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# Network effects and strategic effects: essays on multilevel technology adoption

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Dissertation

# NETWORK EFFECTS AND STRATEGIC EFFECTS: ESSAYS ON MULTILEVEL TECHNOLOGY ADOPTION

by

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# NETWORK EFFECTS AND STRATEGIC EFFECTS: ESSAYS ON MULTILEVEL TECHNOLOGY ADOPTION

(Order No. )

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## ABSTRACT

This dissertation analyzes the network effects and strategic effects in technology and certification adoption.

The first chapter analyzes the externalities of the Electronic Medical Records (EMR) technology. EMR is a multi-level technology, which is characterized by both network effects and strategic effects. Differentiated adoption levels might yield different external effects to neighboring potential adopters. By using a panel of U.S. hospitals' EMR adoption and applying a set of flexible reduced-form regressions, I find the presence of a complementary effect for the first-level EMR adoption, and a competitive effect for higher-level adoption.

Chapter two studies the network effects and strategic effects of EMR technology adoption among hospitals using a dynamic structural model. I estimate this dynamic structural model by applying the methods developed by Bajari, Benkard and Levin (2007) (BBL), and Pakes, Ostrovsky and Berry (2007) (POB), which provide a two-step algorithm for estimating dynamic games. The primary result is the presence of both competition and complementation in this adoption. Furthermore, I perform some counterfactual experiments. The first experiment is to compare hospitals' adoption behaviors in monopoly and duopoly markets, and I find that network effects and strategic interactions are important in the duopoly market. I then perform a policy experiment to examine the effect of the government's incentive programs for EMR adoption, and I find it would greatly stimulate adoption.

The third chapter studies the adoption of LEED (Leadership in Energy & Environmental Design) certification, which is an internationally recognized building certification system that evaluates environmental impact. Competition may affect not only certification adoption but also the adoption of quality standards. LEED offers four levels of certifications to indicate the different standards of environmental impact. By using a detailed dataset of LEED registrations in the U.S. and applying the Multinomial Test of Agglomeration and Dispersion (MTAD) developed by Rysman & Greenstein (2005), we find the allocation of certification levels is more agglomerated than independent random choice would predict.

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# List of Abbreviations

| | |
|---|---|
| ARF | Area Resource Files |
| ARRA | American Recovery and Reinvestment Act |
| BBL | Bajari, Benkard, and Levin (2007) |
| CDR | Clinical Data Repository |
| CIOC | Chief Information Officer Consortium |
| CPOE | Computerized Practitioner Order Entry |
| EHR | Electronic Health Record |
| EMR | Electronic Medical Records |
| HIMSS | Healthcare Information and Management Systems Society |
| HSA | Health Service Area |
| MTAD | Multinomial Test of Agglomeration and Dispersion |
| LEED | Leadership in Energy and Environmental Design |
| POB | Pakes, Ostrovsky and Berry (2007) |
| RHIOs | Regional Health Information Organizations |
| USGBC | U.S. Green Building Council |

# Chapter 1

# Externalities in the Adoption of Electronic Medical Records Technology

## 1.1 Introduction

Electronic Medical Records (EMR) technology allows health care providers to create, store, organize, retrieve and share patients' information electronically, rather than via paper. It consists of a system of applications with wide functionality. Some EMR applications store, organize and retrieve the patients' demographic and clinical information. Some help the doctors make better decisions by providing medication history, recommending drugs and coordinating care among providers. Barack Obama once said in his speech, "To improve the quality of our health care while lowering its cost, we will make the immediate investments necessary to ensure that, within five years, all of America's medical records are computerized. This will cut waste, eliminate red tape and reduce the need to repeat expensive medical tests." In 2009, the U.S. devoted \$19.2 billion and established an incentive program to stimulate the adoption of EMR technology. People expect that the widespread adoption of EMR could reduce health spending while simultaneously leading to better outcomes.

EMR is a technology with externalities, so that the timing of adoption depends not only on stand-alone benefits of technology, but also on the others' adoption behaviors. On the one hand, the incentives to adopt EMR increase as other health providers adopt it and are willing to share information, which shows the importance of positive network effects and cooperation. On the other hand, improved quality by EMR adoption might attract more patients. Keeping market demand constant, the profits of adoption would decline over the number of adopters. That shows the presence of a countervailing competitive effect. This paper primarily studies externalities of EMR adoption by separating different adoption levels. It is, to my knowledge, the first paper to treat the adoption as different levels.

EMR adoption is a dynamic adoption process involving several levels. It is highly possible that differentiated EMR adoption levels would yield different external effects to neighboring potential adopters. The EMR applications possess various functions and features. For example, Enterprise EMR is the basic EMR application, which underlies other potential add-ins. Clinical Data Repository (CDR) is also a basic EMR application that provides a real-time database to store, organize, and retrieve patient information. Computerized Practitioner Order Entry (CPOE) is an advanced EMR application, which can improve health service quality by reducing illegible handwriting, presenting the patients' medical history and allergies, and recommending the right medications. A basic EMR system with Enterprise EMR and CDR provides the construction of a database that stores and consolidates patients' information, which can then be retrieved and analyzed by the advanced EMR applications. Thus, this basic level of adoption could yield a positive network effect by providing a database that can be shared by other health care providers, and stimulate the neighboring hospitals' adoption of EMR. Miller and Tucker (2009) study the adoption of Enterprise EMR. They show the presence of a positive network effect for basic EMR adoption, by examining state privacy protection regulation that may inhibit adoption, due to the suppression of network effects.

On the other hand, a sophisticated EMR system with advanced EMR applications might have a competitive effect. These advanced applications, including CPOE, help doctors make better decisions by providing patients' medical history, recommending the right drugs, checking errors for the tests, and better coordinating care among providers. Improved quality and better service attract more patients from the market. Hospitals gain from the adoption of advanced EMR applications, but the gains would decline over the number of adopters. Schmidt-Dengler (2006) studies the adoption of another health technology - Magnetic Resonance Imaging (MRI) and finds a competitive effect of this adoption among U.S. hospitals. An advanced level of EMR technology might also have this competitive effect, similarly to MRI.

Previous papers examine only the basic EMR adoption, or a comprehensive health information technology adoption, without separating different levels. for example, Miller and Tucker (2009) study the basic level of EMR adoption and find the presence of network effects. Lee, McCullough and Town (2013) find no evidence of network externalities, by measuring a comprehensive health IT adoption and implementation. However, mine is the first paper, that identifies the externalities for different adoption levels, by treating the EMR adoption as different types.

To study the externalities, I use 2009 EMR adoption data from HIMSS (Healthcare Information and Management Systems Society). They contain adoption status and timing information, as well as some hospital characteristics. This dataset provides the adoption time of various EMR applications. I observe the adoption for some common and typical EMR applications, such as Enterprise EMR, CDR, and CPOE. I divided these observed applications into two levels, based on the EMR Adoption Model from the HIMSS Analytics Database. The first level contains basic and simple applications, which can be used to store, organize and retrieve patients' information. The second level consists of more advanced and sophisticated applications, which improve the health service quality by presenting medical history, recommending drugs, and helping the health care providers to make better decisions. A hospital is a level 1 adopter if it has only adopted the first level of EMR applications, and a hospital is considered as a level 2 adopter if it has already installed both levels' applications. The market is defined according to the HSA (Health Service Area) measure, which is developed by Makuc et al. (1991). HSA is a geographic region that is self-contained with respect to health care service. It usually consists of 3-4 counties. I apply this market measure to the HIMSS adoption data, and get 712 HSA markets. The markets in my data cover about 88.8% of the HSA markets in the entire U.S.

I apply a set of reduced-form regressions to show the presence of a complementary effect for the first-level EMR adoption, and a competitive effect for higher-level adoption. Active hospitals include level 1 adopters and non-adopters. Level 1 adopters make decisions about whether to upgrade to level 2. I estimate this policy function by a logit regression. Nonadopters make decisions about whether to adopt and which level to adopt. I use multinomial logistic regression to capture their decisions. Taking the choice of not adopting as the baseline response, I regress hospitals' adoption choices on a set of variables which might affect the adoption decisions, such as the number of level 1 adopters, level 2 adopters, total number of hospitals, market and hospital characteristics, time trend, etc. The results from the regressions confirm my hypotheses. There is a positive network effect for the first level of EMR adoption, and a competitive effect for the higher-level adoption, that is, your neighboring hospitals' adoption of the first level would stimulate your adoption of EMR, while their adoption of the higher-level would deter your adoption.

