyzed diffusion processes at the individual or organizational level, but relatively few studies examined how both individual and organizational factors influence the diffusion of innovations. Even though studies have explored the multi-level network effects on innovation diffusion, most have remained limited to a top-down approach. For example, Tsai (2002) examined how organizational structure and inter-unit competition affect individual knowledge-sharing behavior. Hansen et al. (2005) explored how networks within teams and between units affect the diffusion of knowledge from one individual to another. Both studies used organizational aspects (top) to predict individual behavior (bottom) and began to consider how inter-organizational networks affect the diffusion of knowledge from intra-organizational networks. Current diffusion research has focused more on bottom-up approaches. For example, Battilana & Casciaro (2012) propose a bottom-up approach that examines how an individual's social status (intra-organizational network) leads organizations to adopt new policies or make organizational changes in response to institutional pressures.

Similar to the sociological perspective described above, studies on policy diffusion consider the bottom-up approach, describing how local governments may act as agenda setters and exert pressure on state government policy actions. For example, Shipan & Volden (2006) examined how national-state pressures, state-state diffusion and local-state diffusion factors combine to influence the adoption of anti-smoking policies in a state.

Schreurs (2008) also discussed how local government initiatives are linked to national climate change policies and how international networks play a role in the diffusion of climate change policy ideas among local governments. However, policy diffusion research rarely examined how policies are disseminated in society through individual networks in which social relationships are expected to facilitate the flow of information. For example, applying the framework of institutional collective action, Feiock et al. (2010) explored how communication networks of elected officials (discussion, advice, and information sharing) in local government in Orlando, Florida, were associated with the risk of collaboration, information exchange and the commitment of network members. Although their research did not investigate what policy ideas were exchanged, it should be expected that policy ideas are likely to be disseminated through communication networks.

2.6 Summary and Research Questions

In short, epidemiological, sociological and public policy research has recognized that the mechanisms propelling the diffusion of innovations should include structural proximity and network connections. Actors, actor similarities, actor actions and network connections between actors combine to facilitate the diffusion of innovations. Actors can be individuals, organizations or different levels of government. Actions refer to decisions made by actors on whether to adopt ideas, technologies, policies or institutions. Network connections refer to the communication networks in which information diffusion may occur. Communication exists in various types of networks, such as kinship networks, friendship networks, advice networks or cooperation networks. The early stages of network diffusion research usually studied the same units of analysis. More recent studies on network diffusion have extended the focus of research from the same unit of analysis to the interaction between two units of analysis, i.e., multi-level networks. The multilevel network perspective not only provides a new way to analyze the mixed effects of the two levels but also resolves the theoretical debate on whether individual behavior is constrained by social structures such as organizations (Hansen et al., 2005; Tsai, 2002).

In contrast to top-down approaches, both sociological and public policy research have proposed bottom-up diffusion models that depict how the actions of lower-level actors can influence the actions of higher-level actors. Shipan and Volden (2006) argued that local government decisions on anti-smoking policies put pressure on state governments to adopt anti-smoking policies, yet their research overlooks the role of networks in the diffusion process. Organizations can distribute or access information through their formal or informal relationships with other organizations. Also, Battilana and Casciaro (2012) claimed that individuals who occupy important network positions have more power to influence organizations to adopt new institutions. However, their research focused on individual networks in the organization and did not consider that individuals could receive new information from their external relationships. Therefore, current approaches on multi-level or bottom-up diffusion networks have not explored how intra-organizational networks with external connections influence the diffusion of innovation in inter-organizational networks (Paruchuri et al., 2019). It remains unknown how individuals and organizations receive adoption information from their networks separately and make adoption decisions collectively at the organizational level.

Taken all together, the theoretical framework for policy adoption in this study is shown in Figure 2.6.1. At the organizational level, coercive pressures, normative pressures and internal determinants can independently influence policy adoption. The coupling of mimetic pressure, perceived competition, network interaction and spatial proximity will influence the adoption of new policies by susceptible organizations. At the individual level, the coupling of social proximity with network interaction and spatial proximity will influence susceptible individuals to become institutional entrepreneurs, collectively influencing an organization's policy adoption decisions. Bottom-up policy diffusion occurs when network interaction or spatial proximity is involved in the policy adoption process at the individual and organizational levels.

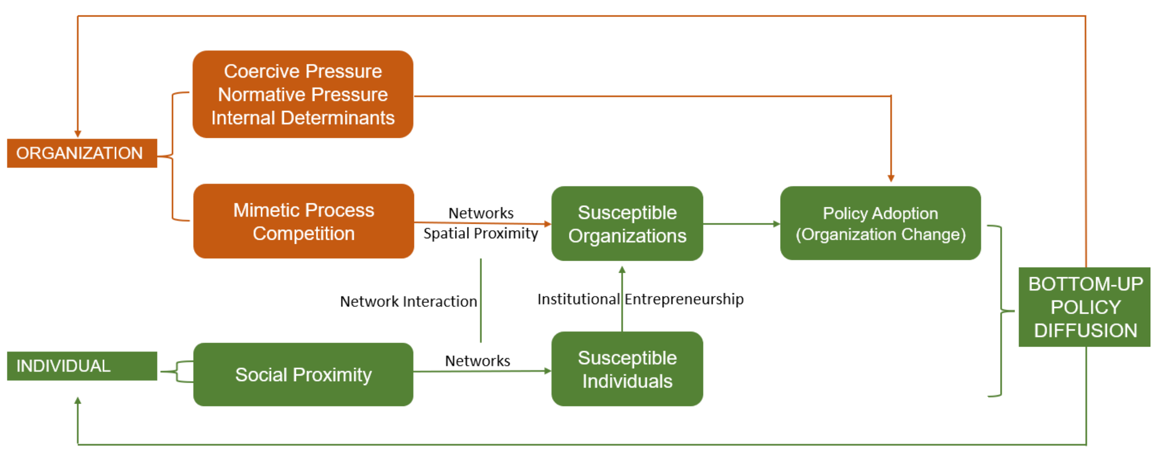

Figure 2.6.1 Theoretical Framework for Policy Adoption

Figure 2.6.2 is an example of a fully nested cross-layer network, showing bottom-up diffusion occurring in an inter-organizational network. The upper-level nodes refer to organizations, while the lower-level nodes refer to individuals. Lower-level nodes have cross-level connections only within the same upper-level node. Inter-organizational networks comprise organizational ties connected by upper-level nodes. Intra-organizational networks contain individual ties connected by lower-level nodes within the same organization. For example, a healthcare provider is linked to a hospital. The healthcare provider refers patients to other internal healthcare providers or to external healthcare providers. These referral relationships can be aggregated into referral relationships between hospitals. Thus, when hospitals A and B adopt a new policy, information about the policy may be passed to hospital C through organizational or personal relationships. Hospital C also receives information about non-adoption from hospital D. Depending on the amount of exposure to policy information by the hospitals and their providers contacted, Hospital C has the ability to decide whether to adopt the new policy. Thus, the coupling of the internal and external networks of the organization should enrich our understanding of how bottom-up diffusion occurs. To address this situation, the main focus of this study is to examine how the organization's internal networks and its external linkages play a role in bottom-up diffusion.

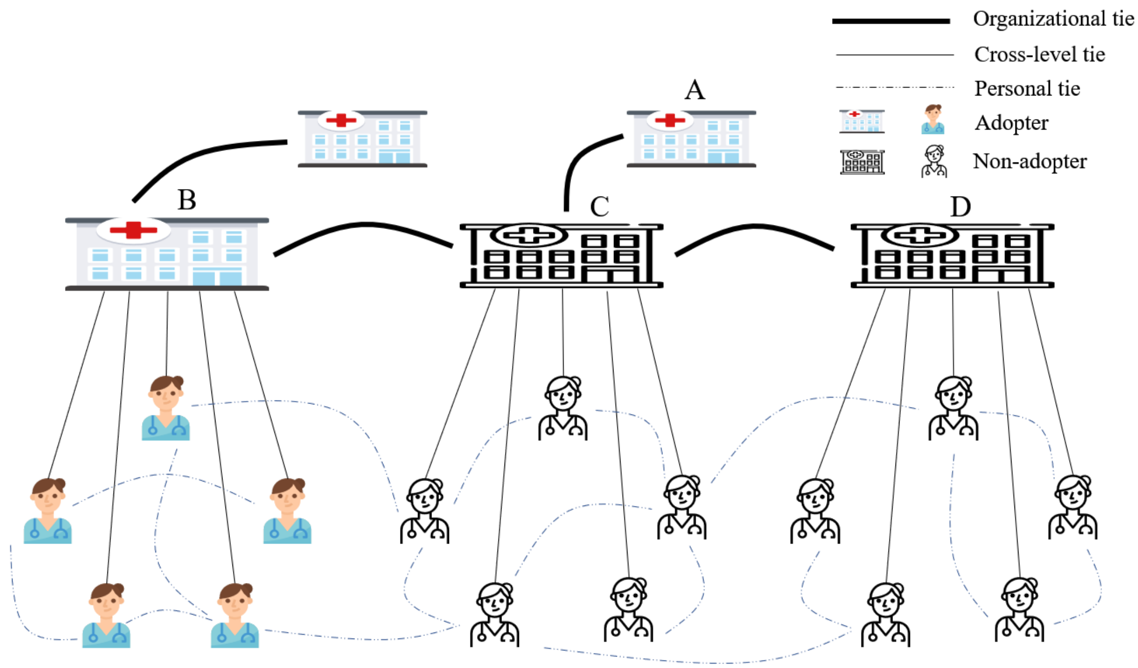

Figure 2.6.2 Example of a Fully Nested Cross-level Network

CHAPTER 3 DIFFUSION NETWORKS AND SPATIAL PROXIMITY

Building on the reviews in Chapters 1 and 2, this chapter develops precise hypotheses to understand how networks and spatial proximity affect the bottom diffusion of EMRs. The network diffusion process elucidates how information on the adoption of EMRs spreads from one person to another through direct network connections and how influential network locations accelerate the diffusion of EMRs information. As for spatial proximity, it is argued that a geographically close distance between actors creates a space where imitative behavior or local knowledge spillovers are likely to occur. The following sections summarize how network and spatial proximity effects are associated with the diffusion of EMRs and propose the corresponding hypotheses.

3.1 Direct Networks and Diffusion

The seminal work of Granovetter (1973) asserted that weak and strong relationships play different roles in information acquisition. A weak relationship is defined as a relationship that someone has with an acquaintance. A strong relationship represents someone who has a relationship with a close friend. Strong relationships are usually found in homogeneous groups in which people have close ties with people who have similar interests and backgrounds. Close ties with similar interests usually convey overlap and redundant information between two people. In contrast, weak ties exist between two people who are likely to have different backgrounds, and therefore the nature of the knowledge embedded in weak ties is diverse and heterogeneous. However, some studies claim that strong relationships provide better quality information than weak relationships. Strong ties enable rich and deep information to flow from one person to another.

Krackhardt (1992) argued that it is not enough for Granovetter to consider ties as a variable on a continuum from weak to strong. Researchers need to clarify what constitutes a strong or weak bond, as different relationship characteristics have different functions. For example, an actor may interact frequently with other colleagues in the workplace, but that actor may not benefit from this "strong relationship" (Granovetter defines a strong relationship as the frequency of interaction). Conversely, an actor has a best friend in the same workplace, but they do not interact often in the workplace. Given this situation, they both know that the other one is there and is always ready to help. This is an interesting argument that takes the network research from one dimension of Granovetter to all possible dimensions for different purposes. The ways that ties are constituted in a given context need to be studied with caution. Furthermore, Cowan et al. (2000) depicted explicit and tacit knowledge embedded in different types of ties. Explicit knowledge, highly codified knowledge, such as training manuals, can be conveyed by weak ties. Tacit knowledge is knowledge that we know, but that cannot be codified, verbalized or transferred effortlessly. As the transfer of tacit knowledge is costly, strong ties act as a basis to sustain the transfer of tacit knowledge to occur. It is worth noting that the strong can carry not only tacit knowledge but also explicit knowledge. Both strong and weak ties contribute in some way to knowledge acquisition between two people. Whichever type of relationship a person has, it should carry either explicit or tacit knowledge.

Research on the association between ties and innovation/knowledge transfer has shifted from a focus on tie strength to a focus on internal and external ties. For example, Hansen (1999) investigated 120 new product development projects managed by 41 divisions of an electronics company and explored the role of weak ties in sharing knowledge between these divisions. The findings showed that weak relationships between units facilitate project teams to find useful knowledge from other divisions. When knowledge to complete a project is not complex, weak inter-unit links reduce the time taken to complete the project. However, weak inter-unit links often act as a barrier to the transfer of complex knowledge by the project team. Strong inter-unit links play a greater role in the transfer of complex knowledge across divisions. Therefore, this study concludes that neither weak nor strong inter-unit ties lead to effective knowledge transfer. Weak and strong ties each have advantages and disadvantages in complex and non-complex knowledge transfer across organizational subunits.

Using the same research design and data, Hansen (2002) further explored how a project team's interunit linkage path (measured by closeness) and access to existing knowledge from other divisions affect the time to complete the project. The results indicated that project teams with shorter inter-unit contact paths and greater access to existing knowledge from other divisions were more likely to speed up project completion times. The findings also showed that having direct links to other divisions tends to reduce the problem of transferring non-coded knowledge. However, it costs more to maintain direct links than indirect links. Using direct links to transfer codified knowledge may not be necessary. Therefore, both network links and knowledge content should be considered when exploring how knowledge transfer between units occurs.

Furthermore, scholars argued that the knowledge transfer process should be divided into different stages. Hansen et al. (2005) defined three knowledge sharing stages: knowledge seeking (decisions about whether to seek knowledge across division), search costs and transfer costs, and argued that the factors that affect the knowledge transfer stages might not be the same. Their results suggest that network attributes have different effects on the various stages of knowledge sharing. For example, a team's intra-connectivity may reduce sought knowledge, but a team's number of inter-unit connections may increase sought knowledge. Both the strength of a team's inter-unit ties and perceived competition may increase the cost of search.

Thus, the strength of ties, internal or external ties, cross-unit ties and attributes of knowledge will influence whether knowledge can be transferred from one person to another. Similarly, these factors will determine whether a hospital adopts an EMR (Zeltzer, 2017). If a healthcare provider has ties to external healthcare providers whose hospitals have adopted EMRs, it is likely that this healthcare provider will be influenced by these external healthcare providers and change his/her attitude towards adopting EMRs.

Hypothesis 1: A hospital will be more likely to adopt EMRs as most of its providers exposed to external providers whose hospitals have adopted EMRs.

In contrast to the first hypothesis, a hospital decision on EMRs adoption can also be influenced by its formal relationships. For hospitals belonging to the same hospital system, a centralized administration may exercise legitimate authority to force all the hospitals to adopt EMRs (Gopalakrishna-Remani et al., 2019; Sherer et al., 2016). When we observe that one of the hospitals in the hospital system has adopted EMRs, the decision is likely made by the top managers in the hospital system and can be considered as an experiment of EMRs deployment. When the experimental hospital successfully achieves the system's proposed goals, the implementation of EMRs to all the system hospitals should be anticipated. Likewise, hospitals in the same hospital system create more opportunities for them to interact with others. For example, doctors may work in different hospitals in the same hospital system. If a hospital needs to decide whether to adopt EMRs, the hospital can assess the costs and benefits of adopting EMRs using information shared by its formally connected hospitals.