The remainder of the chapter is structured as follows. Section 1.2 talks about the background of EMR technology. Section 1.3 describes the data that I use. Section 1.4 discusses the estimation, and Section 1.5 presents the results.

## 1.2 Background

This section discusses the benefits and costs of Electronic Medical Records (EMR) adoption, the relevant government policies and regulations in more details.

EMR originated in the 1970s. By using computers, information is easily accessible and shared, which increases the internal quality of the health care provider and promotes the cooperation among various providers. Miller and Tucker (2011) find that the adoption of EMR can significantly reduce neonatal mortality. However, some studies show that the adoption of EMR has not met the expectation. For example, Jones et al. (2010) and Agha (2010) show that the implementation and use of EMR had a limited improvement in quality. Some studies show the benefits of EMR vary across patients or hospitals. McCullough, Parente, and Town (2013) find that the EMR adoption reduces mortality for the most complex patients but does not affect outcomes for the median patient. The external effect of EMR is also controversial. To share the information and generate the network effect, the health providers need to be willing to cooperate and coordinate. Regional Health

Information Organizations (RHIOs) are one of the organization systems that aim to promote information sharing. However, some surveys and studies find that RHIOs are not very effective. Adler-Milstein, Bates, and Jha (2011) find that among approximately 180 reported RHIOs, only 75 are operational, covering just 13% of US hospitals and 3% of ambulatory practices. Although the system of information-sharing organizations is far from complete and effective, the existence itself still shows the great incentives of hospitals to cooperate and share information.

Another barrier to EMR adoption is the issue of privacy protection. Patients are concerned that their health information is not protected during information transfer. To ease this concern, federal government enacted HIPAA (Health Insurance Portability and Accountability Act) in 2002, which provided federal protection for confidentiality of health information. However, the effect of HIPAA on EMR adoption is two-fold. On the one hand, it stimulates adoption by reducing the patients' concerns about privacy protection. On the other hand, legal procedures may make information sharing even harder. Miller and Tucker (2009) shows in their paper, that privacy protection regulation would inhibit the adoption of the first level EMR application, by suppressing the network effects. This result also indicates the presence of network effects in the adoption of the first level.

The high EMR adoption costs are also a concern for health providers. The cost structure includes installation, training, and operational costs. A cost study by the CIOC[1] shows that the 5-year costs of EMR range from \$2,161.62 to \$2,963.47 per bed. To address the problem of high entry cost, the American Recovery and Reinvestment Act (ARRA) in 2009, allocated \$19.2 billion dollars to support EMR adoption. The U.S. government started the Medicare and Medicaid EMR/EHR Incentive Programs, which provide incentives to EMR adoption.[2]

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[1] The CIOC (Chief Information Officer Consortium) is a forum in which chief information officers and senior technical executives/leaders within the long term care (LTC) industry can work together, learn from each other and collaborate with each other to grow the effectiveness of the utilization of information technology within LTC.

[2] Note there is another government policy that would affect the supply side of EMR market. By the Affordable Care Act enacted in 2010, a 2.3% excise tax will be levied on the total revenues of medical device companies. This may somehow affect the innovation, price, and production of EMR technology

## 1.3 Data

I use 2009 EMR adoption data from HIMSS (Healthcare Information and Management Systems Society). They contain adoption status and timing information, as well as some hospital characteristics, such as whether it is a general, or academic hospital, and the number of staffed beds. The dataset covers the majority of U.S. community hospitals, including 90 percent of non-profit, 90 percent of for-profit, and 50 percent of government-owned (non-federal) hospitals. It excludes hospitals with fewer than 100 beds.

This dataset provides the adoption time of various EMR applications. I observe the adoption about some common and typical EMR applications, such as Clinical Data Repository, Computerized Practitioner Order Entry. I divided these observed applications into two levels, based on the EMR Adoption Model from the HIMSS Analytics Database. The EMR adoption model has been developed by HIMSS Analytics to assess the status of EMR adoption and implementation in hospitals. This model identifies the level of EMR capabilities ranging from the basic EMR application that stores patients' information, through a paperless EMR environment with full data analytics and data sharing capabilities.

According to this EMR Adoption Model, the lower stages contain basic and simple applications, which can be used to store, organize and retrieve patients' information, such as Enterprise EMR, Clinical Data Repository (CDR), and basic Clinical Decision Support (CDS). Enterprise EMR is the basic EMR application, which underlies other potential add-ins. CDR is a real time database that consolidates data from a variety of clinical sources and provides physicians access for retrieving and reviewing results. The basic CDS is usually contained in a CDR, and it's used for rudimentary conflict checking. I call the adoption of these applications as the first level adoption in my study.

The intermediate stages from the EMR Adoption Model consist of more advanced and sophisticated applications, which improve the health service quality and help the health care providers to make better decisions. These applications include Computerized Practitioner Order Entry (CPOE) and Physician Documentation (PD). CPOE and PD can be used to present medical history and allergy information, provide treatment guidelines, decrease delay in order completion, reduces errors related to handwriting, provides error-checking for tests and coordinate care across providers. I call the adoption of CPOE and PD as the second level adoption in this study.

The Adoption Model from the HIMSS Analytics Database also include some higher stages. The highest stage requires that the hospital has a completely paperless EMR environment, where clinical information can be readily analyzed, and shared with all entities within a health information exchange. However, I study only the first and second levels in this chapter. A hospital is a level 1 adopter if it has only adopted the first level of EMR applications, and a hospital is considered as a level 2 adopter if it has already installed both levels' applications.

The market is defined according to the HSA (Health Service Area) measure, which is developed by Makuc et al. (1991). HSA is a geographic region that is self-contained with respect to health care service. It usually consists of 3-4 counties. I apply this market measure to the HIMSS adoption data, and get 712 HSA markets. The markets in my data cover about 88.8% of the HSA markets in the entire U.S.

I also use 2009 data of Area Resource Files (ARF) to capture market-level characteristics. Area Resource Files (ARF) provide county-level information on demographic, environmental and health resource variables. Some sources include the American Hospital Association and the U.S. Census Bureau. I draw the information about population, as well as the number of people who are eligible for Medicare from this dataset, aggregate them into HSA-level and merge this information with the adoption data. The population variable is used to approximate the total demand in the market. The effect of the Medicare program on EMR adoption is of great interest. On the one side, Medicare programs typically pay hospitals a flat fee per hospital case, with a different per-case price for each distinct diagnostically related case. This payment scheme will stimulate adoption in the sense that hospitals would like to avoid expensive duplicate tests. On the other side, this might deter adoption because of the high initial cost of EMR adoption.

As a result, I create a panel data covering 3112 hospitals' adoption decisions from 1997 to 2009. Table 1.1 reports the summary statistics for 2009. The number of hospitals in each HSA market ranges from 1 to 77, with a mean of 4.37. Up to 2009, the mean number of level 2 adopters is 2.43 and the mean number of level 1 adopters is 1.43. The adoption rates for different adoption levels exhibit different patterns, as shown in Figure 1.1. It shows the adoption rates of "only level 1" (level 1 adopters), "level 2" (level 2 adopters), and "level 1" (including both level 1 and level 2 adopters).[3] In my dataset, the adoption rate of only level 1 starts from 15% in 1997 and increases slowly up to 2005. It falls slightly afterwards to 32% in 2009, indicating some hospitals upgrade from level 1 to level 2. The adoption rate of level 2 increases over time, from a very low value of 7% in 1997 to 55% in 2009. The adoption peak of level 2 is around 2004. The adoption rate of level 1 EMR starts from 22% to a very high value of 87% in 2009.

## 1.4 Estimation

I apply a set of reduced-form regressions to show the presence of a complementary effect for the first-level EMR adoption, and a competitive effect for higher-level adoption. Active hospitals include level 1 adopters and non-adopters. Level 1 adopters make decisions about whether to upgrade to level 2. I estimate this policy function by a logit regression. Non-adopters make decisions about whether to adopt and which level to adopt. I use multinomial logistic regression to capture their decisions. Taking the choice of not adopting as the baseline response, I regress hospitals' adoption choices on a set of variables which might affect the adoption decisions, such as the number of level 1 adopters, level 2 adopters, total number of hospitals, market and hospital characteristics, time trend, etc.

Active hospitals include level 1 adopters and non-adopters. Level 1 adopters make decisions about whether to upgrade to level 2. I estimate this policy function by a logit regression as follows:

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[3] Note that level 1 adopters have only installed the first level, and level 2 adopters have installed both levels.

$$P(a_{it} = 2|L = 1) = \phi\left(\lambda_0 + \lambda_H H_{1it}\right) \tag{1.1}$$

where $\phi(\cdot)$ is the cumulative distribution function of the standard logistic distribution, $L$ denotes the hospital $i'$s adoption status ($L = 1$ means it is level 1 adopter), and $a_{it} = 2$ means that hospital $i$ upgrades to level 2 at time $t$. The vector $H_{1it}$ consists of a set of variables which might affect hospital $i$'s adoption decision at time $t$, including the number of level 1 adopters, level 2 adopters, total number of hospitals, market and hospital characteristics (whether it is an academic hospital, a general hospital, and the number of staffed beds), time trend, and state fixed effects.

Similarly, Non-adopters make decisions about whether to adopt and which level to adopt. I use multinomial logistic regression to capture their decisions. Taking the choice of not adopting as the baseline response, I regress hospital $i$'s adoption choices on $H_{0it}$, where $H_{0it}$ is a set of variables which might affect the adoption decisions at time $t$, such as the number of level 1 adopters, level 2 adopters, total number of hospitals, market and hospital characteristics, time trend, etc.

The variables of primary interest include number of level 1 adopters, number of level 2 adopters, and total number of hospitals in the market, since these variables capture the potential competitive effects or network effects. If we observe negative and significant coefficients, it shows the competitive effects in EMR adoption. If we otherwise see positive and significant coefficients, we find the presence of network effects.

## 1.5 Results and Conclusion

Table 1.2 presents the adoption policy results for non-adopters. Specification I regresses the decisions (Not Adopt, Adopt level 1 or Adopt level 2) on the number of level 1 adopters, the number of level 2 adopters, market and hospital characteristics, and a time trend. Specification II is the same as Specification I, but without the region fixed effects. My variables of interest are "number of level 1 adopters" and "number of level 2 adopters," which capture the external effects of adoption. The coefficient on number of level 1 adopters is positive and significant, showing the presence of a complementary effect. The coefficient on number of level 2 adopters is negative and significant, indicating that the advanced EMR adoption has a competitive effect. To put these estimates in context in these specifications, increasing one level 1 adopter in the HSA market would increase the odds ratio of adopting level 1 to not adopting, by 3% (Specification II), while increasing one level 2 adopter in the HSA market is expected to decrease the odds ratio of adopting level 2 to not adopting, by 2.64% (Specification I). Note “the number of hospitals in the market” is negative and significant, which might also indicate the competitive effects of EMR technology.

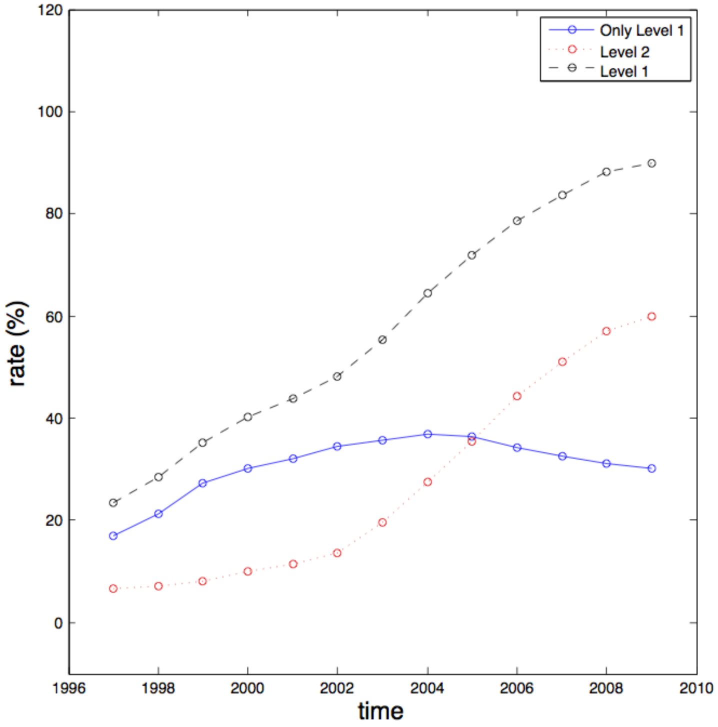
The adoption policy results for level 1 adopters are reported in Table 1.3. Specifications I and II regress the choices on variables of primary interest, and other covariates, with and without region fixed effects. The coefficient on number of level 1 adopters is still positive and significant in both regressions, indicating that the upgrade decision is stimulated by the neighboring hospitals’ adoption of level 1 EMR.

To sum up, in these regressions, my variables of interest are “number of level 1 adopters” and “number of level 2 adopters,” which capture the external effects of adoption. The coefficient on number of level 1 adopters is positive and significant, showing the presence of a complementary effect. The coefficient on number of level 2 adopters is negative and significant, indicating that the advanced EMR adoption has a competitive effect. EMR is a multilevel technology which is characterized with externalities. This paper shows the presence of a complementary effect for the first-level EMR adoption, and a competitive effect for higher-level adoption. A hospital is more likely to adopt EMR if its neighboring hospitals have adopted level 1, but less likely to adopt EMR if its neighboring hospitals have adopted level 2.

One concern arises regarding the causal effect of these externalities. Adoption decisions may be correlated among hospitals as a result of the omitted factors that affect adoptions. I include the state fixed effects in the first-stage regressions, in order to control the unobserved state-level factors. However, some unobserved market-level factors that are persistent over time might still cause a bias when estimating the causal effects. One way to solve this problem is to use IVs. Hospitals that share the same ownership or belong to the same system, but serve different geographical markets, might have similar adoption decisions. This kind of IVs are similar to the IVs used in Miller and Tucker (2009), Jin (2005), and will be considered in my future study.

Another concern is that hospitals might be forward-looking when making decisions. They may consider the effects of their adoption on neighboring hospitals' adoption decisions, which would in turn, affect their current decisions. A more comprehensive empirical model will be discussed in Chapter 2.