Hypothesis 2: A hospital will be more likely to adopt EMRs as its system hospitals have adopted EMRs.

3.2 Network Positions and Diffusion

A number of studies have investigated the association between network structure and diffusion of innovations (Contractor & DeChurch, 2014). Valente & Davis (1999) argued that opinion leaders or those who occupy a central position in a network are more likely to spread innovations because these network connections can act as potential communication channels for passing on information. Network centrality can be measured in terms of centrality closeness, centrality betweenness, or structural holes. The main hypothesis is that those who occupy a central position in a network will have more power to influence others and accelerate the spread of innovations. For example, Oleas et al. (2010) explored the role of local leaders in the diffusion of agricultural knowledge in Chimaltenango, Guatemala. The study showed that the capacity of local farmer leaders relies on social relationships with multiple organizations to obtain new agricultural knowledge.

In terms of network centrality, structural hole theory has been extensively studied. According to structural holes theory, those who occupy a brokerage position in a network are expected to have access to non-redundant information and have the power to control it. The concept of structural holes theory is shown in Figure 2.3 below. The diagram shows that Z is connected to U and V, while there are no connections (holes) between U and V. In this case, Z has a dominant position in the network, obtaining and controlling non-redundant information from U and V (Burt, 2005). Likewise, Fleming et al. (2007) analyzed collaborative patenting data for 35,400 inventors from 1975 to 2002 and found that inventors with more structural holes tend to engage in more innovative activities, but that structural holes may hinder the diffusion of innovations. In their work, Reagans & McEvily (2003) combined structural holes theory with tie strength to explore the knowledge transfer process in contract R&D firms. Their findings suggested that structural holes, as measured by network density, may impede knowledge transfer.

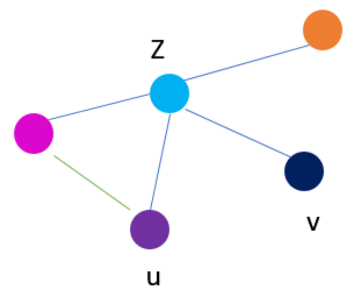

Figure 3.2.1 Structural Holes (Burt, 2005)

In terms of network environments, Aral & Van Alstyne (2011) collected email messages exchanged by employees of an executive recruitment company with 14 offices and used the content of these emails to examine how structural holes and content messages determine employee performance. The results showed that employees in a cohesive network (with fewer structural holes) and a high bandwidth environment (with high message refresh rates, large topic space, and high information overlap) are more likely to access novel information. For employees in diverse networks (more structural holes), low bandwidth environments (low information refresh rates, small information topic space and low information overlap) can provide more novelty. Thus, Aral & Van Alstyne (2011) suggested that structural holes play a broker role in managing how network content is associated with information diffusion, contrary to the findings of Reagans & McEvily (2003). Furthermore, actors with more structural holes are likely to become institutional entrepreneurs, influencing organizations to adopt a new institution (Battilana, 2006; Battilana et al., 2009; Battilana & Casciaro, 2012).

Network positions enable actors to have more power to decide whether to disseminate information about an innovation to other actors and influence their organizations to adopt an innovation. Hence, as for the diffusion of EMRs, if an individual healthcare provider occupies an important network position within a hospital and has more external contacts that have already adopted EMRs, the provider may take advantage of the information flow to pressure her hospital to consider implementing EMRs. If more influential healthcare providers within the hospital are connected with external healthcare providers whose hospitals have already adopted EMRs, then the hospital is more likely to adopt EMRs.

Hypothesis 3: A hospital will be more likely to adopt EMRs as most of its influential healthcare providers are connected with external healthcare providers whose hospitals have adopted EMRs.

Likewise, a healthcare provider may change her attitude towards EMR adoption if she is tied with an external provider who occupies a significant network position in the hospital that has adopted EMRs. These external healthcare providers act as opinion leaders influencing followers' decisions on the implantation of EMRs. Hence, hospitals are more likely to adopt EMRs if more of those followers within the hospital are connected to those external opinion leaders whose hospitals have already adopted EMRs.

Hypothesis 4: A hospital will be more likely to adopt EMRs as most of its healthcare providers are exposed to external influential providers whose hospitals have adopted EMRs.

At the hospital level, hospitals that act as leaders in the health industry typically show higher motivation to implement innovations. Thus, a hospital holding an important position in the inter-hospital network is more likely to become an institutional entrepreneur and an early adopter of EMRs.

Hypothesis 5: A hospital occupying an important network position is more likely to adopt EMRs.

3.3 Spatial Proximity and Diffusion

Spatial proximity has been found to be a robust predictor of innovation diffusion. Spatial proximity creates a space where imitative behavior, interaction or localized knowledge spillovers are possible (Autant-Bernard et al., 2007). The argument for spatial proximity follows a series of propositions. Siting decisions involve a considerable degree of selection processes, with companies seeing location as a means of realizing economic benefits such as lower logistics or production costs, the possibility of recruiting skilled or low-cost staff, or opportunities for R&D collaboration with universities. Companies with similar characteristics may congregate in the same area, such as an industrial park, due to the pursuit of similar economic incentives.

However, the mechanisms of information dissemination between companies are not only based on homogeneous characteristics. Competition and interaction play different roles in facilitating the diffusion of innovations. From a competitive perspective, clustered firms with similar characteristics have the potential to form a competitive environment. Spatial proximity creates more opportunities for managers to observe and note the incidence of innovation adoption from rival firms. The diffusion of innovation is driven by competition, and the process of diffusion is based on imitative behavior. From an interaction perspective, spatial proximity creates more opportunities for employees to interact and exchange information informally with other employees in rival firms. This information may be communicated back to these employees' companies and shape decisions about innovation (Berry & Baybeck, 2005; Berry & Berry, 1990; Breschi & Lissoni, 2001). Researchers found that EMR non-adopter hospitals in low population density areas are more likely to become adopters when neighboring hospitals adopted EMRs. Lower population density increases competition for healthcare providers and the probability of transferring relevant knowledge between hospitals (Angst et al., 2010). Based on the above discussion, this study hypothesizes:

Hypothesis 6: A hospital will be more likely to adopt an EMR as its neighboring hospitals have adopted it.

In addition, researchers have noted that networks can negatively moderate the effect of spatial proximity on knowledge transfer. Spatial proximity reduces the cost of information search and increases the efficiency and effectiveness of communication, yet information features within a geographic region are often less novel and useful than information transferred across regions. This is because local contexts and networks within a geographical area build homogenized knowledge of local actors. Local actors in the same network are more likely to participate in the same local activities and to share perspectives on issues. As a result, local actors often find redundant information when seeking advice from network actors in the same geographical area. That is, acquiring information from network actors in different geographical areas facilitates local actors' acceptance of heterogeneous information (Bell & Zaheer, 2007; Hansen & Løvås, 2004). As far as EMRs adoption is concerned, healthcare providers may gain more useful information from their distant network connections and make the decision to adopt.

Hypothesis 7: A hospital will be more likely to adopt EMRs as most of its healthcare providers are exposed to distant and networked healthcare providers whose hospitals have already adopted EMRs.

CHAPTER 4 RESEARCH METHODS AND DATA PREPROCESSING

4.1 Data Sources

For the purpose of modeling the impact of network contagion and spatial proximity on EMRs adoption, this study collected data from five sources for the period from 2009 to 2015. All the data sources were publicly available and free of charge.

First, the Physician Shared Patient Patterns data were collected from CMS and contains referrals from one provider to another within a certain time frame in the Medicare program.[9] The dataset contains referrals higher than 11 times between healthcare providers within 30/60/180 days in the Medicare program. Prior study has indicated that 60-days of a referral period is a suitable measure. The available referral data contain years from 2011 to 2015. National Provider Identifier is used to establish referral networks. In their study, Barnett et al. (2011) examined the relationship between provider self-report networks and Medicare claim-based networks in the Boston Hospital Referral Region. The results concluded that two providers who shared more Medicare patients are more likely to increase the recognition of referral relationships and advice relationships. Thus, it is plausible to use referral networks to construct healthcare provider networks.

Second, the National Plan and Provider Enumeration System data were downloaded from CMS and comprise of detailed profiles of healthcare and linked with active National Provider Identifier (NPI) .[10]

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[9] CMS, Referral Data FAQs, Retrieved December 16, 2021, from https://www.cms.gov/Regulations-and-Guidance/Legislation/FOIA/Referral-Data-FAQs

[10] CMS, NPI Files, Retrieved December 16, 2021, from http://download.cms.gov/nppes/NPI_Files.html

Third, EMRs adoption data (2009-2015) were obtained from Healthcare Information and Management Systems Society (HIMSS) Analytics Database. [11] The database includes over 700 variables such as levels of EMRs adoption, EMRs vendors, and hospital characteristics (e.g., ownership, size, specialty).

Fourth, the Internet demand and supply data were collected from Federal Communications Commission (FCC).[12] The Internet demand is measured by broadband users per 1k households. The broadband users are defined as Residential Fixed Connections at least 768 kbps downstream and greater than 200 kbps upstream per 1000 Households at the county level. The number of broadband providers reflects Internet supply measured by the number of providers of Residential Fixed Connections at least 3 Mbps downstream and at least 768 kbps upstream at the county level.

Fifth, population density per square mile of land area data were obtained from the 2010 Census survey.[13]

4.2 Data Pre-processing

4.2.1 Address Matching

The data pre-processing consisted of four main steps. First, this study used NPI data from NPPES to match with HIMSS data. The crosswalk variables were the address of the NPPES NPI and the hospital address of the HIMSS. However, the challenge in matching

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[11] The HIMSS Foundation, https://foundation.himss.org/. The data were obtained by filing an application for academic research.

[12] FCC, Form 477 County Data on Internet Access Services, Retrieved December 16, 2021, from https://www.fcc.gov/form-477-county-data-internet-access-services

[13] The U.S Census Bureau, Retrieved December 16, 2021, https://www.census.gov/en.html

their addresses is that the addresses have not been collated and lack a standard format and length. Some addresses use abbreviations for street names or directions (e.g., “St.” for “Street,” “N” for “North”). Some addresses have extra spaces (e.g., “ 3351 Fairfax Dr” vs. “3351 Fairfax Dr”) or periods (e.g., NW vs. NW.). Table 4.1 below summarizes the seven address representation issues.

Table 4.2.1 Misrepresentation of Addresses

Variation of Address	Example
1. Abbreviations	101 Michigan Ave. vs. 101 Michigan Avenue
2. Missing fields	101 Michigan Ave. vs. 101 Michigan
3. Missing periods	101 Michigan Ave. vs. 101 Michigan Ave
4. Differences in letter cases	101 Michigan Ave. vs. 101 MICHIGAN AVE.
5. Incorrect address order	101 Michigan Ave. vs. 101 Avenue Michigan
6. Differences in phonetics and spelling	101 Michigan Ave. vs. 101 Michigna Ave.
7. Leading space	“101 Michigan Ave.” vs. “ 101 Michigan Ave.”

One possible way to solve the address matching problem is to apply Fuzzy Matching. With Fuzzy Matching, the match does not require both candidates to have the exact address, allowing a partial match of the two addresses. For example, an individual healthcare provider accidentally types “Faifrax Dr” as “Fairfax Dr”. We can use “Fairfax Dr” to partially match “Faifrax Dr”, which means that an inconsistent position of the address is allowed. However, this approach requires some degree of formatting of the address and may only be suitable for solving the 3rd to 6th problems above.

Alternatively, this study developed a solution to match the difference between the NPI address of NPPES and the HIMSS hospital address. This study extracted the first five digits of the postal code and the first few positions of the address and then combined them into a single string. For example, there is an address, “3351 Fairfax Dr” with a postal code of “22201”. City names and state names can be ignored as the postal code already provides enough information to identify the location. When the first seven positions of the postal code and address are combined into one string, we get a string of “222013351 Fa“. The first five positions of the string are the postcode of the address, while the positions between 6 and 12 are the first seven positions of the primary address. This study explored the first 6, 7 and 8 positions of the primary address, and the results showed that the first seven positions of the address returned the most satisfactory results. In addition, as some addresses contained extra leading spaces, extra spaces between two words, or different patterns of letter case and periods, this study removed these unnecessary spaces and periods and converted all letters to lower case. After data cleaning, Fuzzy Matching, which allows one different position of an address to be matched, was used to match addresses between NPIs of NPPES and HIMSS hospitals. Through the data cleaning and matching process described above, this study successfully addressed the 3rd, 4th and 7th problems in Table 4.2 and significantly reduced the incidence of the 1st, 2nd and 6th problems. For example, by using postcode 60611, the addresses in the table above can be converted to the new form below.

Table 4.2.2 Alignment of Misrepresented Addresses

Variation of Address	Example	Result
1. Abbreviations	60611101 mic vs. 60611101 mic	Correct
2. Missing fields	60611101 mic vs. 60611101 mic	Correct
3. Missing periods	60611101 mic vs. 60611101 mic	Correct
4. Differences in letter cases	60611101 mic vs. 60611101 mic	Correct
5. Incorrect address order	60611101 mic vs. 60611101 ave	Incorrect
6. Differences in phonetics and spelling	60611101 mic vs. 60611101 mic	Correct
7. Leading space	60611101 mic vs. 60611101 mic	Correct

A limitation of using postal codes as a crosswalk in conjunction with addresses is that postal codes may be incorrectly recorded and changed when postal boundaries are realigned. Other limitations of using this method of data pre-processing are that incorrect address order is not resolved, and spelling errors that appear in the first seven positions of the address are not fully corrected. Increasing the number of positions of fuzzy matching may alleviate this problem, but increasing the true positive rate of matching performance also increases the false positive rate. Therefore, applying fuzzy matching, which allows one different position of an address to be matched, is not an ideal method for detecting an address with more than one positional error.

Figure 4.2.1 provides a flow of the data preprocessing. As noted in the Data Sources section, the NPPES data includes the identity and address of the unique individual healthcare provider.