Figure 1.1: Adoption Rates

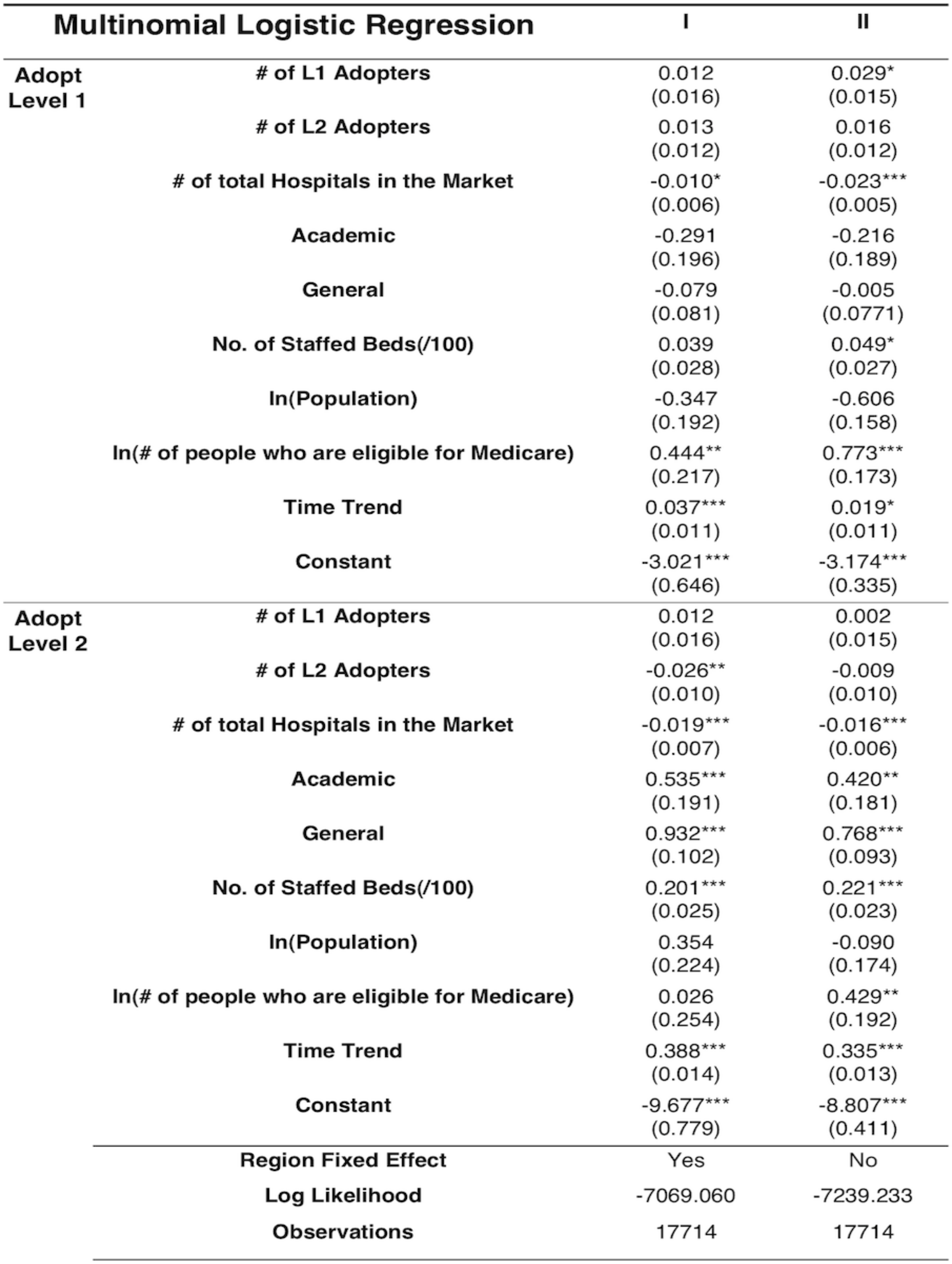


Only Level 1: Hospitals that have only adopted the first level of EMR (level 1 adopters).
Level 1: Hospitals that have adopted the first level (including both level 1 and level 2 adopters).
Level 2: Hospitals that have adopted both levels (level 2 adopters).

Table 1.1: Statistics Summary

| **Variables** | Description | **Source** | **Mean** | **Sd** | **Min** | **Max** |
|---|---|---|---|---|---|---|
| **Only L1 Installed** | Number of hospitals in HSA that had only installed L1 | HIMSS | 1.43 | 1.86 | 0 | 26 |
| **L2 Installed** | Number of hospitals in HSA that had installed L2 | HIMSS | 2.43 | 4.18 | 0 | 44 |
| **# of Hosptials** | Number of hospitals in HSA | HIMSS | 4.37 | 5.77 | 1 | 77 |
| **Staffed Beds** | Number of staffed beds | HIMSS | 144.11 | 160.8 | 2 | 1080 |
| **Academic** | Indicator for whether a hospital is academic | HIMSS | 0.06 | 0.23 | 0 | 1 |
| **General** | indicator for whether a hospital is a general medical&surgical hospital | HIMSS | 0.58 | 0.49 | 0 | 1 |
| **Population(1000)** | Population in HSA | ARF | 187.24 | 481.19 | 1.55 | 8253.4 |
| **Medicare(1000)** | Number of People in HSA who are eligible for Medicare | ARF | 26.62 | 58.75 | 0.33 | 957.2. |
| **Time** | | 2009 | | | | |
| **# of Hospitals** | | 3112 | | | | |
| **# of Markets** | | 712 | | | | |

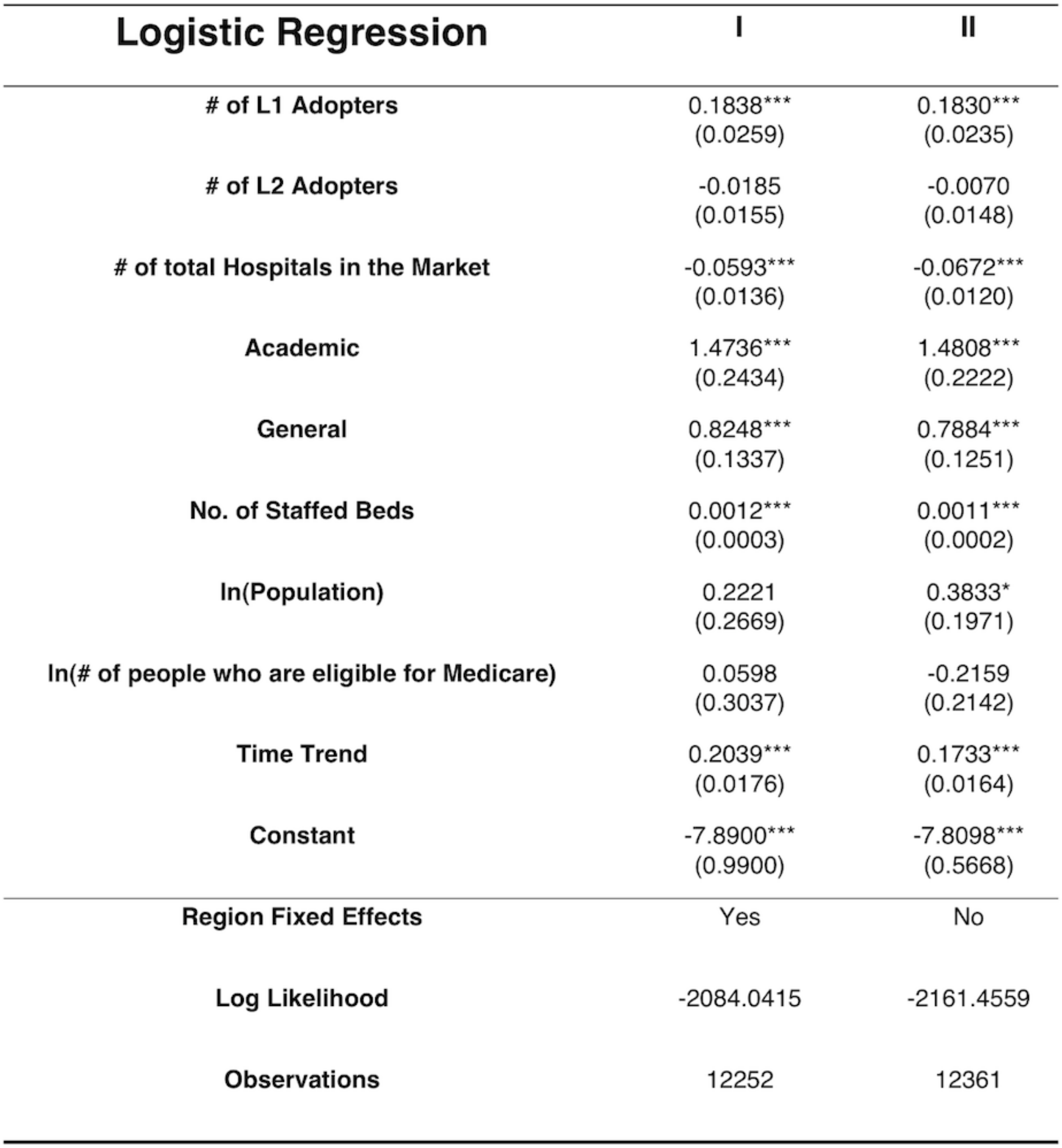
Table 1.2: Results of Multinomial Logistic Regression



| Multinomial Logistic Regression | | I | II |
|---|---|---|---|
| Adopt Level 1 | # of L1 Adopters | 0.012<br>(0.016) | 0.029*<br>(0.015) |
| | # of L2 Adopters | 0.013<br>(0.012) | 0.016<br>(0.012) |
| | # of total Hospitals in the Market | -0.010*<br>(0.006) | -0.023***<br>(0.005) |
| | Academic | -0.291<br>(0.196) | -0.216<br>(0.189) |
| | General | -0.079<br>(0.081) | -0.005<br>(0.0771) |
| | No. of Staffed Beds(/100) | 0.039<br>(0.028) | 0.049*<br>(0.027) |
| | ln(Population) | -0.347<br>(0.192) | -0.606<br>(0.158) |
| | ln(# of people who are eligible for Medicare) | 0.444**<br>(0.217) | 0.773***<br>(0.173) |
| | Time Trend | 0.037***<br>(0.011) | 0.019*<br>(0.011) |
| | Constant | -3.021***<br>(0.646) | -3.174***<br>(0.335) |
| Adopt Level 2 | # of L1 Adopters | 0.012<br>(0.016) | 0.002<br>(0.015) |
| | # of L2 Adopters | -0.026**<br>(0.010) | -0.009<br>(0.010) |
| | # of total Hospitals in the Market | -0.019***<br>(0.007) | -0.016***<br>(0.006) |
| | Academic | 0.535***<br>(0.191) | 0.420**<br>(0.181) |
| | General | 0.932***<br>(0.102) | 0.768***<br>(0.093) |
| | No. of Staffed Beds(/100) | 0.201***<br>(0.025) | 0.221***<br>(0.023) |
| | ln(Population) | 0.354<br>(0.224) | -0.090<br>(0.174) |
| | ln(# of people who are eligible for Medicare) | 0.026<br>(0.254) | 0.429**<br>(0.192) |
| | Time Trend | 0.388***<br>(0.014) | 0.335***<br>(0.013) |
| | Constant | -9.677***<br>(0.779) | -8.807***<br>(0.411) |
| | Region Fixed Effect | Yes | No |
| | Log Likelihood | -7069.060 | -7239.233 |
| | Observations | 17714 | 17714 |