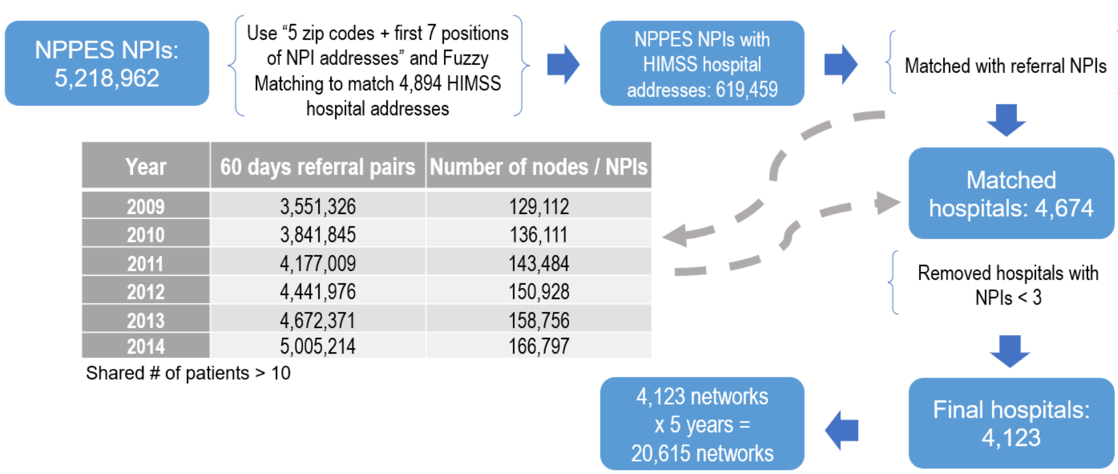

Figure 4.2.1 Data Pre-processing Flow

4.2.2 NPIs and Hospital Matching

The HIMSS dataset is hospital-level data, including basic information about the hospital and the variables are associated with EMRs usage. The CMS referral network contains NPIs and the number of patients shared between two individual healthcare providers. To construct the referral network for individual providers with hospital information, data pre-processing was first done to match 5,218,962 NPPES NPIs addresses with 4,894 HIMSS hospital addresses. There were 619,459 NPPES NPIs successfully matched. Next, 619,459 NPPES NPIs with hospital addresses were matched with referral NPIs. All of the referral NPIs were matched, and the number of matched hospitals is 4,674. It is expected that some hospitals have only a small number of individual providers, as CMS referral data contain only two providers shared more than ten patients in a 60-day period. If an individual provider does not refer/receive more than ten patients to/from the same individual provider within a 60-day period, then the individual provider's information will not be collected in the CMS referral data. The purpose of excluding individual providers that share a low number of patients is to reduce the probability of individual providers being identified.

Moreover, this study was interested in understanding the network effects on EMR adoption within and between organizations. It is possible to observe that some hospitals have only one eligible individual healthcare provider and are unable to form an intra-organizational network. Hospitals that were unable to initiate an intra-organizational network were excluded from the analysis for this study. In addition, when a hospital has two eligible individual healthcare providers, the number of possible network configurations is two, with or without connectivity. When a hospital has three individual healthcare providers, the number of possible network configurations increases exponentially to eight (Figure 4.2). Furthermore, a network containing three nodes is conventionally considered to be the minimum number for a group or clique. Therefore, 551 hospitals with fewer than three eligible individual healthcare providers were excluded from the analysis of this study. The final figure for the analysis was 4,123 hospitals.

NPIs = 2 vs. NPIs = 3

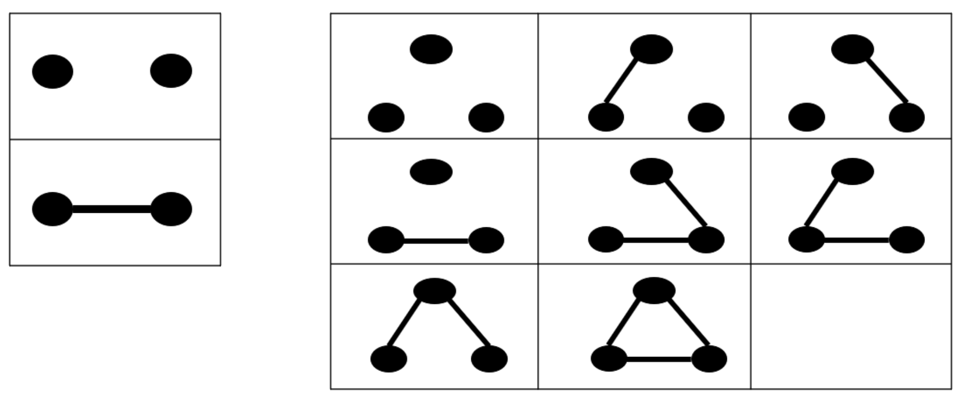

Figure 4.2.2 Network Configurations

Although the survey period for this study was five years, hospitals may not have the same number of individual healthcare providers over a five-year period. Therefore, for this study, an internal organizational network was created for each hospital. Network properties were calculated for each year for both internal and external connections. The network properties for individual providers were aggregated to hospital-level data and used for model estimation. The total number of intra-organizational networks was 20,615 (4,123 hospitals * 5 years).

4.3 Statistical Methods

This study introduces two statistical methods for modeling the adoption process: survival analysis and multi-state Markov modeling. The variable for EMRs adoption is a time-event distribution with right censoring, i.e., if a hospital did not adopt EMRs during the study period, we would not be able to know whether the hospital adopts EMRs in the future. The Cox proportional hazards model, event history or survival analysis is an appropriate method for analyzing the time-event data type, which provides the flexibility to estimate both time-invariant and time-varying predictors (Cox, 1972; Zhang et al., 2018). For survival analysis, No EMRs Capabilities was used as a reference group, coded as “0”, reflecting “survival,” while any level of EMRs adoption is considered as “1”, reflecting “dead.” Another approach to analyzing the different stages of EMRs adoption is multi-state Markov models (Jackson, 2019; Hougaard, 1999; Metzger & Jones, 2016). Multi-state Markov models extend the concept of Cox proportional hazards models to Markov chains, accepting that the adoption process of EMRs transitions between different events. i.e., different levels of adoption of EMRs. The dependent variable of a multi-state Markov model is time-to-transition between different levels of EMRs adoption. For example, a transition in a multi-state Markov model might reflect an upgrade from No EMRs Capabilities (1) to Basic EMRs (2), or from Basic EMRs (2) to Comprehensive EMRs (4). There were six upgrades in the adoption of EMRs, and these were estimated simultaneously in the multi-state Markov model.

4.4 Variable Definitions

4.4.1 EMRs Variables

Following Furukawa et al. (2010) and Fareed et al. (2015), the level of EMRs adoption for a hospital was categorized as No EMRs Capabilities, Basic EMRs, Intermediate EMRs, or Comprehensive EMRs based on the implementation of eight core EMRs element technologies. The definitions of each level of EMRs adoption are summarized below.

1. **No EMRs Capabilities**: the hospital does not install any EMRs or does not meet all the requirements of Basic EMRs.
2. **Basic EMRs**: the hospital has implemented information systems at pharmacy, radiology and laboratory, as well as Clinical Data Repository (CDR). A hospital is coded as “1” if Basic EMRs is adopted. A hospital is coded as “0” if the hospital does not meet all the requirements of Basic EMRs.
3. **Intermediate EMRs**: in addition to basic EMRs technologies, the hospital has implemented Nursing Documentation (DOC) and Electronic Medication Administration Records (EMAR). A hospital is coded as “1” if Intermediate EMRs is adopted. A hospital is coded as “0” if it does not install any EMRs components or only install Basic EMRs.
4. **Comprehensive EMRs**: in addition to basic EMRs and intermediate EMRs, the hospital has implemented Clinical Decision Support (CDS) and Computerized Physician Order Entry (CPOE). A hospital is coded as “1” if Comprehensive EMRs

is adopted. A hospital is coded as “0” if it does not install any EMRs components, only install Basic EMRs, or only install intermediate EMRs.

Table 4.4.1 Levels of EMRs Adoption

Levels of EMR Adoption	EMR Components
Non-Adoption	Does not meet the requirements of Basic EMRs
Basic EMRs	Implemented information systems at pharmacy, radiology and laboratory, as well as Clinical Data Repository.
Intermediate EMRs	Basic EMRs + Implemented Nursing Documentation and Electronic Medication Administration Records
Comprehensive EMRs	Basic EMRs + Intermediate EMRs + Implemented Clinical Decision Support and Computerized Physician Order Entry.

4.4.2 Predictors for Survival Analysis

In Chapter 3, this study proposed seven hypotheses to address the research questions. The corresponding variables are Hospital System Pressure, Hospital Network Centrality, Spatial Contagion, External Provider Equal Contagion, Internal Influential Provider Contagion and External Influential Provider Contagion (Table 4.4.2).

Table 4.4.2 Summary of Hypotheses

	Variables	Hypotheses
Organization Variables	Hospital System Pressure (H2)	+
	Hospital Network Centrality (H5)	+
	Spatial Contagion (H6)	+
Aggregated Individual Contagion	External Provider Equal Contagion (H1)	+
	Internal Influential Provider Contagion (H3)	+
	External Influential Provider Contagion (H4)	+
Interaction	Spatial Contagion x External Provider Equal Contagion (H7)	-

In this study, the contagion variable was used as a critical factor to explain how a focal hospital's decision on EMRs adoption was influenced by its networked or neighboring hospitals' decisions on EMRs adoption. Typically, the contagion threshold is set as 50% of events giving EMRs a level of contagion and giving networked or neighboring hospitals an equal chance of influencing the focal hospital. If a focal hospital is exposed to more than 50% of networked or neighboring hospitals that have implemented EMRs, then the probability of the focal hospital being influenced to adopt EMRs is sooner. However, the average EMR adoption rate in 2009 was approximately 80%. It is not appropriate to use a 50% contagion rate as a threshold to study the contagion effect of EMRs. Hence, a 75% contagion rate for EMRs was arbitrarily chosen for this study to raise the threshold criteria and make more reasonable predictions.

1. **Hospital System Pressure**: this variable is a binary measure. It is coded as "1" if at least one hospital from the hospital system has adopted EMRs. It is coded as "0" if no hospitals from the hospital system adopt EMRs
2. **Hospital Network Centrality**: the hospital's network degree centrality score is measured by the number of connected hospitals. The external connections of individual healthcare providers were used as hospital connections and converted to binary connections between hospitals. For example, an inter-hospital connection was established between hospital X and hospital Y when a X1 individual healthcare provider in hospital X were connected to a Y1 individual healthcare provider in hospital Y.
3. **Spatial Contagion**: this variable is a binary measure. It is coded as "1" if more than 75% of the hospital's neighboring hospitals (within 30 miles) have adopted EMRs. It is coded as "0" if less than 75% of the hospital's neighboring hospitals (within 30 miles) have adopted EMRs. A sensitivity test of the neighboring distance (10, 20, 30, 40 and 50 miles) is conducted in Chapter 5. The sensitivity test illustrates that using 30 miles as a distance measure to predict the effect of spatial contagion on the EMRs adoption obtains a smallest p value (0.004).
4. **External Provider Equal Contagion**: this variable is calculated in two steps. An individual healthcare provider is viewed as a susceptible provider when more than 75% of her external individual healthcare providers are adopters. Then the number of susceptible providers is normalized by the total number of individual healthcare

providers within the focal hospital. Thus, a hospital's External Provider Equal Contagion is measured by:

$$= \frac{number\ of\ susceptible\ providers}{total\ number\ individual\ healthcare\ providers}\ x\ 100$$

5. **Internal Influential Provider Contagion**: this variable is calculated by three steps.
    a. Identify influential individual healthcare providers who are top 25% of the degree centrality score within a hospital.
    b. Assign "1" to those influential individual healthcare providers (susceptible providers) if 75 % of their external connected individual healthcare providers whose hospitals have adopted EMRs.
    c. Calculate the percentage of those susceptible providers.
    d. A hospital's Internal Influential Provider Contagion is measured by:

$$= \frac{number\ of\ susceptible\ providers\ (influential\ egos)}{total\ number\ of\ influential\ individual\ healthcare\ providers}\ x\ 100$$

6. **External Influential Provider Contagion**: this variable is calculated by three steps.
    a. Identify individual healthcare providers whose external individual healthcare providers are top 25% of the degree centrality score within their hospitals.
    b. Assign "1" to those individual healthcare providers (susceptible providers) if 75% of their external influential providers have adopted EMRs.
    c. Calculate the percentage of those susceptible providers.
    d. A hospital's External Influential Provider Contagion is measured by:

$$= \frac{number\ of\ susceptible\ providers}{total\ number\ of\ providers\ who\ connected\ to\ external\ influential\ providers} x\ 100$$

4.4.3 Predictors for Multi-State Markov Modeling

In a multi-state Markov model, the dependent variable consists of six time-to-transitions between different levels of EMRs adoption. The simultaneous estimation of the contagion effect of each transition becomes more complex. Contagion estimates for EMRs adoption aim to understand how the decisions of peer hospitals influence the decision of a focal hospital. In a multi-state Markov model, if a focal hospital has already implemented Basic EMRs, the contagion effect that drives the focal hospital to upgrade from Basic EMRs to Intermediate EMRs may come from peer hospitals that have already adopted Intermediate EMRs or Comprehensive EMRs. The contagion effect on the focal hospital may not simply be influenced by the adoption of a peer hospital with a next higher level of EMRs than the focal hospital. Rather, the contagion effect on the focal hospital may be cumulative from peer hospitals that have adopted any higher level of EMRs. Therefore, the previous contagion variables for the survival analysis need to be modified to meet the estimates of the multi-state Markov model. The following contagion variables are defined similarly to the above variables but with modifications to the cumulative contagion effect for the use of EMRs.

1. **Hospital System Pressure**: this variable is a binary measure. It is coded as “1” if at least one hospital from the hospital system has adopted higher levels of EMRs than the focal hospital. It is coded as “0” if hospitals from the hospital system have the same or lower levels of EMRs adoption status.

2. **Hospital Network Centrality**: the hospital's network degree centrality score is measured by the number of connected hospitals.
3. **Spatial Contagion**: this variable is a binary measure. It is coded as "1" if more than 75% of the hospital's neighboring hospitals (within 30 miles) have adopted higher levels of EMRs than the focal hospital. It is coded as "0" if less than 75% of the hospital's neighboring hospitals (within 30 miles) have the same or lower levels of EMRs adoption status. The 30 miles measure of neighboring hospitals here aims to make the results comparable to the binary survival analysis.
4. **External Provider Equal Contagion**: this variable is calculated in two steps. An individual healthcare provider is viewed as a susceptible provider when more than 75 % of her external individual healthcare providers are adopters of higher levels of EMRs than the focal hospital. Then the number of susceptible providers is normalized by the total number of individual healthcare providers within the focal hospital. A hospital's External Provider Equal Contagion is measured by:

$$= \frac{number\ of\ susceptible\ providers}{total\ number\ individual\ healthcare\ providers}\, x\ 100$$

5. **Internal Influential Provider Contagion**: this variable is calculated by three steps.
    a. Identify influential individual healthcare providers who are top 25% of the degree centrality score within a hospital.
    b. Assign "1" to those influential individual healthcare providers (susceptible providers) if 75 % of their external connected individual healthcare providers whose hospitals have adopted higher levels of EMRs than the focal hospital.

c. Calculate the percentage of those susceptible providers.

d. A hospital's Internal Influential Provider Contagion is measured by:

$$= \frac{number\ of\ susceptible\ providers\ (influential\ egos)}{total\ number\ of\ influential\ individual\ healthcare\ providers}\ x\ 100$$

6. **External Influential Provider Contagion**: this variable is calculated by three steps.

   a. Identify individual healthcare providers whose external individual healthcare providers who are top 25% of the degree centrality score within their hospitals.

   b. Assign "1" to those individual healthcare providers (susceptible providers) if 75% of their external influential providers have adopted higher levels of EMRs than the focal hospital.

   c. Calculate the percentage of those susceptible providers.

   d. A hospital's External Influential Provider Contagion is measured by:

$$= \frac{number\ of\ susceptible\ providers}{total\ number\ of\ providers\ who\ connected\ to\ external\ influential\ providers}\ x\ 100$$

4.4.4 Control Variables

Previous research has indicated that hospital resources, hospital type and hospital ownership are key factors that influence the likelihood of a hospital adopting or upgrading EMRs. The HIMSS dataset has three variables related to hospital resources, number of beds, number of staffed beds and number of full-time employees. All three variables are significantly and positively correlated. However, all three variables had a certain number of missing values. The number of beds produced a smaller number of missing values compared to the number of staffed beds and the number of full-time employees. Therefore, the number of beds was chosen for this study to reflect the concept of hospital resources. A hospital with more beds means that the hospital has more resources to support the implementation of EMRs. Also, hospitals with more beds may need EMRs to validate the accuracy of the management process and to expedite the transaction of clinical data (Angst et al., 2010; Fareed et al., 2015). The data from this study showed that the distribution of bed numbers across hospitals was highly skewed. Thus, logarithmic transformation of the variable was taken and included in the model specification.