Standard errors are reported in parentheses below estimate. *p $< 0.10$, **p $< 0.05$, ***p $< 0.01$

Table 1.3: Results of Logistic Regression



| Logistic Regression | I | II |
|---|---|---|
| **# of L1 Adopters** | 0.1838***<br>(0.0259) | 0.1830***<br>(0.0235) |
| **# of L2 Adopters** | -0.0185<br>(0.0155) | -0.0070<br>(0.0148) |
| **# of total Hospitals in the Market** | -0.0593***<br>(0.0136) | -0.0672***<br>(0.0120) |
| **Academic** | 1.4736***<br>(0.2434) | 1.4808***<br>(0.2222) |
| **General** | 0.8248***<br>(0.1337) | 0.7884***<br>(0.1251) |
| **No. of Staffed Beds** | 0.0012***<br>(0.0003) | 0.0011***<br>(0.0002) |
| **ln(Population)** | 0.2221<br>(0.2669) | 0.3833*<br>(0.1971) |
| **ln(# of people who are eligible for Medicare)** | 0.0598<br>(0.3037) | -0.2159<br>(0.2142) |
| **Time Trend** | 0.2039***<br>(0.0176) | 0.1733***<br>(0.0164) |
| **Constant** | -7.8900***<br>(0.9900) | -7.8098***<br>(0.5668) |
| **Region Fixed Effects** | Yes | No |
| **Log Likelihood** | -2084.0415 | -2161.4559 |
| **Observations** | 12252 | 12361 |

Standard errors are reported in parentheses below estimate. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

## Chapter 2

# Cooperation and Competition: The Multilevel Adoption of Electronic Medical Records in U.S. Hospitals

### 2.1 Introduction

This chapter studies the diffusion of Electronic Medical Records (EMR) technology among hospitals, by a dynamic structural model. EMR is a multilevel technology and is characterized by both network effects and strategic effects. In a dynamic strategic environment, when a hospital makes decision about whether to adopt and which level to adopt, it considers not only the stand-alone benefits, but also the effects of its decision on other hospitals' future adoption decisions, as its adoption would affect the others' payoffs of adoption. By affecting others' adoption decisions, this hospital's expected discounted present value of payoffs of adoption would be affected as well. In addition, as a result of different externalities generated from the multilevel technology, hospitals' adoption behaviors would be different from the adoption of a single-level technology. In order to capture these characteristics, I develop a dynamic structural model of this multilevel technology adoption. The model takes the strategic interactions of forward looking hospitals into account. Hospitals are assumed to possess private information and make adoption decisions by maximizing their discounted present value of payoffs. The model also addresses the complexity of externalities, by separating hospitals at different adoption levels.

My model builds on the theoretical framework developed by Ericson and Pakes (1995). The active hospitals in each HSA market include non-adopters and level 1 adopters. Each period they make adoption decisions: Non-adopters decide whether to adopt EMR, and which level to adopt, while level 1 adopters may choose to upgrade to level 2. The hospitals are forward looking, and make adoption decisions so as to maximize the present discounted value of their expected stream of profits. Time is discrete and infinite. Each decision period is one year.

I estimate this dynamic structural model using a panel of U.S. hospitals' EMR adoption decisions from 1997 to 2009. I recover revenue and cost parameters for different adoption levels by applying the methods developed by Bajari, Benkard and Levin (2007) (BBL), and Pakes, Ostrovsky and Berry (2007) (POB), which provide a two-step algorithm for estimating dynamic games, under the assumption that the behavior is consistent with Markov perfect equilibrium. In the first stage of the estimation, I apply a set of flexible reduced-form regressions to recover the hospitals' policy functions and the transition between the states. For example, I use multinomial logit regression to capture non-adopters' decisions. I regress non-adopters' adoption choices on a set of variables which might affect the adoption decisions, including the number of level 1 adopters, level 2 adopters, total number of hospitals, market and hospital characteristics, time trend. I assume that exogenous market-level characteristics follow a first-order autoregressive process and use OLS to examine the evolution of exogenous variables. In the second stage of the estimation, I use forward simulation to compute the value functions conditional on action, and the probabilities of actions predicted by the model. By applying moments method to fit the probabilities of actions predicted from the model to the real data, I recover the parameters for the revenue and cost functions.

The primary result is the presence of both competition and complementation in this adoption. The adoption of the basic level has a complementary effect that can stimulate the neighboring hospitals' adoption, while the adoption of the advanced level has a competitive effect that would deter the others' adoption. After the recovery of estimates for the underlying primitives, I perform some counterfactual experiments. I solve the Markov Perfect Nash Equilibrium (MPNE) and compute the Bellman value functions, as well as the probabilities of choices in various states, using Pakes and McGuire (1994, 2001) algorithm.

Affected by the complementary effect of the first level adoption, and the competitive effect of higher-level adoption, the adoption probabilities vary across states. Using these probabilities, I then simulate the adoption behaviors in monopoly and duopoly markets. By comparing the different adoption behaviors in monopoly and duopoly markets, I find that network effects and strategic interactions are important in the duopoly market. The probability of adoption depends greatly on the other hospital's adoption level. Hospitals may preempt in the adoption game of higher-level EMR in order to deter the other's adoption. Non-adopters adopt EMR earlier in the monopoly markets than in the duopoly market.

I then perform a policy experiment to examine the effect of the government's incentive programs for EMR adoption. High entry costs are always big barrier to EMR adoption. To stimulate adoption, the federal government established "The Medicare and Medicaid EMR/EHR Incentive Programs" in 2009, which provide incentives to EMR adoption. Eligible professionals can receive up to \$44,000 through the Medicare program and up to \$63,750 through the Medicaid program, and eligible hospitals can receive incentive payments totaling some \$2 million or more. This formula is part of Health Information Technology for Economic and Clinical Health (HITECH) Act, which is part of the American Recovery and Reinvestment Act (ARRA). My policy experiment examines the effect of a 5% cost reduction and finds it would greatly stimulate adoption. It could accelerate a large hospital's adoption of higher-level EMR by nearly half a year, and a small hospital's adoption by nearly 5 years. Therefore this incentive program has huge effects and this effect varies across hospitals. This result has policy implications including how to optimally allocate the incentive package. The counterfactual experiments can be extended to examine a larger state space or study other relevant policies.

The remainder of the paper is structured as follows. Section 2.2 describes the relevant literature, Section 2.3 describes the data that I use. Section 2.4 talks about the dynamic structural model that I develop, and Section 2.5 explains the estimation method. Section 2.6 presents and interprets the empirical results. Section 2.7 describes the counterfactual experiments and Section 2.8 concludes this chapter.

## 2.2 Literature Review

My research contributes to the existing literature in several ways. First, It builds on the literature on entry models. It is developed by Bresnahan and Reiss (1990, 1991) , Berry (1992), and Mazzeo (2002). These authors model the entry or quality choice by examining a discrete game played among potential entrants. Seim (2006) studies a static game of entry with endogenous product-type choices, in which differentiated products have non-uniform competitive effects. She assumes that the firms receive private profit shocks each period. Schmidt-Dengler (2006) studies the adoption of nuclear magnetic resonance imaging (MRI) technology. MRI is a competitive technology, in the way that the benefits of adoption decline over the number of adopters. He considers a dynamic complete information game, to examine the strategic interaction of hospitals. Augereau, Greenstein and Rysman (2006) study the adoption of 56K modems by internet service providers (ISPs), and analyze the role of competition.

There is also a growing literature that studies the estimation of dynamic models. These studies include Rust (1987), Hotz and Miller (1993), Hotz, Miller, Sanders and Smith (1994), Bajari, Benkard and Levin (2007), Pakes, Ostrovsky and Berry (2007), Schmidt-Dengler (2006), and Aguirregabiria and Mira (2007). Previous papers that apply these methods include Ryan (2011) and Collard-Wexler (2010). In my study, I follow the method proposed by Bajari, Benkard and Levin (2007), which provides a two-step algorithm for estimating dynamic games. The first stage aims to estimate the policy functions and law of state transitions. Using the first-stage results, the structural parameters are recovered from simulating value functions and imposing optimality conditions for equilibrium in the second stage. I use method of moments in the second stage, which is similar to Pakes, Ostrovsky and Berry (2007).