The composition of individual healthcare providers in a hospital may also determine a hospital's willingness to comply with institutional pressures (Fareed et al., 2015). In this study, the hospital type variable was operationalized as hospital specialty to express the institutional characteristics of the hospital. The original classification of hospital specialties included Academic, Acute Psychiatric, Acute Rehabilitation, Cardiology, Critical Access, Eye, Ear, Nose & Throat, General Medical, General Medical & Surgical, Long Term Acute, Oncology, Orthopedic, Pediatric, "Pediatric, Women's Health," Women's, and Other Health Specialty. As some specialties overlap with each other and some specialties have only a small number of hospitals, this study reclassifies these specialties to make the classifications more mutually exclusive and to give these specialties a sufficient number of hospitals for statistical analysis (statistical power). General Medical & Surgical and General Medical were combined as General Medical. Pediatric, "Pediatric, Women's Health," and Women's were combined as Pediatric &

Women's Health. Acute Psychiatric, Acute Rehabilitation, Cardiology, Eye, Ear, Nose & Throat, Oncology, Orthopedic and Other Specialty were combined as Other Specialty.

Hospital ownership status affects a hospital's expectation of return on EMRs investment and the extent to which the hospital perceives stakeholder pressure (Boonstra & Broekhuis, 2010; Fareed et al., 2015). The hospital ownership variable reflects whether a hospital is owned, managed or leased.

In addition, a hospital's decision to adopt EMRs may be constrained by potential health needs and local Internet infrastructure.

A hospital may anticipate potential growth in hospital operations and decide to implement or upgrade EMRs to meet potential health-seeking demand. Health-seeking demand is measured by county-level population density per square mile of land area. A county with a larger population usually means higher potential health-seeking demand. The data from this study showed that the distribution of the population density in the county where the hospital is located is highly skewed and needs to be normalized. Therefore, a logarithmic transformation was applied to this variable.

Local Internet infrastructure should consider both Internet supply and Internet demand. Internet supply is seen as an important player when hospitals use EMRs to import or export health records with external data warehouses and insurance companies. If Internet supply is short or limited, hospitals may see less benefit in adopting or upgrading EMRs and decide not to adopt or upgrade EMRs. For the purposes of this study, Internet supply was measured by the number of broadband providers in the county where the hospital was located. A county with a high number of broadband providers means that the Internet market is competitive. In a competitive market, broadband providers are more likely to provide a better quality of Internet services for their customers. Furthermore, Internet demand reflects the willingness of Internet users to use EMRs. Suppose there is a large number of Internet users in a hospital's service area. In that case, the hospital may adopt EMRs to provide these users with online appointments, telemedicine, or preventive care services. Thus, in this study, Internet demand is measured by the hospital's county broadband subscribers per 1000 households.

The control variables described above are summarized below. It is important to note that all of the control variables in this study were used specifically as time-invariant variables, as those variables are relatively small and barely change across years. These control variables are included in survival analysis and the multi-state Markov model.

1. **Hospital Size**: hospital size measures the number of beds in the hospital (logged) in 2009.
2. **Hospital Type**: hospital type is a categorical variable referring to Academic, Critical Access, General Medical, Long-Term Acute, Pediatric & Women's Health, or Other Specialty in 2009. All the categories are converted to dummy variables. The Academic hospitals are used as the reference group. It should be noted that the Academic hospitals are not necessary to reflect university-owned hospitals. If a hospital offers an internship training program, the respondents may define itself an Academic hospital (e.g., INOVA).
3. **Hospital Ownership**: hospital ownership is a categorical variable reflecting a hospital is owned, managed or leased in 2009. The owned hospital is a hospital

owned by a central organization. The managed hospital is a hospital's daily operation contracted and managed by another organization. The leased hospital is that a hospital authorizes another organization with the right to manage the facility and gain benefits. The hospital ownership categories are converted to dummy variables. The leased hospitals are used as the reference group.

4. **County Population Density**: county population density measures population density per square mile of land area in a county in 2010 (logged).

5. **County Broadband User**: county broadband user measures Residential Fixed Connections at least 768 kbps downstream and greater than 200 kbps upstream per 1000 Households in 2009. It is a categorical variable including users larger than 800 or between 1 and 200, 201 and 400, 401 and 600, or 601 and 800.

6. **County Broadband Provider**: county broadband provider measures the number of broadband providers of Residential Fixed Connections at least 3 Mbps downstream and at least 768 kbps upstream in 2009. The FCC raw data assigned 1 for a county with 1, 2 or 3 broadband providers. Other values stay with their original representation.

CHAPTER 5 STATISTICAL ANALYSIS AND RESULTS

5.1 Descriptive Analysis

Figure 5.1.1 summarizes EMRs adoption rates by hospital between 2009 and 2015. The year 2009 was critical, as noted in Chapter 1. The U.S. government enacted the Health Information Technology for Economic and Clinical Health (HITECH) Act to provide smaller hospitals with significant financial incentives (i.e., Meaningful Use) to implement EMRs. The HITECH Act was a component of the American Recovery and Reinvestment Act of 2009 (ARRA), which authorized roughly $36 billion investment in the nation's health information technology. The HITECH Act has been demonstrated as an effective policy instrument to tackle the slow progress of EMRs adoption and upgrades (Holmgren, Patel & Adler-Milstein, 2017). Figure 5.1.1 also revealed the HITECH Act effect that shows a rapid acceleration in the rate of Comprehensive EMRs adoption between 2009 and 2015.

Overall, the distribution of EMRs adoption exhibits that the majority of hospitals (81%) implemented EMRs in 2009, regardless of the levels of EMRs. In 2015, almost all hospitals (99%) had satisfied the requirements of the Basic EMRs adoption. Specifically, in 2009, the non-adoption rate of EMRs was 19%, and the adoption rates of Basic, Intermediate and Comprehensive EMRs were 34%, 25%, and 21%, respectively. In 2010, the distribution of EMRs adoption displayed comparatively equal percentages for each level of EMRs, and the adoption rates of Basic, Intermediate and Comprehensive EMRs were about 29%. The adoption rates of Basic EMRs had decreased by 5% from 2009 to

2010. Intermediate and Comprehensive EMRs collectively contributed to an increase of 11% in the EMRs adoption rate from 2009 to 2010.

The implementation of Comprehensive EMRs has been displaying tremendous growth since 2009. The adoption rate of Comprehensive EMRs was 21% in 2009 and had increased to 90% in 2015. The growth of Comprehensive EMRs was attributable to the enactment of the HITECH Act, which has been demonstrated as an effective means of the rapid acceleration of the adoption and upgrades of EMRs (Sherer, Meyerhoefer & Peng, 2016).

It should be noted that the present data were retrieved from the HIMSS self-reported survey and have excluded incomplete data points between 2009 and 2015. A self-reported survey means that hospitals are invited to voluntarily participate in the HIMSS EMRs survey. A hospital that does not adopt any EMRs or adopt a lower level of EMRs might have less willingness to disclose its EMRs status and decline the survey invitation. It is also known as social desirability bias, in which hospitals tend to answer questions according to how their answers will be viewed favorably by others instead of answering truthfully. As a result, the number of hospitals that adopted EMRs is likely to be overestimated.

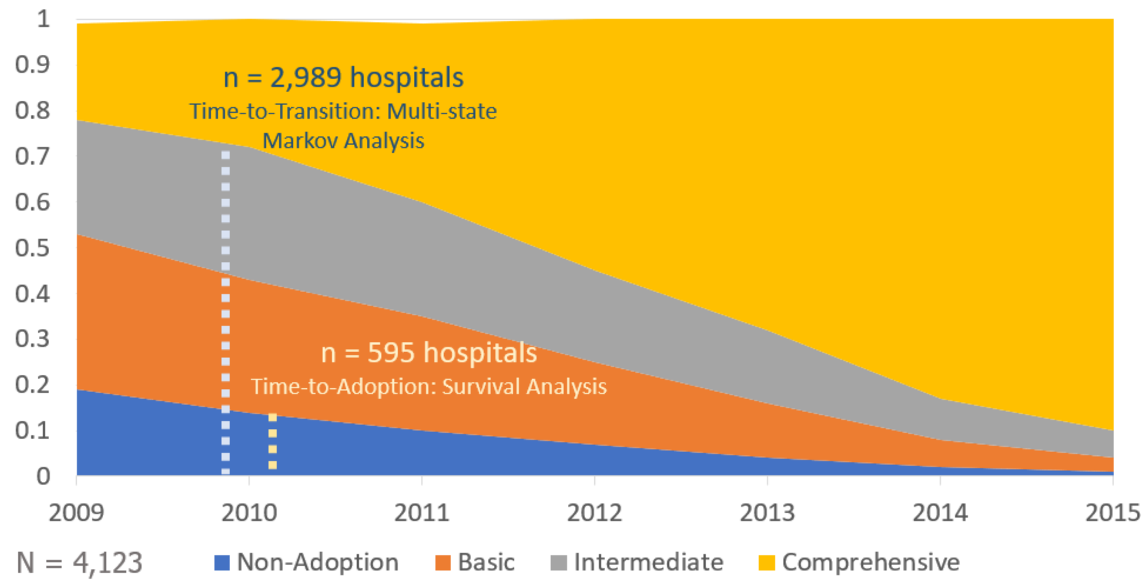

Figure 5.1.1 EMRs Adoption

Tables 5.1.1 and 5.1.2 present a descriptive analysis of control variables, defined in Chapter 4, for both survival analysis and the multi-state Markov models. The variances of control variables in the two models were analyzed separately due to different selection methods of eligible hospitals. As for the survival model, the dependent variable represents a hospital's time or speed to adopt EMRs. If a hospital has adopted any levels of EMRs in 2010 (i.e., time equals zero), the hospital is excluded from the survival analysis for this study. The total number of eligible hospitals that have not yet adopted EMRs in survival analysis was 595. In the multi-state Markov model, the dependent variable reflects a hospital's time or speed to adopt or upgrade EMRs (i.e., transition) during the study period. There are 2,989 hospitals that have made at least one transition between 2010 and 2015.

Hospital size distributions in both survival and multi-state Markov models are highly skewed. A logarithmic transformation was applied to reduce the skewness of the variable. The values of log-transformed Hospital Size were between 0.69 and 7.00 (median = 3.89; mean = 4.14) in the survival model and between 0.69 and 7.15 (median = 4.62; mean = 4.53) in the multi-state Markov model.

In the survival model, the largest and second-largest percentages of Hospital Type were General Medical hospitals (49.87%) and Critical Access hospitals (41.39%). The rest of the hospital types came up with comparatively small percentages (about 9%) of hospitals. In the multi-state Markov model, the greatest and the second greatest percentages of Hospital Type were General Medical hospitals (65.31%) and Critical Access hospitals (25.09%). The remainder of Hospital Type exhibited relatively low percentages (about 10% of hospitals).

Hospital Ownership in survival analysis illustrated that the majority of the hospitals were owned by central organizations (91.52%). The percentage of hospitals that were managed or leased is relatively low, as compared to the hospitals owned by central organizations. Likewise, Hospital Ownership displayed similar percentages in each category in the multi-state Markov model. There were 92.97% of hospitals owned by central organizations. The high percentages of hospitals owned by central organizations in both models elaborated that most hospitals did not perceive the excessive influence of external stakeholders on their decisions on EMRs implementation.

The distribution of County Population Density was transformed by logarithm to reduce the skewness of the original data. The mean and median of County Population Density in the survival model were 4.69 and 4.44. The logged value of County Population Density ranged between -1.20 and 11.15. Hospitals' County Population Density in the multi-state Markov model ranged from -1.61 and 11.15 (median = 4.99; mean = 5.14). The maximum number of County Population Density for both survival and multi-state Markov models is the same, indicating that the two model's hospital might be the same hospital and was a EMRs non-adopter in 2009. The minimum numbers of County Population Density differ between the two models, implying that one hospital was a EMRs non-adopter in 2009 and the other hospital was a EMRs adopter. If both are EMRs non-adopters in 2019, we should observe the same minimum number of County Population Density in both models. It is because the survival analysis estimates how fast "EMRs non-adopters" become EMRs adopters, and the multi-state Markov model estimates factors that expedite or slow down transitions from "EMRs non-adopters, Basic EMRs adopters or Intermediate EMRs adopters" to upper levels of EMRs adopters. Thus, it can be concluded that the hospital with the lowest number of County Population Density in the multi-state Markov model is a EMRs adopter.

As for hospitals' County Broadband User in the survival model, 43.29% of hospitals were located in counties with the number of broadband users between 401 and 600 per 1000 households. A quarter of hospitals were located in counties with the number of broadband users between 201 and 400 per 1000 households. Likewise, a quarter of hospitals were located in counties with the number of broadband users between 601 and 800 per 1000 households. In the multi-state Markov model, the County Broadband User variable exhibited a remarkably similar distribution of the percentages as the variable in the survival analysis. The County Broadband User variables in both models can be inferred that over 50% of the counties have more than 50% of households who have access to broadband services. The high broadband access rates are likely to pressure hospitals to implement EMRs in response to potential online patient scheduling demand or potential telehealth business.

The deployment of EMRs in a hospital requires robust and high-speed broadband services for data transactions between data warehouses. In both survival analysis and multi-state Markov modeling, hospitals' number of County Broadband Provider ranged from 0 to 14 (median = 4 vs. 4; mean = 3.84 vs. 4.13), indicating that most hospitals were located in counties where there are more than three broadband service providers. A hospital with more options to choose broadband service providers will facilitate competition in the broadband service market and create a higher likelihood of receiving a better quality of broadband services. Therefore, well-established broadband infrastructure is expected to provide hospitals with more incentives to accelerate the adoption or upgrades of EMRs.

Table 5.1.1 Descriptive Analysis

	Survival Model		Multi-State Markov Model	
	N	%	N	%
Hospital Type				
Academic	29	3.67	98	3.28
Critical Access	327	41.39	750	25.09
General Medical	394	49.87	1,952	65.31
Long Term Acute	13	1.65	119	3.98
Pediatric or Women	11	1.39	29	0.97
Other	16	2.03	41	1.37
Hospital Ownership				
Leased	21	2.66	81	2.71
Managed	46	5.82	129	4.32
Owned	723	91.52	2,779	92.97
County Broadband User				
1-200	44	5.57	107	3.58
201-400	203	25.70	663	22.18
401-600	342	43.29	1,323	44.26
601-800	183	23.16	828	27.70
> 800	18	2.28	68	2.28
Total N	790	100.00	2,989	100.00

Table 5.1.2 Descriptive Analysis (cont.)