This paper also adds to the literature of network effects. Saloner and Shepard (1995) show that network effects will stimulate the adoption of a network technology, by examining the banks' adoption of automated teller machines. Rysman (2004) shows the presence of positive network effects in the Yellow Pages market and examines the welfare trade-off between competition and standardization. Gowrisankaran and Stavins (2004) develop various methods to analyze the network externalities for the automated clearinghouse (ACH) electronic payments system and find that the network externalities are large. Farrell and Klemperer (2007) provide a comprehensive analysis of switching costs and network effects. Tucker (2008) examines what user characteristics confer the greatest network benefits by analyzing the adoption of video-messaging technology in an investment bank.

This study contributes to a growing literature about health IT adoption as well. Miller and Tucker (2009) examine the presence of network benefits form EMR adoption. They present evidence that due to the suppression of network effects, state privacy protection regulation may inhibit adoption. However, they discuss only the basic EMR application, which underlies other potential add-ins including data repository and order entry. The hospitals are not forward looking, thus they do not interact strategically in their study. Lee, McCullough and Town (2013) find no evidence of network externalities from health IT. They measure the health IT comprehensively, without treating each level differently. Angst, Agarwal, Sambamurthy and Kelley (2010) study the EMR diffusion from the perspective of social contagion. By fitting a heterogeneous diffusion model, they show social contagion effects would accelerate the diffusion of EMR. Previous work on health IT adoption also includes Simon et al. (2006) and Kazley and Ozcan (2007). However, mine is the first paper, to my knowledge, that identifies the adoption patterns for different adoption levels by developing and estimating a dynamic structural model.

## 2.3 Data

My primary data are 2009 EMR adoption data from HIMSS (Healthcare Information and Management Systems Society), which are the same data as I used in the first chapter. More details about the data can be found in the first chapter (section 1.3). They contain adoption status and timing information, as well as some hospital characteristics, such as whether it is a general, or academic hospital, and the number of staffed beds.

This dataset provides the adoption time of various EMR applications. I observe the adoption about some common and typical EMR applications, such as Clinical Data Repository, Computerized Practitioner Order Entry. I divided these observed applications into two levels, based on the EMR Adoption Model from the HIMSS Analytics Database. More details about this model can be found in section 1.3. The first level contains basic and simple applications, which can be used to store, organize and retrieve patients' information. These EMR applications include Enterprise EMR, Clinical Data Repository, and Clinical Decision Support. The second level consists of more advanced and sophisticated applications, which improve the health service quality by presenting medical history, recommending drugs, and helping the health care providers to make better decisions. These applications are Computerized Practitioner Order Entry and Physician Documentation. A hospital is a level 1 adopter if it has only adopted the first level of EMR applications, and a hospital is considered as a level 2 adopter if it has already installed both levels' applications.

The market is defined according to the HSA (Health Service Area) measure, which is developed by Makuc et al. (1991). HSA is a geographic region that is self-contained with respect to health care service. It usually consists of 3-4 counties. I apply this market measure to the HIMSS adoption data, and get 712 HSA markets. The markets in my data cover about 88.8% of the HSA markets in the entire U.S.

I also use 2009 data of Area Resource Files (ARF) to capture market-level characteristics. Area Resource Files (ARF) provide county-level information on demographic, environmental and health resource variables. Some sources include the American Hospital Association and the U.S. Census Bureau. I draw the information about population, as well as the number of people who are eligible for Medicare from this dataset, aggregate them into HSA-level and merge this information with the adoption data. The population variable is used to approximate the total demand in the market. The effect of the Medicare program on EMR adoption is of great interest. On the one side, Medicare programs typically pay hospitals a flat fee per hospital case, with a different per-case price for each distinct diagnostically related case. This payment scheme will stimulate adoption in the sense that hospitals would like to avoid expensive duplicate tests. On the other side, this might deter adoption because of the high initial cost of EMR adoption.

As a result, I create a panel data covering 3112 hospitals' adoption decisions from 1997 to 2009. The focus of the chapter is how hospitals make adoption decisions, so let's take a look at the hazard rates. Table 2.3 shows the hazard rates for hospitals at different adoption levels. In the first figure, the hazard rate is the ratio of the number of non-adopters that adopt level 1, to the total number of non-adopters each year. This rate is steady over time, around 6%. The second and third figures show the hazard rates of non-adopters that adopt level 2, and level 1 adopters that upgrade to level 2, respectively. There is an adoption peak around 2004.

## 2.4 Model

I develop a dynamic structural model, capturing the external effects yielded by each adoption level. My model builts on the theoretical framework developed by Ericson and Pakes (1995). The active hospitals in each HSA market include non-adopters and level 1 adopters. Each period they make adoption decisions: Non-adopters decide whether to adopt EMR, and which level to adopt, while level 1 adopters may choose to upgrade to level 2. The hospitals are forward looking, and make adoption decisions so as to maximize the present discounted value of their expected stream of profits. Time is discrete and infinite. Each decision period is one year.

### 2.4.1 State Variables

The state $s_{it}$[1] for hospital $i$ in market $j$ at time $t$, is captured by the following variables

$$s_{it} = \{x_{it}, \epsilon_{it}\} \tag{2.1}$$

$$x_{it} = \{n_{1jt}, n_{2jt}, n_j, z_{jt}, f_i\} \tag{2.2}$$

---

[1] For simplicity, I use $s_{it}$ to denote the state for hospital $i$ in market $j$ at time $t$, instead of $s_{ijt}$.

where $x_{it}$ is the observed state, and $\epsilon_{it}$ is the unobserved state. The variable $n_{1jt}$ denotes the number of level 1 adopters, the variable $n_{2jt}$ denotes the number of level 2 adopters in market $j$ at time $t$, and the variable $n_j$ denotes the number of total hospitals in market $j$, which is constant over time. The reason to include both $n_{1jt}$ and $n_{2jt}$ is to separately quantify the different external effects. Let $z_{jt} = \{Pop_{jt}, Med_{jt}\}$ denote exogenous market characteristics, where $Pop_{jt}$ is the population in market $j$ at time $t$ and $Med_{jt}$ denotes the number of people who are eligible for Medicare in market $j$ at time $t$. Let $f_i = \{Academic_i, General_i, Beds_i\}$ capture hospital $i$'s characteristics, where $Academic_i$ is the indicator of whether it is an academic hospital, $General_i$ indicates whether it is a general hospital, and $Beds_i$ denotes the number of staffed beds in hospital $i$. These characteristics are constant over time and are not affected by the adoption decisions (the adoption of EMR is considered as a relatively small decision, and will not affect these hospital characteristics). The unobserved vector $\epsilon_{it}$ is the private profit shock, which is an idiosyncratic type I extreme value term, distributed i.i.d. The vector $\epsilon_{it}$ includes private profit shocks associated with each action that hospital $i$ might take at time $t$.

### 2.4.2 Adoption Level and Action

Let $L$ denote the adoption level: a non-adopter is at level $L = 0$, a level 1 hospital is at level $L = 1$ , and a level 2 hospital is at level $L = 2$. Non-adopters and level 1 adopters are the active hospitals in the market. The action for active hospitals is denoted by $a$. Non-adopters make decisions about whether to adopt and which level to adopt. Let $a = 0$ denote the action of not adopting, $a = 1$ denote the action of adopting the first level and becoming level 1 adopters, and $a = 2$ denote the decision of adopting both levels and becoming level 2 adopters. Level 1 adopters make decisions about whether to upgrade to level 2. Let $a = 1$ denote the action of not upgrading, and $a = 2$ denote the action of upgrading to level 2 and becoming level 2 adopters.

### 2.4.3 Revenue and Cost Function

Let $R_L(s|\gamma)$ denote the per-period revenue function for a hospital at level $L$ ($L = 0, 1, 2$) and in state $s$. The revenue functions are linear in $s$, and the revenue of not adopting is normalized to 0. Specifically,

$$R_L(s_{it}|\gamma) = 0 \qquad (L = 0) \tag{2.3}$$

$$R_L(s_{it}|\gamma) = \gamma_L x_{it} \qquad (L = 1, 2) \tag{2.4}$$

where $x_{it} = \{n_{1jt}, n_{2jt}, n_j, z_{jt}, f_i\}$ and $\gamma_L$ is the vector of parameters. The revenue functions depend on hospital $i$'s own characteristics and market-level characteristics. The externalities of adoption are captured by $n_{1jt}, n_{2jt}, n_j$. Previous evidences show that academic and general hospitals are more likely to adopt. The revenue of adoption is expected to increase over the size of the hospital. Because there are a large amount of non-profit and government-owned hospitals in the U.S., which make a lot of efforts to improve quality, the revenue functions for these hospitals can be considered as the total gains from quality and sales.