	Min	Median	Mean	Max
Survival Model				
Hospital size (logged)	0.693	3.892	4.139	7.006
County Population Density (logged)	-1.204	4.441	4.689	11.149
County Broadband Provider	0	4	3.844	14
Multi-State Markov Model				
Hospital size (logged)	0.693	4.615	4.531	7.149
County Population Density (logged)	-1.609	4.992	5.139	11.149
County Broadband Provider	0	4	4.136	14

5.2 Survival Analysis

5.2.1 Introduction of Survival Analysis

The Cox (proportional hazards or PH) model is the most commonly used approach for analyzing time-to-adoption data. It can be expressed by the hazard function and a set of time-invariant and time-varying covariates (Cox, 1972; Kleinbaum & Klein, 2012). The Cox hazard function is formulated as:

$$h(t) = \lim_{\Delta t \to 0} \frac{P(t \leq T < t + \Delta t \mid T \geq t)}{\Delta t}$$

where T = survival time ($T \geq 0$); $P(t \leq T < t + \Delta t \mid T \geq t)$ = P (individual fails in the interval [$t,\ t + \Delta t$] | survival up to time t). The hazard function can be extended to:

$$h(t) = h_0(t)\, exp(\beta x + \gamma X_g(t))$$

where $h_0(t)$ is the baseline hazard function. β and γ are coefficients of time-invariant and time-varying covariates. In this study, γ refers to Hospital System Pressure, Hospital Network Centrality, Spatial Contagion, Internal Influential Provider Contagion, External Provider Equal Contagion, External Influential Provider Contagion. β refers to the control variables specified in Chapter 4.

5.2.2 Results of Survival Analysis

To understand what distance between two hospitals is suitable to measure the effect of Spatial Contagion on EMRs adoption, Table 5.2.1 illustrates a robustness test of Spatial Contagion by considering hospitals within 10, 20, 30, 40 and 50-mile radii of a focal hospital. Table 5.2.2 shows factors that influence hospitals' speed of EMRs adoption in different model specifications. In Table 5.2.2, M1 exhibits univariable models, indicating that each independent variable's effect on the outcome variable was estimated respectively. M2-M6 explored how the survival models change when control variables (M2), organizational variables (M3), aggregated individual contagion variables (M4), and interaction variables (M5 and M6) are specified consecutively.

The findings showed that hospitals' EMRs adoption within 20-mile and 30-mile radii of a focal hospital had statistically significant effects on the focal hospital's EMR adoption ($P < 0.05$ and $P < 0.01$). However, using a 30-mile radius to construct the Spatial Contagion measure produced a larger hazard ratio and a smaller p-value, suggesting that the 30-mile radius measure outperformed the 20-mile radius measure. That is, as more than 75% of a hospital's 30-mile neighboring hospitals have adopted EMRs, the hospital's hazard rate of EMRs adoption increased by 26% ($P < 0.01$). Thus, this study hypothesizes that hospitals within a 30-mile radius of a focal hospital are likely to have a Spatial Contagion effect on EMRs adoption of the focal hospital.

In Table 5.2.2, the univariable models present that all interested variables had statistically significant effects on EMRs adoption, although Internal Influential Provider and External Influential Provider Contagion displayed unexpected directions of the hypotheses.

As for the multivariable models, M2 was intended to estimate the effects of control variables on the speed of EMR adoption, containing Hospital Size, Hospital Type, Hospital Ownership, County Population Density, County Broadband Users and County Broadband Providers. M2 shows that as Hospital Size increased by one unit, the hospital's hazard rate of EMRs adoption increased by 32% ($P < 0.001$). Compared to academic hospitals, long-term acute hospitals were less likely to adopt EMRs, and the hazard rate of EMRs adoption was decreased by 77% ($P < 0.001$). Also, both hospital size and long-term acute hospitals had robust and significant effects on the speed of EMRs adoption across all models. However, the remainder of the control variables did not suggest any statistically significant impact on the speed of EMRs adoption.

M3 includes control variables and three organizational variables constructed by the hospital level. The findings indicated that Hospital Contagion had a significant positive effect on the speed of EMRs adoption. When at least one hospital in a focal hospital's hospital system has adopted EMRs, the focal hospital's hazard rate of EMRs adoption was brought up by 18% ($P < 0.1$).

M4 presents control variables and three aggregated individual contagion variables, Internal Influential Provider Contagion, External Provider Equal Contagion and External Influential Provider Contagion. The results revealed that hospitals with higher scores of External Influential Provider Contagion had a higher probability of accelerating EMRs adoption. A unit increase in a hospital's External Influential Provider Contagion was expected to increase the hospital's hazard rate of EMRs adoption by 63% ($P < 0.05$). In contrast, hospitals having higher scores of Internal Influential Provider Contagion were slow to adopt EMRs. One unit increase in a hospital's Internal Influential Provider Contagion was associated with a 44% decrease in the hospital's hazard rate of EMRs adoption ($P < 0.001$). The finding did not support hypothesis three: a hospital will adopt EMRs if most of its influential individual healthcare providers are exposed to external individual healthcare providers whose hospitals have adopted EMRs. The unexpected finding may be caused by a cofounding effect of Hospital Size.

On the one hand, the influential individual healthcare providers in this study were constructed by those who sent or received higher numbers of referral patients at a hospital. On the other hand, Hospital Size reflects a hospital's resources and fewer levels of management, implying that and employees often have more autonomy in decision-making. At smaller hospitals, those influential individual healthcare providers may have busy schedules and do not have sufficient resources or technical support to adapt to EMRs. As a result, they may pressure the hospital administration not to adopt EMRs. At larger hospitals, the implementation of EMRs is comparatively smooth because providers can request technical support from hospitals to learn EMRs and have less autonomy to influence the decision on EMRs adoption (Lorenzi et al., 2009). This study further validated the cofounding effect in M5 and M6.

M5 shows the effects of control variables, organizational variables, aggregated individual contagion variables and an interaction effect variable (Hospital Size and Internal Influential Provider Contagion) on the speed of EMRs adoption. The interaction variable was introduced to estimate if the negative effect of Internal Influential Provider Contagion in M4 is varied by Hospital Size. The findings showed that Hospital System Pressure and External Provider Equal Contagion still have statistically positive effects on the speed of EMRs adoption, but the interaction effect of Hospital Size and Internal Influential Provider Contagion did not suggest statistical significance.

M6 contains all variables in M5 and an additional interaction term of Spatial Contagion and External Provider Equal Contagion. The results revealed that both interaction effects had statistically significant effects on the speed of EMRs adoption. The interaction effect of Hospital Size and Internal Influential Provider Contagion demonstrated that a small hospital is inclined to slow down EMRs adoption if its influential individual healthcare providers were exposed to more external EMRs adopters. Conversely, the interaction effect of Spatial Contagion and External Provider Equal Contagion indicated that a hospital would expedite the adoption of EMRs if most of its individual providers were exposed to distant and networked individual providers whose hospitals have adopted EMRs.

In summary, the final model of M6 illustrates that a hospital was more willing to accelerate the adoption of EMRs if most of its individual providers were exposed to external individual providers whose hospitals have adopted EMRs (hypothesis 1). But hypothesis 3 was not supported and showed an unanticipated effect; a hospital was slow to deploy EMRs if most of its influential individual providers were exposed to external individual providers whose hospitals have adopted EMRs. This impact of slowly adopting ERMs was stronger for smaller hospitals. Finally, hypothesis 7 was supported that a hospital quickened to implement EMRs if most of its individual providers were exposed to distant and networked individual providers whose hospitals have adopted EMRs.

Table 5.2.1 Robustness Test of Spatial Contagion

Threshold: 75%	HR	95% CI[1]	p-value
Spatial Contagion (10 miles)	1.099	0.939, 1.286	0.238
Spatial Contagion (20 miles)	1.180	1.020, 1.365	0.026
Spatial Contagion (30 miles)	1.256	1.076, 1.465	0.004
Spatial Contagion (40 miles)	1.128	0.960, 1.322	0.138
Spatial Contagion (50 miles)	1.142	0.970, 1.348	0.117

Table 5.2.2 Survival Analysis

	Univariable models	Multivariable models				
	M1	M2	M3	M4	M5	M6
	HR	HR	HR	HR	HR	HR
Hospital System Pressure	1.30 ***		**1.18** +		**1.18** +	1.17
Hospital Network Centrality	1.07 *		1.01		0.99	0.99
Spatial Contagion	1.26 **		1.13		1.14	**1.85** *
Internal Influential Provider Contagion	0.51 ***			**0.56** ***	**0.33** **	**0.31** **
Hospital Size * Internal Influential Provider Contagion					1.14	**1.17** +
External Provider Equal Contagion	1.28 +			**1.63** *	**1.64** *	**2.16** ***
Spatial Contagion * External Provider Equal Contagion						**0.55** +
External Influential Provider Contagion	0.82 +			0.93	0.91	0.91
Hospital Size	1.30 ***	1.32 ***	1.31 ***	1.25 ***	1.18 **	1.18 **
Academic vs Critical Access	0.45 ***	1.06	1.03	1.08	1.04	1.08
Academic vs General Medical	0.69 *	0.99	0.96	1.00	0.94	0.98
Academic vs Long-Term Acute	0.13 ***	0.23 ***	0.21 **	0.25 **	0.22 ***	0.24 **
Academic vs Pediatric & Women	0.78	1.05	1.07	1.15	1.10	1.16
Academic vs Other Specialty	0.39 ***	0.76	0.76	0.74	0.71	0.73
Leased vs Managed	1.05	1.11	1.11	1.15	1.13	1.12
Leased vs Owned	0.81	1.17	1.27	1.19	1.27	1.26
County Population Density	1.08 ***	1.03	1.01	1.02	1.00	1.00
County Broadband Users	1.09 *	0.95	0.95	0.94	0.94	0.94
County Broadband Providers	1.03 **	0.98	0.98	0.99	0.99	0.99

+P < .1, *P < .05, **P < .01, ***P < .001

5.3 Multi-State Markov Models

5.3.1 Introduction of Multi-State Markov Models

The fundamental concept of the multi-state Markov model is to estimate a process in which an actor moves through a series of stats in continuous time. The multi-state transition hazard function is expressed as:

$$\alpha_{gh}(t) = \lim_{\Delta t \to 0} \frac{P(S(t+\Delta t)\ = h \mid S(t)\ =\ g)}{\Delta t}$$

The transition intensity or hazard rate $\alpha_{gh}(t)$ which expresses the instantaneous risk of a transition from state g into state h at time t ($h, g \in S$). The multi-state Markov models can also obtain the mean sojourn time in a given state and the number of actors in different states at a particular transition. The transition states are assumed to follow the Markov process and allow time-invariant and time-varying covariates to be incorporated through transition intensities to explain conditional variance among actors in different states. For example, a covariate may increase the probability of arriving at one state but decrease the probability of arriving at another state (Jackson, 2021; Metzger & Jones, 2016; Zhang et al., 2019). Thus, this study applied the multi-state Markov model to investigate factors that influence hospitals' speed of movement between different levels of EMRs adoption.

The multi-state transition hazard function can be extended as:

$$\alpha_{gh}(t, X(t))\ =\ \alpha_{0,gh} exp(\beta_{gh}^{T} X(t))$$

where β_{gh} is the set of regression parameters corresponding to the explanatory variable *X(t)*, defined in Chapter 4. *X(t)* are the control variables, Hospital System Pressure, Hospital

Network Centrality, Spatial Contagion, Internal Influential Provider Contagion, External Provider Equal Contagion, and External Influential Provider Contagion.

The multi-state Markov model is often applied to disease research with stages of severity. Figure 5.3.1 is a simplified version of transitions of COVID-19 patients. The left transition chart elaborated an infected patient’s four possible stages of severity: 1) no symptoms at stage one, 2) mild symptoms at stage two, 3) hospitalization at stage three, or 4) death at stage four. The patient can enter any stages of severity and recover from stages two and three. The right trend chart exhibited that a patient arrived at stage one and moved to stage two. Next, the patient recovered from stage two and became at stage one. The patient then developed severe symptoms and was hospitalized. Suddenly, the patient died. The covariates that accelerate or retard those transitions between stages may be varied but can be simultaneously estimated in the multi-state Markov model (Ursino et al., 2021).

Figure 5.3.2 illustrates conceptual transitions of EMRs adoption or upgrades in this study. The left chart depicts transitions between different levels of EMRs, and the transition process is assumed to be progressive, implying that hospitals can only move to upper levels of EMRs. This assumption is realistic because hospitals rarely downgrade the functionality of the implemented EMRs. The right part in Figure 5.3.2 shows a transition rate matrix of EMRs adoption or upgrades. The sum of each row’s values in the matrix is equal to zero.

Table 5.3.1 presents a year-state transition matrix of EMRs adoption or upgrades. The matrix counts over all hospitals, for each state *from* and *to*, that the number of times (years) a hospital had an observation of state *from* followed by an observation of state *to*. Thus, there were 347 hospitals that moved from the EMRs non-adoption state to the

Comprehensive EMRs state, 923 hospitals upgraded from Basic EMRs to Comprehensive EMRs, and 1,320 hospitals upgraded from Intermediate EMRs to Comprehensive EMRs. The number of transitions from EMRs non-adopters to Basic EMRs adopters was 145. The number of transitions from EMRs non-adopters to Intermediate EMRs adopters was 52. Their transition rates were displayed in Figure 5.3.3.