The cost structure includes fixed costs and variable costs. Non-adopters ($L = 0$) incur

$$C^a_L(s_i|c) = 0 \qquad (a = 0, \quad L = 0) \tag{2.5}$$

$$C^a_L(s_i|c) = c^a_L + c_B Beds_i \qquad (a = 1, 2, \quad L = 0) \tag{2.6}$$

Similarly, level 1 adopters' cost to upgrade to level 2 is denoted by $C^2_1(s_i|c)$. No cost is incurred when level 1 adopters stay at level 1. Specifically

$$C^a_L(s_i|c) = 0 \qquad (a = 1, \quad L = 1) \tag{2.7}$$

$$C^a_L(s_i|c) = c^a_L + c_B Beds_i \qquad (a = 2, \quad L = 1) \tag{2.8}$$

In the above cost functions, the variables $c_0^1, c_0^2$ and $c_1^2$, capture the fixed costs of adoption. These fixed costs are different for adopting only level 1, adopting level 2, and upgrading from level 1 to level 2. Let $c_B Beds$ denote the variable cost, where $Beds$ is the number of staffed beds in the hospital. The parameter $c_B$ is assumed to be the same across different cost functions. This variable cost is used to capture the effects of the hospital size on costs, since the cost of EMR is expected to increase with hospital size. The typical EMR adoption costs include the installation, training, and maintenance. I assume hospitals incur no annual operational cost, once they pay the installation cost. The cost information is not publicly available.Miller and Tucker (2009) show the annual costs of a hospital with 181 beds are around \$3,188,496.

In addition, each period the active hospital has an *i.i.d.* private profit shock $\epsilon_L^a$, which is associated with actions. The vector of parameters to be estimated is

$\theta = (\gamma_1, \gamma_2, c_0^1, c_0^2, c_1^2, c_B)$.

### 2.4.4 Timing of the Game

In the adoption game, active hospitals play as follows:

1. At the beginning of each period $t$, hospital $i$ observes the current state $s_{it}$ .

2. Non-adopters decide on whether to adopt, and which level to adopt. Level 1 adopters choose to stay at level 1 or upgrade to level 2. The adoption is irreversible.

3. After all these decisions are made, hospitals incur cost if they decide to adopt or upgrade. They receive revenue based on the level at the beginning of each period. Adoption affects revenue in the next period.

4. Markets evolve to the next period.

### 2.4.5 Equilibrium

In each period, hospitals make adoption decisions to maximize the expected present discounted value of its profits, given the strategies of the others. When making decisions, they only consider the current state and their private shocks.

Hospital $i$'s strategy at $t$: $\sigma_{it}$, is a mapping from state vectors to actions:

$$\sigma_{it} : s_{it} \rightarrow a_{it}$$

The value function for a hospital at adoption level $L$ ($L = 0, 1, 2$ ) and in state $s$, is denoted by $V_L(s)$. The Bellman equations are as follows:

$$V_0(s) = \max_{a \in \{0,1,2\}} \left\{ \beta E \left[ V_a(s')|s \right] + \epsilon_0^a - C_0^a(s) \right\} \tag{2.9}$$

$$V_1(s) = R_1(s) + \max_{a \in \{1,2\}} \left\{ \beta E \left[ V_a(s')|s \right] + \epsilon_1^a - C_1^a(s) \right\} \tag{2.10}$$

$$V_2(s) = R_2(s) + \beta E \left[ V_2(s')|s \right] \tag{2.11}$$

Non-adopters maximize their profits by choosing whether to adopt, and which level to adopt, while level 1 adopters choose whether to upgrade. Level 2 adopters are assumed inactive, as I do not model a higher level in this paper and the adoption process is considered irreversible.

The equilibrium is a Markov Perfect Nash Equilibrium, which is defined as the strategy $\sigma*$ that satisfies:

$$V(s|\sigma*_i, \sigma*_{-i}) \geq V(s|\sigma'_i, \sigma*_{-i})$$

$for$ any $\sigma_i'$ , and any $s$ .

## 2.5 Estimation

For the estimation, I apply the method based on Bajari, Benkard, and Levin (2007), which provides a two-step algorithm for estimating dynamic games under the assumption that the behavior is consistent with Markov perfect equilibrium. In the first stage, I recover the policy functions for the state variables. In the equilibrium actually played in the data, the agents are assumed to have correct beliefs about the environment as well as the other players' behaviors. These beliefs are captured by flexible reduced-form regressions. In the second stage, the structural parameters are estimated by imposing the optimality conditions. The forward-looking agents choose their actions by maximizing the expected discounted present value of the profits, given their beliefs in the equilibrium. I apply the method of forward simulation to obtain the value functions conditional on different actions, then the probabilities of each action, and as in BBL, I don't have to compute the equilibrium even once, since the policy functions are estimated from the data. The structural parameters are recovered by maximizing the predicted probabilities of the observed actions, which is similar to the moments method in Pakes, Ostrovsky, and Berry (2007).

### 2.5.1 The First Step: Transitions Between States

The first step aims to examine the policy functions and the evolution of states. The state variables next period are functions of the current state. Hospitals make adoption decisions based on the current state they face. The decision-making process and state transitions are characterized by different specifications of reduced-form regressions.

#### Adoption Decisions for Hospitals

Active hospitals include level 1 adopters and non-adopters. Level 1 adopters make decisions about whether to upgrade to level 2. I estimate this policy function by a logit regression as follows:

$$P(a_{it} = 2 | s_{it}, L = 1) = \phi\left(\lambda_0 + \lambda_H H_{1it}\right) \tag{2.12}$$

where $\phi(\cdot)$ is the cumulative distribution function of the standard logistic distribution, and $a_{it} = 2$ means that the hospital upgrades to level 2. The vector $H_{1it}$ consists of a set of variables which might affect the adoption decision, including the number of level 1 adopters, level 2 adopters, total number of hospitals, market and hospital characteristics, time trend, and region fixed effects. I experiment with several specifications of this logistic regression, trying to control the covariates that may affect the decision.

Non-adopters make decisions about whether to adopt and which level to adopt. I use multinomial logistic regression to capture their decisions. Taking the choice of not adopting as the baseline response, I regress hospitals' adoption choices on $H_{0it}$, where $H_{0it}$ is a set of variables which might affect the adoption decisions, such as the number of level 1 adopters, level 2 adopters, total number of hospitals, market and hospital characteristics, time trend, etc. In order to make this policy function more flexible, various specifications will be examined and compared.

#### Evolution of Market Variables

In this part, I examine the probability distributions determining the evolution of the relevant market variables. The exogenous market-level profit shifters $z = \{Pop, Med\}$: population and number of people who are eligible for Medicare in the market, are assumed to follow a first-order autoregressive process AR(1) as below:

$$z_{t+1} = \mu_0 + \mu_1 z_t + \omega_t \tag{2.13}$$

where $\omega_t$ is a shock following a normal distribution, i.e., $\omega_t \sim N(0, \sigma^{\mu})$.

### 2.5.2 The Second Step: Recovering Structural Parameters

The first step recovers policy functions that describe the law of motion for states. The second step finds parameters that rationalize these observed policy functions, as the optimal actions.

One benefit of the BBL method is that it significantly reduces the computational burden. Since the revenue and cost functions are linear in all parameters, so are the value functions. This avoids computing the value functions many times for different sets of parameters. I apply forward simulation to get the value functions only once to estimate the parameters.

The per-period profit function for hospital $i$ at level $L$ and time $t$ is:

$$
\begin{aligned}
\pi_L(s_{it}, \sigma_i(s)|\theta) &= R_L(s_{it}|\theta) - \sum_{a\in\{0,1,2\}} \Big\{ 1(a, L=0) \left[ C_0^a(s_{it}|\theta) - \epsilon_0^a \right] \Big\} \\
&\quad - \sum_{a\in\{1,2\}} \Big\{ 1(a, L=1) \left[ C_1^a(s_{it}|\theta) - \epsilon_1^a \right] \Big\}
\end{aligned} \tag{2.14}
$$

where the indicator function $1(a, L = 0)$ indicates that the non-adopter takes the action $a$ ($a = 0, 1\, or\, 2$), and $1(a, L = 1)$ indicates that a level 1 adopter takes action $a$ ($a = 1, 2$).