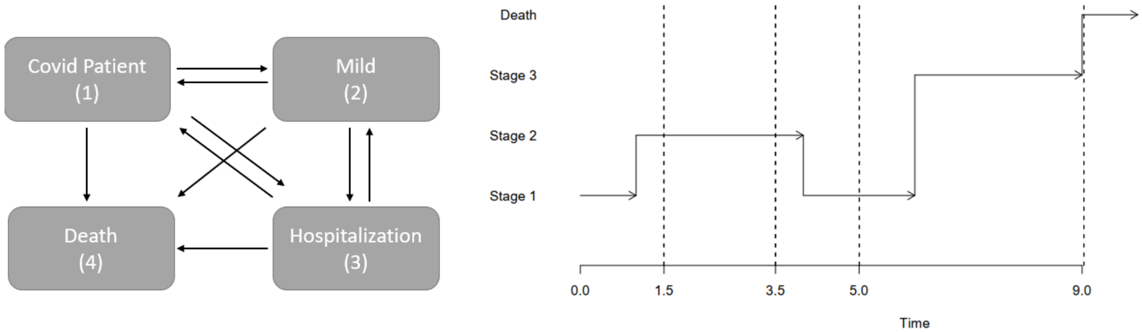

Figure 5.3.1 Transitions of COVID-19 Patients

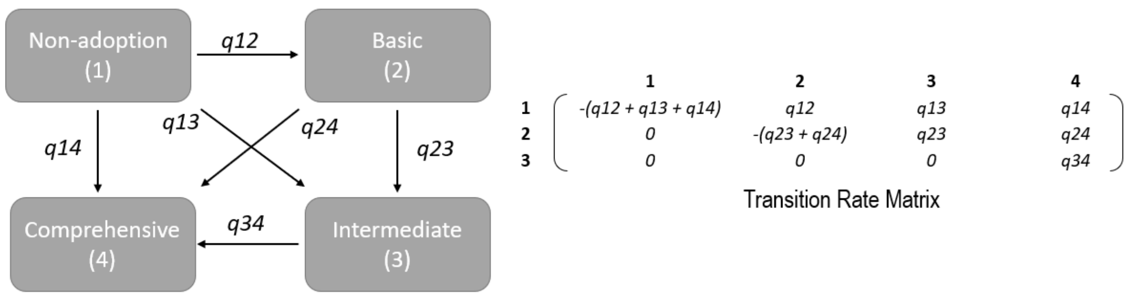

Figure 5.3.2 Transitions of EMRs Adoption or Upgrades

Table 5.3.1 Observed Year-State Transitions

	1	**2**	**3**	**4**
1	1,050	145	52	347
2	0	2,444	304	923
3	0	0	2,782	1,320

$$
\begin{array}{cc}
 & \begin{array}{cccc} \mathbf{1} & \mathbf{2} & \mathbf{3} & \mathbf{4} \end{array} \\
\begin{array}{c} \mathbf{1} \\ \mathbf{2} \\ \mathbf{3} \end{array} &
\left(\begin{array}{cccc} -0.341 & 0.091 & 0.032 & 0.218 \\ 0 & -0.334 & 0.083 & 0.251 \\ 0 & 0 & -0.321 & 0.321 \end{array} \right)
\end{array}
$$

Figure 5.3.3 Transition Rate Matrix

5.3.2 Results of Multi-State Markov Models

Tables 5.3.2 and 5.3.3 present the results of multi-state Markov models. Table 5.3.2 estimated all the variables listed in Chapter 4 except the interaction effect of Spatial Contagion and External Provider Equal Contagion. The full model with the interaction effect variable was specified in Table 5.3.3. In the following discussion, the analysis focuses on the start states of each transition and investigates factors that influence the transition speed. When a transition hazard rate is higher than one and statistically significant, it means that hospitals move quickly from the current state to another state of EMRs adoption. Conversely, when a transition hazard rate is lower than one and statistically significant, it means that hospitals are slow to change to another state of EMRs adoption and prefer to stay with the current EMRs state. Figures 5.3.4 - 5.3.7 are the test of goodness of fit between observed and expected values. The results showed that the lines of observed and expected values in each state were very close, implying that the model performance was acceptable.

5.3.2.1 Start State: EMRs non-adoption

When hospitals were EMRs non-adopters (state 1), they could decide to adopt either Basic EMRs (state 2), Intermediate EMRs (state 3), or Comprehensive EMRs (state 4), or stay with the current EMRs state. Tables 5.3.2 illustrates that as a hospital has not implemented EMRs and at least one of the hospitals in its hospital system has adopted any levels of EMRs, the hospital's hazard rate of moving to Basic EMRs adoption was decreased by 32% ($P < 0.05$). As a hospital has not adopted EMRs and its network centrality increased by one unit, the hospital's hazard rate of implementing Basic EMRs increased by 23% ($P < 0.01$). There were no statistically significant variables in the transition from EMRs non-adopters to Intermediate EMRs adopters. Lastly, Hospital System Pressure, Hospital Network Centrality, Spatial Contagion, and External Provider Equal Contagion had significant positive effects on the transition from EMRs non-adopters to Comprehensive EMRs adopters. As Hospital System Pressure increased by one unit, EMRs non-adopters' hazard rate of deploying Comprehensive EMRs increased by 45% ($P < 0.01$). As EMRs non-adopters' network centrality increased by one unit, their hazard rate of implementing Comprehensive EMRs increased by 10% ($P < 0.1$). The increase in EMRs non-adopters' Spatial Contagion was associated with the increase in the hazard rate of the transition from EMRs non-adopters to Comprehensive EMRs adopters by 38% ($P < 0.05$). A unit increase in EMRs non-adopters' External Provider Equal Contagion was expected to increase the hazard rate of adopting Comprehensive EMRs by 79% ($P < 0.05$). Additionally, the interaction variable of Spatial Contagion and External Provider Equal Contagion did not make statistically significant effects on the transitions from EMRs non-adopters to any levels of EMRs adopters.

5.3.2.2 Start State: Basic EMRs Adopters

When hospitals have adopted Basic EMRs (state 2), they could decide to adopt either Intermediate EMRs (state 3) or Comprehensive EMRs (state 4) or stay with the current state. The findings exhibited that Hospital System Pressure had negative effects on the transitions from Basic EMRs adopters to Intermediate EMRs adopters, or from Basic

EMRs adopters to Comprehensive EMRs adopters. For hospitals that have adopted Basic EMRs, their transitions to higher levels of EMRs were slower as their system hospitals have adopted higher levels of EMRs. The increase in Basic EMRs adopters' External Provider Equal Contagion was associated with the increase in the hazard rate of moving from Basic EMRs adopters to Comprehensive EMRs adopters by 103% ($P < 0.001$). Table 5.3.3 showed that the interaction effect of Spatial Contagion and External Provider Equal Contagion on the transition from Basic EMRs adopters to Comprehensive EMRs adopters was statistically negatively significant. It suggested that Basic EMRs adopters would decrease the speed of adopting Intermediate EMRs if most of its individual providers were exposed to geographically close and networked providers whose hospitals have adopted Intermediate EMRs or Comprehensive EMRs. On the contrary, Basic EMRs adopters would increase the speed of moving to Intermediate EMRs if most of its individual providers were exposed to geographically distant and networked providers whose hospitals have adopted Intermediate EMRs or Comprehensive EMRs.

5.3.2.3 Start State: Intermediate EMRs Adopters

When hospitals have adopted Intermediate EMRs (state 3), the hospitals can only upgrade to Comprehensive EMRs (state 4) or stay with the current state. The findings illustrated that one unit increase in Intermediate EMRs adopters' External Provider Equal Contagion would increase their hazard rate of Comprehensive EMRs adoption by 22% ($P < 0.01$). The increase in Intermediate EMRs adopters' External Provider Equal Contagion was associated with the increase in the hazard rate of the transitions from Intermediate

EMRs adopters to Comprehensive EMRs adopters by 29% ($P < 0.1$). Table 5.3.3 showed that the interaction effect of Spatial Contagion and External Provider Equal Contagion on the transitions from Intermediate EMRs adopters to Comprehensive EMRs adopters was statistically negatively significant. It suggested that Intermediate EMRs adopters would slow down the speed of implementing Comprehensive EMRs if most of its individual providers were exposed to geographically close and networked providers whose hospitals have implemented Comprehensive EMRs. Conversely, Intermediate EMRs adopters would accelerate the upgrade of Comprehensive EMRs if most of its individual providers were exposed to geographically distant and networked providers whose hospitals have adopted Comprehensive EMRs.

5.3.2.3 Summary

In summary, the factors that influence hospitals' speed to change between different levels of EMRs did not illustrate a consistent pattern. It suggested that the study of diffusion of EMRs should consider what factors are critical for hospitals in each stage of the diffusion. The results showed that Hospital System Pressure could speed up the transition from EMRs non-adopters to comprehensive EMRs adopters, yet it slowed down the transition from EMRs non-adopters to Basic EMRs adopters. The position of Hospital Network Centrality accelerated the transition from EMRs non-adopters to Basic EMRs adopters, or from EMRs non-adopters to Comprehensive EMRs adopters. The increase in Spatial contagion was associated with rapid transitions from EMRs non-adopters to Comprehensive EMRs adopters, or from Intermediate EMRs adopters to Comprehensive

EMRs adopters. External Provider Equal Contagion played an important role in rapid transitions from EMRs non-adopters to Comprehensive EMRs adopters, from Intermediate EMRs adopters to Comprehensive EMRs adopters, or from Intermediate EMRs adopters to Comprehensive EMRs adopters. Finally, the interaction effect of Spatial Contagion and External Provider Equal Contagion showed that hospitals changed quickly from Basic EMRs adopters and Intermediate EMRs adopters, or from Intermediate EMRs adopters to Comprehensive EMRs adopters if most of its individual providers were exposed to geographically distant and networked providers whose hospitals have adopted upper levels of EMRs.

Table 5.3.2 Multi-State Markov Modeling (without interaction)

From	State 1	State 1	State 1	State 2	State 2	State 3
To	State 2	State 3	State 4	State 3	State 4	State 4
Hospital System Pressure	0.68*	1.32	1.45**	0.79+	0.81**	1.04
Hospital Network Centrality	1.23**	1.11	1.10+	0.99	0.98	0.99
Spatial Contagion	0.86	1.83	1.38*	0.86	1.11	1.22**
External Provider Equal Contagion	1.34	0.86	1.79*	1.15	2.03***	1.29+
Spatial Contagion * External Provider Equal Contagion	-	-	-	-	-	-
Internal Influential Provider Contagion	0.78	0.88	0.78	1.34	0.75+	0.88
External Influential Provider Contagion	0.83	2.64	1.02	0.61*	1.24	1.06
Hospital Size	1.08	1.23	1.09	1.07	1.05	1.08
Academic vs Critical Access	1.04	11.02	0.73	3.22+	0.96	1.11
Academic vs General Medical	0.96	17.53	0.67	3.70*	0.99	1.04
						**
Academic vs Long-Term Acute	0.52	0.07	0.13**	0.93	0.15***	0.05*
Academic vs Pediatric & Women	0.01	0.31	1.37	2.43	0.70	1.01
Academic vs Other Specialty	0.48	22.29	0.71	3.25	0.85	0.55
Leased vs Owned	0.68	1.13	2.01+	0.94	1.00	1.01
Leased vs Managed	0.69	1.16	1.44	1.19	1.02	1.12
County Population Density	1.15+	0.74*	0.94	0.92	1.01	0.99
County Broadband Users	0.99	1.06	0.99	0.97	1.02	0.98
County Broadband Providers	0.94	0.94	1.01	1.02	0.99	1.01

+P < .1, *P < .05, **P < .01, ***P < .001

Table 5.3.3 Multi-State Markov Modeling (with interaction)

From	State 1	State 1	State 1	State 2	State 2	State 3
To	State 2	State 3	State 4	State 3	State 4	State 4
Hospital System Pressure	0.68*	1.32	1.44**	0.79+	0.80**	1.04
Hospital Network Centrality	1.23**	1.11	1.1+	0.99	0.98	0.99
Spatial Contagion	0.80	2.31	1.76	1.05	1.21+	1.31**
External Provider Equal Contagion	1.27	1.04	2.22*	1.73+	2.46***	1.57*
Spatial Contagion * External Provider Equal Contagion	1.09	0.73	0.73	0.50*	0.76	0.72+
Internal Influential Provider Contagion	0.78	0.89	0.79	1.29	0.74*	0.87
External Influential Provider Contagion	0.83	2.66	1.03	0.61*	1.24	1.05
Hospital Size	1.07	1.23	1.09	1.08	1.05	1.08
Academic vs Critical Access	1.02	15.73	0.74	3.33+	0.98	1.11
Academic vs General Medical	0.95	25.13	0.68	3.79*	1.00	1.04
Academic vs Long-Term Acute	0.50	0.06	0.13**	0.98	0.15***	0.05***
Academic vs Pediatric & Women	0.01	0.27	1.39	2.57	0.71	1.00
Academic vs Other Specialty	0.47	32.49	0.72	3.35	0.87	0.55
Leased vs Owned	0.68	1.12	1.99+	0.96	1.01	1.01
Leased vs Managed	0.68	1.16	1.42	1.21	1.02	1.11
County Population Density	1.15+	0.74*	0.94	0.93	1.02	0.99
County Broadband Users	0.99	1.06	0.98	0.96	1.02	0.98
County Broadband Providers	0.94	0.94	1.01	1.02	0.99	1.01

+P < .1, *P < .05, **P < .01, ***P < .001

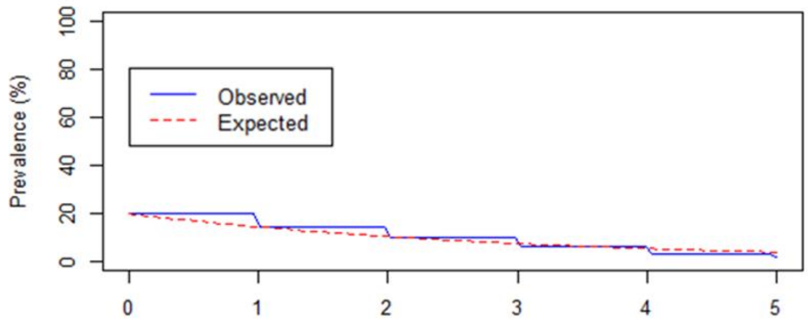

Figure 5.3.4 Goodness of Model Fit Test for State 1

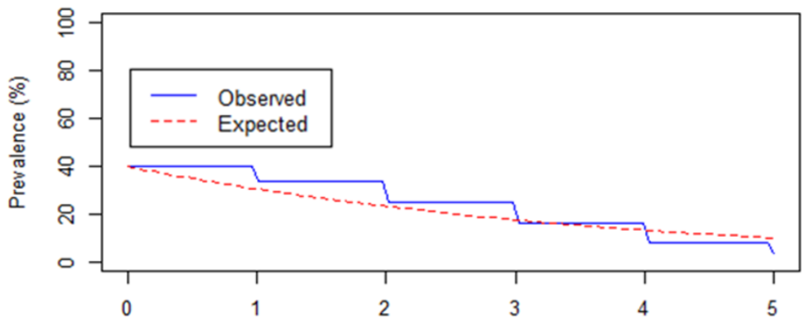

Figure 5.3.5 Goodness of Model Fit Test for State 2

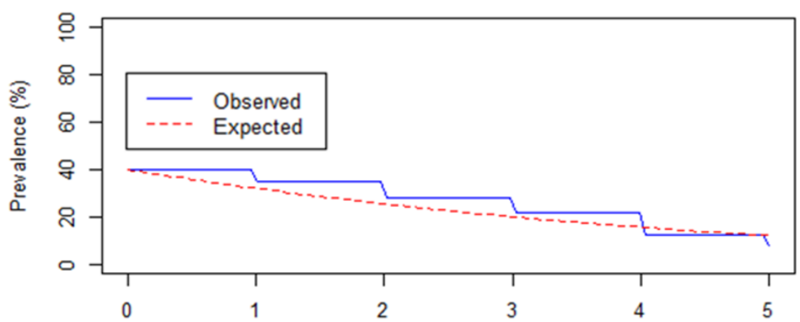

Figure 5.3.6 Goodness of Model Fit Test for State 3

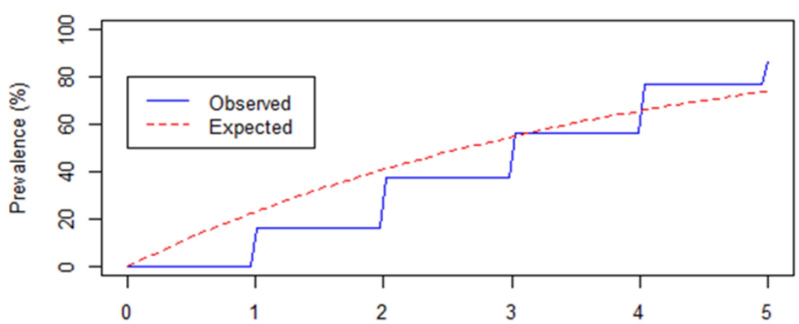

Figure 5.3.7 Goodness of Model Fit Test for State 4

5.4 EMRs Contagion Analysis of Washington, D.C. Hospitals

In sections 5.2 and 5.3, this study introduced survival analysis and multi-state Markov models with a representative sample to discover significant factors that impact the process of EMRs adoption. The two statistical inference models are useful when researchers are interested in the estimation of a general pattern between predictors and outcome variables. When researchers aim to explore a modest variation of the data or a variation of a subset of the data, it may be valuable to specify a small hospital network with a boundary to restrict the spatial contagion/spillover effect. Thus, this study selected seven hospitals in Washington, D.C. and examined factors that influence individual hospitals to change their decisions on EMRs adoption. In addition to the definitions of contagion measures in Chapter 4, this section will analyze how a hospital's network size, network density, and the average degree centrality of internal individual healthcare providers influence the diffusion of EMRs.

Figure 5.4.1 presents the EMRs inter-network pattern between 2009 and 2014. Node attributes, ranging from one to four, reflect the level of EMRs adoption from non-adopters to comprehensive EMRs adopters. Edge width is proportional to the logged number of referral patients between two hospitals. Tables 5.4.1 – 5.4.7 exhibits D.C. hospitals' levels of EMRs adoption, properties of inter-hospital and intra-hospital networks, and network contagion factors. Network size is defined as the number of eligible individual healthcare providers in the hospital. Network density reflects the total number of actual referral connections divided by all possible referral connections. Average degree centrality of internal providers refers to the sum of degree centrality scores of individual providers divided by the total number of individual providers. The degree centrality of the inter-hospital network reflects the number of connected hospitals of a given hospital. The maximum degree centrality score is six, implying that the hospital shared patients with all other hospitals in the network. Additionally, Hospital System Pressure aims to clarify whether a formal network relationship influences a hospital's decision behavior. Hospital System Pressure is coded as one if at least one of a focal hospital's system hospitals adopted a higher level of EMRs. "NA" appears when a hospital has adopted comprehensive EMRs, and there is no further data that we should follow.

5.4.1Transitions of EMRs Adoption or Upgrades

There were five possible transitions of EMRs adoption or upgrades between 2009 and 2014. All hospitals had at least one transition of EMRs adoption except hospital 38649. Hospital 38649 has adopted a comprehensive EMRs system in or before 2009. In general, the EMRs adoption in D.C. did not show a complete sequential transition trend. A hospital's EMRs could be upgraded with a sequential transition. For example, hospital 13831 upgraded EMRs from the intermediate level (3) to the comprehensive level (4). A hospital's EMRs could also be upgraded with a non-sequential transition. For instance, hospital 19306 upgraded EMRs from the basic level (2) to the comprehensive level (4).

Those hospitals' inter-networks did not have substantial change between 2009 and 2014. All the hospitals had at least five connections with other hospitals between 2009 and 2014 except hospital 38649. Hospital 38649 connected four hospitals in 2009 but had less than three hospital connections in the following years. Its comprehensive EMRs adoption had an important influence on other hospitals in 2009 but the effects were more modest between 2010 and 2014. Those hospitals' properties of intra-networks varied between 2009 and 2014. Some hospitals' network sizes were relatively stable, for example, hospitals 19306 and 38649 (Tables 5.4.2 and 5.4.7). Some hospitals' network sizes changed significantly. For instance, hospital 33981 had 329 individual healthcare providers in 2009, but the number was increased to 411 in 2014 (Table 5.4.5). Because network density and average degree centrality of internal providers were greatly influenced by network size, both values exhibit similar trends as network size.

In the first transition between 2009 and 2010, both hospitals 33926 and 33981 did not fulfill the requirements of basic EMRs adoption in 2009 but adopted intermediate EMRs in 2010. Because both hospitals are affiliated with the same hospital system, a potential reason to influence their decisions on adopting intermediate EMRs might have been under pressure from their hospital system. Tables 5.4.4 and 5.4.5 presented that their hospital system had at least one hospital that implemented EMRs in 2009. A hospital system's decision on initial EMRs implementation in a hospital can be considered as an experiment with an intention to deploy EMRs in all the system hospitals. When the experiment successfully achieves the system's proposed goals, the deployment of EMRs to all the system hospitals should be anticipated. Another potential reason may be attributable to the hospital 33981's high scores of external provider equal contagion and external influential provider contagion, implying that most of hospital 33981's external influential providers' hospitals have adopted EMRs. Therefore, it is possible that hospital 33981 considered mimicking other hospitals' decisions on EMRs adoption or perceived pressure from those external EMRs adopters. Then hospital 33981 might discuss the EMRs adoption matter with its system hospital 33926, and both hospitals collectively decide to adopt intermediate EMRs in 2010.

As for 2010 and 2011, no transition of EMRs adoption occurred in the period.

There was one transition of EMRs adoption that occurred between 2011 and 2012. Hospital 13831 upgraded its EMRs from the intermediate level in 2011 to the comprehensive level in 2012 (Table 5.4.1). Hospital 13831's values of external provider contagion and external influential provider contagion were not high compared to other hospitals, but the values gradually increased from 2009 to 2011. Most importantly, at least one hospital in its hospital system began to adopt comprehensive EMRs in 2011. Thus, hospital 13831's external provider contagion, external influential provider contagion and Hospital System Pressure may jointly contribute to the adoption of comprehensive EMRs in 2012.

In 2012 and 2013, hospitals 19695, 33926, 33981 and 38458 upgraded their EMRs status in 2012 to higher levels of EMRs in 2013 (Tables 5.4.3, 5.4.4, 5.4.5 and 5.4.6). Hospitals 19695 and 38458 advanced their basic EMRs to comprehensive EMRs. Hospitals 33926 and 33981 upgraded their intermediate EMRs to comprehensive EMRs.

The determinants of hospital 19695's EMRs transition were likely driven by internal demand and external provider equal contagion (Tables 5.4.3). The internal demand referred to the change of network size from 2009 to 2012. Hospital 19695's network size contained 128 individual providers in 2009 and increased to 142 individual providers in 2012. The increased number of individual providers reflected the growth of hospital business and became an essential factor for hospital 19695 to upgrade its basic EMRs to comprehensive EMRs. Hospital 19695's external provider equal contagion was 0.09 in 2009 and gradually increased to 0.47 in 2012. The external influence was also an important element to determine hospital 19695's transition of EMRs adoption in 2012. As for hospital 38458, the transition of EMRs adoption appears to be influenced by internal demand only (Tables 5.4.6). The network size included 78 individual providers in 2009 and gradually increased to 90 individual providers in 2012, implying that hospital 38458 might be under pressure from the expansion of hospital business to upgrade EMRs.

As noted earlier, hospitals 33926 and 33981 were in the same hospital system and had the same transition from EMRs non-adopters in 2009 to intermediate EMRs adopters in 2010. Hospital System Pressure seemingly continued to show its impact after 2010. Both hospitals upgraded again in 2013, from intermediate EMRs to comprehensive EMRs (Tables 5.4.4 and 5.4.5). However, the upgrade of EMRs did not occur either in 2011 or 2012. Thus, Hospital System Pressure might not be a convincing reason for interpreting the EMRs adoption in 2013.

The internal demand might be a suitable explanation of the EMRs transition. Between 2009 and 2014, both hospitals' network sizes were significantly enlarged. In 2009, 2012 and 2014, hospital 33926 had 266, 299 and 331 individual providers, and hospital 33981 had 329, 376 and 411 individual providers, respectively. Therefore, before 2013, both hospitals experienced business expansion and were likely to anticipate a potential business expansion in the future. In 2013, the business expansion might become a vital factor to explain the upgrade of EMRs in hospitals 33926 and 33981.

Finally, there was one transition of EMRs adoption between 2013 and 2014. Hospital 19306 was a late adopter in D.C., upgraded EMRs from the basic level to the comprehensive level in 2014 (Table 5.4.2). The transition of EMRs adoption might result from external adopters' pressure. Hospital 19306's hospital system had at least one hospital that implemented a higher level of EMRs since 2010, but the hospital did not make any EMRs upgrade decision until 2013. However, the hospital's External Provider Equal Contagion reached 0.98, inferring that almost all of those external individual providers' hospitals have adopted intermediate or comprehensive EMRs. Also, the hospital's External Influential Provider Contagion reached 0.92, implying that almost all of those external influential providers' hospitals have adopted intermediate or comprehensive EMRs. Hence, as a late adopter, hospital 19306's EMRs upgrade decision might be caused by external adopters' pressure.

In short, theoretically, an EMRs adoption decision can be explained by the inter-hospital network, the intra-hospital network or the hospital system network. In practice, when exploring a subset of the hospitals, those factors performed different effects on hospital decisions on EMRs adoption at different time points. In D.C., this study investigated seven hospitals and observed that directly reporting the evolution of inter-hospital networks may not provide sufficient evidence to explain the EMRs adoption decision. A hospital's internal demand of business expansion, external individual providers and hospital system networks play a substantial role in facilitating the transitions of EMRs adoption states, either jointly or respectively.

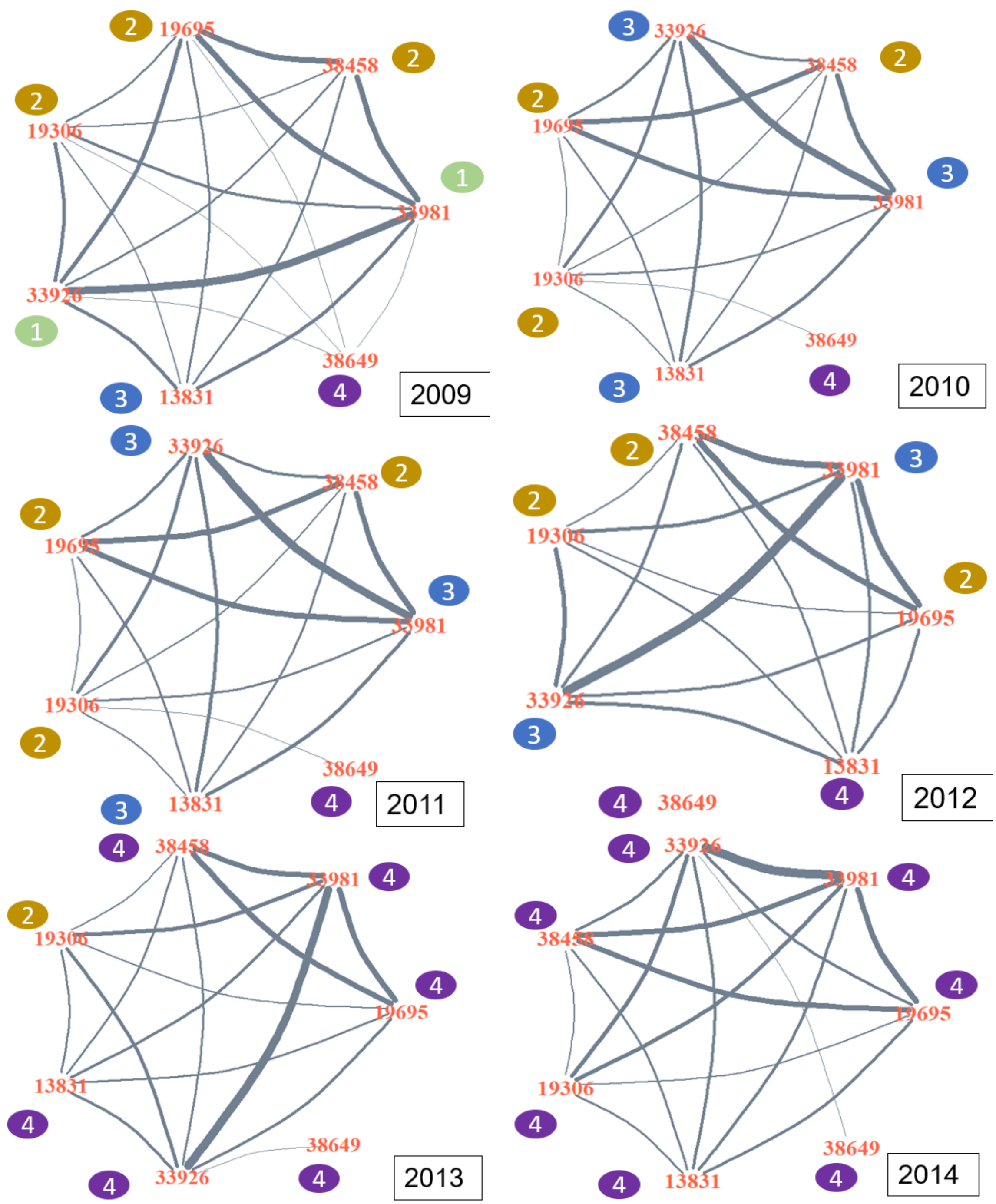

Figure 5.4.1 D.C. Inter-hospital Networks 2009-2014

Table 5.4.1 Network Properties of Hospital 13831

Year	2009	2010	2011	2012	2013	2014
Level of EMRs Adoption	3	3	3	4	4	4
Network Size	75	78	79	84	85	92
Network Density	0.17	0.15	0.16	0.12	0.11	0.08
Avg Degree Centrality of Internal Providers	12.80	11.90	12.33	10.00	8.92	7.26
External Provider Equal Contagion	0.10	0.06	0.22	NA	NA	NA
External Influential Provider Contagion	0.15	0.17	0.22	NA	NA	NA
Internal Influential Provider Contagion	0.00	0.01	0.00	NA	NA	NA
Hospital System Pressure	0	0	1	NA	NA	NA
Degree Centrality of Inter-Hospital network	5	5	5	5	5	5

Table 5.4.2 Network Properties of Hospital 19306

Year	2009	2010	2011	2012	2013	2014
Level of EMRs Adoption	2	2	2	2	2	4
Network Size	66	70	71	78	76	75
Network Density	0.13	0.12	0.13	0.10	0.09	0.10
Avg Degree Centrality of Internal Providers	8.67	8.49	8.76	7.36	6.55	7.33
External Provider Equal Contagion	0.50	0.68	0.70	0.82	0.98	NA
External Influential Provider Contagion	0.46	0.85	0.82	0.88	0.92	NA
Internal Influential Provider Contagion	0.00	0.01	0.01	0.08	0.18	NA
Hospital System Pressure	0	1	1	1	1	NA
Degree Centrality of Inter-Hospital network	6	6	6	5	5	5

Table 5.4.3 Network Properties of Hospital 19695

Year	2009	2010	2011	2012	2013	2014
Level of EMRs Adoption	2	2	2	2	4	4
Network Size	128	127	133	142	144	155
Network Density	0.12	0.11	0.12	0.12	0.12	0.10
Avg Degree Centrality of Internal Providers	15.28	13.78	15.88	16.96	17.71	14.71
External Provider Equal Contagion	0.09	0.44	0.40	0.47	NA	NA
External Influential Provider Contagion	0.12	0.47	0.45	0.47	NA	NA
Internal Influential Provider Contagion	0.00	0.15	0.11	0.11	NA	NA
Hospital System Pressure	0	0	0	0	NA	NA
Degree Centrality of Inter-Hospital network	6	5	6	5	5	5

Table 5.4.4 Network Properties of Hospital 33926

Year	2009	2010	2011	2012	2013	2014
Level of EMRs Adoption	1	3	3	3	4	4
Network Size	266	268	282	299	313	331
Network Density	0.12	0.13	0.13	0.13	0.12	0.12
Avg Degree Centrality of Internal Providers	32.29	34.69	36.30	39.32	36.61	38.47
External Provider Equal Contagion	0.25	0.10	0.07	0.14	NA	NA
External Influential Provider Contagion	0.33	0.12	0.09	0.14	NA	NA
Internal Influential Provider Contagion	0.01	0.00	0.00	0.01	NA	NA
Hospital System Pressure	1	1	1	1	NA	NA
Degree Centrality of Inter-Hospital network	6	5	5	5	6	6

Table 5.4.5 Network Properties of Hospital 33981

Year	2009	2010	2011	2012	2013	2014
Level of EMRs Adoption	1	3	3	3	4	4
Network Size	329	345	352	376	393	411
Network Density	0.13	0.12	0.13	0.12	0.11	0.10
Avg Degree Centrality of Internal Providers	43.76	42.46	45.37	45.26	42.46	41.35
External Provider Equal Contagion	0.63	0.09	0.07	0.12	NA	NA
External Influential Provider Contagion	0.87	0.11	0.09	0.11	NA	NA
Internal Influential Provider Contagion	0.38	0.00	0.00	0.01	NA	NA
Hospital System Pressure	1	1	1	1	NA	NA
Degree Centrality of Inter-Hospital network	6	5	5	5	5	5

Table 5.4.6 Network Properties of Hospital 38458

Year	2009	2010	2011	2012	2013	2014
Level of EMRs Adoption	2	2	2	2	4	4
Network Size	78	76	79	90	95	97
Network Density	0.26	0.27	0.24	0.19	0.18	0.18
Avg Degree Centrality of Internal Providers	19.79	20.00	18.61	17.09	16.53	16.91
External Provider Equal Contagion	0.13	0.15	0.17	0.15	NA	NA
External Influential Provider Contagion	0.13	0.46	0.36	0.39	NA	NA
Internal Influential Provider Contagion	0.00	0.00	0.04	0.02	NA	NA
Hospital System Pressure	1	1	1	1	NA	NA
Degree Centrality of Inter-Hospital network	5	5	5	5	5	5

Table 5.4.7 Network Properties of Hospital 38649

Year	2009	2010	2011	2012	2013	2014
Level of EMRs Adoption	4	4	4	4	4	4
Network Size	18	12	18	16	19	15
Network Density	0.08	0.14	0.03	0.05	0.03	0.04
Avg Degree Centrality of Internal Providers	1.33	1.50	0.56	0.75	0.53	0.53
External Provider Equal Contagion	NA	NA	NA	NA	NA	NA
External Influential Provider Contagion	NA	NA	NA	NA	NA	NA
Internal Influential Provider Contagion	NA	NA	NA	NA	NA	NA
Hospital System Pressure	NA	NA	NA	NA	NA	NA
Degree Centrality of Inter-Hospital network	4	1	2	0	1	1

CHAPTER 6 CONCLUSION

6.1 Summary of Findings

Previous research on innovation diffusion emphasized the same unit of analysis, top-down diffusion, bottom-up diffusion, spatial proximity or network analysis (Berry & Berry, 2007; Fareed et al., 2015; Sherer et al., 2016; Shipan & Volden, 2006). However, the combination of different units of analysis, bottom-up diffusion, spatial proximity and network analysis has not been extensively studied. Using data from the hospital EMRs surveys, healthcare provider referral networks and hospital system networks for the period from 2009 to 2014, this study examines how intra- and inter-organizational networks influence the bottom-up diffusion of EMRs and applies multi-state Markov models to estimate time-to-transition between different levels of EMRs adoption. In Chapter 5, this study conducted three analyses to approach the research questions: survival models, multi-state Markov models and a case study of Washington D.C. hospitals. The survival model aims to examine how fast EMRs non-adopters become adopters. The results illustrated that the hospital system networks, individual healthcare provider networks within and between hospitals, and proximity of hospital locations determine the speed of a hospital to adopt EMRs. By using the same predictors in the survival model, the multi-state Markov model seeks to understand how quick hospitals migrate from one EMRs state to another EMRs state. The findings did not show a consistent pattern of transitions between EMRs states. The main predictors play different roles in each transition with the exception of the transition between EMRs non-adopters and intermediate EMRs adopters. There was no sufficient evidence to explain the transition between EMRs non-adopters and intermediate EMRs adopters. In the case study of the Washington D.C. hospitals, the analysis detailed the micro-transition process of EMRs adoption status and elucidated that the hospital's internal business expansion needs, external individual healthcare providers and the hospital system network jointly or separately influenced the transitions in EMRs adoption status between 2009 and 2014.

6.2 Research Implications

Using the example of EMRs diffusion in U.S. hospitals, this study makes theoretical and methodological contributions to the current diffusion of innovation theory. The first contribution of this study is to propose a bottom-up approach to reexamine the diffusion process. Prior policy diffusion theories in public policy or institutional theories in sociology typically investigate the diffusion of innovations using the government or organization as the unit of analysis (Berry & Berry, 2018; DiMaggio & Powell, 1983). For example, scholars may be interested in exploring whether a centralized organizational system forces the sub-divisions to comply with the adoption of innovations (DiMaggio & Powell, 1983) or whether two geographically close organizations imitate each other's behavior in order to compete for a better market position (Autant-Bernard et al., 2007). Some organizational studies used individual perceptions as a measure to examine the reasons that slow down the innovation adoption rate (e.g., Friedkin, 2004). However, those studies are limited to explain how individuals (bottom) in an organization (up) collectively influence the organization's decisions. Thus, this study uses the example of EMRs diffusion to illustrate how individual healthcare providers interact with the external providers to jointly influence hospital decisions about EMRs adoption.

The second contribution of this study is the application of multi-state Markov models to explore the differences between incremental and disruptive innovations. Most previous research on innovation diffusion emphasized one innovation or one technology and deemed that innovation is an incremental process that follows the trajectory of technological development. Researchers improve a small portion of a previous innovation, testing the response of the market until a satisfactory product is identified. The incremental innovations are often reduced to cumulative S-curves of adoption and estimations of survival analysis. For example, the survival model in Chapter 5 was used to predict the time-to-adoption of EMRs. However, the relationship between innovation and adoption does not always follow an incremental process and may involve disruptive moments in the incremental process. For example, market may have a set of obsolete products (e.g., A, B, C), a set of current products (e.g., D, E, F) and a set of new products (e.g., G, H, I). When scholars intend to understand the factors that influence the incremental migration of customers from existing to new products (e.g., D -> G) or the disruptive migration from obsolete to new products (e.g., A -> G), the multi-state Markov model introduced in this study is an ideal tool for simultaneously estimating the different diffusion stages of a product or innovation.

6.3 Policy Implications

The policy implications of this study include two themes, policy interventions through the lens of network mechanisms as well as differences between the status of hospital EMRs and EMRs performance measures.

First, Chapter 1 discussed that the goal of Accountable Care Organizations (ACOs) is to find patients with challenging medical conditions and provide them with a coordinated network that can collectively monitor the quality of patient care. However, those voluntary healthcare providers of ACOs may come from different hospitals with different types and levels of EMRs adoption. The exchange of electronic patient records among those providers will require advanced EMRs that can be used to standardize data formats (Gruber, 2011). In Chapter 5, both survival models and multi-state Markov models suggested that the individual healthcare provider networks within and between hospitals, the hospital system network, and the spatial closeness of hospitals play different roles in the adoption and updates of EMRs. The results informed policymakers that policy interventions should consider how individual provider networks and hospital networks potentially speed up or slow down the deployment of advanced EMRs in hospitals.

Research has suggested four strategies for policymakers to implement network-based policy interventions in individual networks: individual, segmentation, induction, and alteration (Valente, 2012). The four intervention strategies can be extended to organizational networks and allow policymakers to manipulate the impact of individual healthcare provider networks and hospital networks on the adoption of advanced EMRs. “Individual” intervention strategies aim to identify opinion leaders or change agents who can promote the attitudes or behaviors of their followers. For example, this study used Hospital Network Centrality, Internal Influential Provider Contagion, and External Influential Provider Contagion to reflect the concept of opinion leaders and to predict the adoption and upgrades of EMRs. The “individual” strategy should also consider inviting those individuals and hospital leaders to participate in the early stages of an EMRs intervention program and using the influence of these leaders to attract other individual healthcare providers and hospitals to the program. The “segmentation”-based intervention strategy, rather than identifying specific individuals or organizations, selects a group of individuals or organizations that will shape or change decision-making at the same time. The performance measures of ACOs discussed in Chapter 1 are a good example of the use of the “segmentation” strategies to promote the adoption or upgrades of EMRs. With the “segmentation” strategy, policymakers select ACOs as the intervention group and the group performance measures are designed to meet the quality measures of EMRs (Gruber, 2011; Trotter & Uhlman, 2011).

The “induction”-based intervention strategy aims to activate the process of network flow. The Word-of-Mouth or Snowball approaches are often used to accelerate the spread of interventions through the network. Thus, policymakers should consider applying this approach to offering incentives to those who successfully invite individual healthcare providers or hospitals to participate in EMRs incentive programs. Finally, the “alteration”-based intervention strategy aims to alter the constraints of the network by adding or removing nodes or edges. The emphasis then shifts from fixed networks to dynamic networks. Policymakers should consider organizing EMRs conferences or workshops for individual healthcare providers and hospital representatives to discuss EMRs adoption and establish new relationships (Angst et al., 2010). Those strategies are not mutually exclusive, and one strategy can be used to complement another. For example, policymakers can use a "segmentation" strategy to create a sub-network of networks for interventions, identify influential nodes in the sub-network, and provide these influential nodes with additional incentives to implement the intervention.

Secondly, current EMRs incentives programs (such as the Meaningful Use programs or the Promoting Interoperability Programs) generally use merit or performance-based approach to evaluate the implementation of EMRs in hospitals, but this approach overlooks how the characteristics of hospitals may constrain their decisions on the adoption of EMRs. The conventional design of program evaluation is to establish different sets of criteria for hospitals to meet. For example, these criteria could be basic requirements (Phase one) and advanced requirements (Phase two). Hospitals that meet the requirements will be offered a monetary incentive. If the costs of adoption are the same, then the factors that influence these stages of adoption should exhibit a consistent pattern of coefficients across all models. However, the analysis in Chapter 5 illustrated that the cost of EMRs adoption for hospitals varies depending on the stage of transition. A hospital's decision to adopt or upgrade EMRs is determined by their EMRs states, hospital size, and internal and external provider networks.

A case study in Florida revealed similar findings, specifically that hospitals with abundant resources were more likely to take advantage of the EMRs incentive programs (Monestime, Freeman & Alexandre, 2021). In Florida, the percentage of healthcare providers who participated in the Meaningful Use Medicaid program in 2011 and 2016 was 57% and 21%, respectively, with a higher percentage of attestations achieved by early participants (54%) than later participants (29%). One possible explanation for the low participation and low attestation rates is a policy change in the Meaningful Use Programs in 2017. The new policy requires healthcare providers to implement certified EMRs systems with more advanced features to meet the policy requirements. The new policy does not appear to recognize that later participants may not have sufficient resources to deploy advanced EMRs and meet program goals. Earlier participants might have abundant resources and have deployed advanced EMRs prior to the Meaningful Use program implemented. Hence, the pathway to achieving the program varies depending on the hospital's ability to access EMRs and should be considered in the future program design.

The program design recommendation to policymakers is to consider designing two sets of criteria to bridge the gap between a hospital's EMRs status and hospital performance. The first set of criteria aims to classify a hospital's current EMRs environment into different levels of EMRs readiness, such as basic, advanced, or comprehensive EMRs. The second set of criteria establishes program goals that are ranked as different phases of program requirements (e.g., Meaningful Use Programs). Policymakers should consider the degree of variation between the first and second sets of criteria and provide higher incentives for resource-poor hospitals to meet the requirements. Thus, incentives are not only dependent on the performance of a hospital, but also on the status of the hospital's EMRs.

6.4 Research Limitations and Suggestions for Future Research

This study has several limitations and suggestions for future research. First, the theme of this study is the network, which was constructed from provider referral data from the Medicare program for the period from 2009 to 2014. It is presumed that referral relationships create more communication opportunities between healthcare providers, but it may happen that the patient referral process between two healthcare providers did not initiate any dialogue. If it is the case, the network relationships between healthcare providers in this study may have been over-estimated.

The second limitation of using the referral network data is that the data only include individual healthcare providers who are enrolled in the Medicare program and have shared at least 11 patients with another individual healthcare provider. The data excluded other individual healthcare providers who do not meet the criteria for analysis, leading to under-representation.

The third limitation is that the provider referral network data only cover the period from 2009 to 2014, which means that any attempt to estimate before 2011 or after 2014 may not be reliable. In addition, the Meaningful Use Programs, enacted in 2009, may act as a powerful moderator accelerating the network contagion process. The intervention effect was not eliminated in this study as there was no control or baseline group with which to compare the intervention group.

The fourth limitation is the issue of network endogeneity. In this study, most network variables were constructed using individual provider network data, but this study did not explore how node characteristics (e.g., gender, age, specialty) and network configurations (e.g., homophily, popularity, k-star) affect relationship formation and dissolution (Snijders, Van de Bunt, & Steglich, 2010). It remains underexplored regarding how the interdependence of the network effects impacts the contagion process of EMRs.

The fifth limitation is that healthcare provider data are incomplete. These data were collected from the National Plan and Provider Enumeration System, but there was no information on whether providers switched workplaces from one hospital to another, or whether providers worked for multiple hospitals. Likewise, healthcare providers' registered addresses may not be the same as their place of work. This study simplified the calculation of EMRs contagion and assumed that most healthcare providers affiliated with one hospital and did not change jobs to another hospital.

Therefore, the suggestions for future research should consider collecting more network data by 2009 or selecting an area to survey the healthcare provider network. With network data prior to 2009, scholars can apply the difference-in-difference approach to examine whether the Meaningful Use Programs change the EMRs contagion process. With respect to network surveys, scholars should consider selecting an area and surveying all providers in the area to establish their individual characteristics, advice communication networks and hospital EMRs settings across several years. The research design can help alleviate almost aforementioned limitations by exploring how information about EMRs is disseminated across advice networks and how the change of personal characteristics and network configurations shape decisions on EMRs and future network configurations.

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