The value function conditional on action is the expected discounted present value of all future payoffs:

$$
E\Big( \sum_{\tau=0}^{\infty} \beta^{\tau} \pi_{it+\tau} | s_{it}, \sigma_i, \sigma_{-i} \Big) \tag{2.15}
$$

### 2.5.3 Simulation

I use forward simulation to obtain the value functions. I then apply the Method of Simulated Moments to get the estimates.

For each state $s_{it}$, I simulate the paths of play for every action hospital $i$ might take. States evolve according to the reduced-form policy function in the first step. The future path of play is simulated for a long period (200 periods), until the discounted present value of profits is sufficiently small (the annual discount factor is set to 0.95). I then get the discounted present value of all the payoffs associated with each path of play. The probability of each action is recovered by using the aggregation properties of the extreme value distribution of private shock. The estimates are recovered by maximizing the probabilities of the observed action.

Each period there are two types of active hospitals: non-adopters and level 1 adopters. First I will illustrate the case for non-adopters.

In every period, non-adopter $i$ chooses from “Not Adopt" ($a = 0$), “Adopt level 1" ($a = 1$), and “Adopt level 2" ($a = 2$). I generate three paths of play for each action hospital $i$ might take. The transition of states depends on the policy function estimated in the first step, including the market’s characteristics, other firms’adoption decisions, etc. The length of each path of play is 200 periods. Since all the revenue functions and cost functions are linear in the parameters to be estimated, the value functions conditional on actions can be written as the inner product of the discounted value of the state vector and the vector of parameters:

$$V(s_{it}|a_{it},\theta) = D(s_{it}|a_{it})\theta' \tag{2.16}$$

where $D$ is the expected discounted present value of state vectors.[2]

Three conditional value functions are generated through the above procedure: $V(s_{it}|a_{it} = 0,\theta)$, $V(s_{it}|a_{it} = 1,\theta)$, and $V(s_{it}|a_{it} = 2,\theta)$, which respectively denote the value functions associated with Not Adopt ($a_{it} = 0$), Adopt level 1 ($a_{it} = 1$), and Adopt level 2 ($a_{it} = 2$). I then recover the probabilities of each action predicted by the model: $\widehat{p}_{L=0}(a_{it} = 0|s_{it},\theta)$, $\widehat{p}_{L=0}(a_{it} = 1|s_{it},\theta)$ as well as $\widehat{p}_{L=0}(a_{it} = 2|s_{it},\theta)$.

$$\begin{aligned}\widehat{p}_{L=0}(a_{it} &= k|s_{it},\theta) \\ &= \frac{\exp\left(V(s_{it}|a_{it}=k,\theta)\right)}{\exp\left(V(s_{it}|a_{it}=0,\theta)\right)+\exp\left(V(s_{it}|a_{it}=1,\theta)\right)+\exp\left(V(s_{it}|a_{it}=2,\theta)\right)} \\ & \qquad k = 0,1,2 \end{aligned} \tag{2.17}$$

Similarly, I simulate the value functions conditional on action for each level 1 adopter. Level 1 adopters make decisions about whether to upgrade to level 2. In this case, level 1 adopters stay at level 1 when $a = 1$, and upgrade to level 2 when $a = 2$. The paths of play are generated for each action, and the value functions are recovered. The probabilities of each action predicted by the model are:

$$\widehat{p}_{L=1}(a_{it} = k|s_{it},\theta) = \frac{\exp\left(V(s_{it}|a_{it}=k,\theta)\right)}{\exp\left(V(s_{it}|a_{it}=1,\theta)\right)+\exp\left(V(s_{it}|a_{it}=2,\theta)\right)}, \qquad k = 1,2 \tag{2.18}$$

---

[2] Note that $D$ inclues the expected discounted present value of the private shock $\epsilon$ as well.

After the probabilities of each decision predicted by the model are generated, I develop the moment conditions by maximizing the model's probabilities of the actions actually taken by the hospital in the data. This method is intended to make the probabilities of each action from the model as close as possible to the probabilities observed in the data. Because hospitals are assumed to act optimally in the data, they take the action that brings the most value.

Specifically, for hospital $i$ taking action $k_{it}$ , the moment condition is:

$$E\Big[\Big(1-\hat{p}(a_{it}=k_{it})\Big)\cdot Z_{it}\Big]=0 \tag{2.19}$$

where $k_{it}$ is the observed actions by hospitals in the data and $Z_{it}$ is a vector of exogenous variables, which contain hospital and market characteristics, time fixed effects, etc. These variables are not affected by adoption decisions and are considered uncorrelated to the prediction errors $1-\hat{p}(a_{it}=k_{it})$.

A GMM criterion function is specified as

$$G(\theta)=\Big(1-\hat{p}(a=k)\Big)\cdot Z \tag{2.20}$$

$$\hat{\theta}=\arg\min_{\theta} G(\theta)'WG(\theta) \tag{2.21}$$

where $W$ is a weighting matrix.

## 2.6 Empirical Results

### 2.6.1 First-Stage Regressions

The first-stage results are reported in Tables 2.1 and 2.2.

Table 2.1 presents the adoption policy results for non-adopters. I use several specifications of a multinomial logistic regression to capture the adoption decisions for non-adopters. Specification I regresses the decisions (Not Adopt, Adopt level 1 or Adopt level 2) on the number of level 1 adopters, the number of level 2 adopters, market and hospital characteristics, and a time trend. Specification II is the same as Specification I, but without the region fixed effects. My variables of interest are "number of level 1 adopters" and "number of level 2 adopters," which capture the external effects of adoption. The coefficient on number of level 1 adopters is positive and significant, showing the presence of a complementary effect. The coefficient on number of level 2 adopters is negative and significant, indicating that the advanced EMR adoption has a competitive effect. To put these estimates in context in these specifications, increasing one level 1 adopter in the HSA market would increase the odds ratio of adopting level 1 to not adopting, by 3% (Specification II), while increasing one level 2 adopter in the HSA market is expected to decrease the odds ratio of adopting level 2 to not adopting, by 2.64% (Specification I). Note "the number of hospitals in the market" is negative and significant, which might also indicate the competitive effects of EMR technology.

The adoption policy results for level 1 adopters are reported in Table 2.2. Specifications I and II regress the choices on variables of primary interest, and other covariates, with and without region fixed effects. The coefficient on number of level 1 adopters is still positive and significant in both regressions, indicating that the upgrade decision is stimulated by the neighboring hospitals' adoption of level 1 EMR.

In Specifications III and IV, I add some higher terms of number of level 1 adopters, number of level 2 adopters, and their interaction. The results are similar, and the estimates for these variables of interest are still significant, capturing different network effects. I will use Specification I in the structural model estimation, as it successfully captures the external effects.

### 2.6.2 Structural Parameters

By maximizing the predicted probabilities of the observed action, I get the structural parameters, which are reported in Tables 2.3 and 2.4. I find the presence of both complementary and competitive effects in the adoption.

From the revenue parameters of level 1 and level 2 in Table 2.3, I find a positive and significant effect of number of level 1 adopters, indicating the presence of positive network effects of level 1 EMR adoption. The level 1 installation base in the HSA market will stimulate the adoption of both level 1 and level 2 EMR technology. It is consistent with previous studies that show the positive externalities of EMR adoption. I find such positive network effects are mainly caused by level 1 adoption. Note that this complementary effect is stronger for the level 2 adoption, which makes sense since hospitals that installed the advanced technology can make better use of the applications that generate positive externalities.

The payoffs of level 1 and level 2 both decline significantly with the number of level 2 adopters as well as the total number of hospitals, and these competitive effects are slightly stronger for level 2 adoption. This finding suggests there are negative externalities of EMR adoption as well. The adoption would be deterred if the neighboring hospitals install level 2. If other hospitals adopt the advanced EMR, improve their qualities and thus attract more patients, then the profits of EMR adoption would decrease. This competitive effect may include both business stealing and preemption, as analyzed in Schmidt-Dengler (2006). The negative parameters of the total number of hospitals in each HSA market also indicate the presence of competitive effects of EMR adoption. One explanation might be that the total number of hospitals include level 2 adopters and potential level 2 adopters, which then causes this competitive effect.

From the estimation results, we see that academic and general hospitals are more likely to adopt EMR technology. This is consistent with previous studies. Academic hospitals are always leading in technology adoption. General hospitals can use EMR to cooperate better among all kinds of departments. A typical general hospital normally has an emergency department, which might need the patients' information immediately and urgently. The adoption of EMR in this case seems crucial. Note that larger hospitals have more incentives to adopt EMR, as EMR can promote better cooperation and yield more profits for large hospitals. The positive and significant effect of the number of people who are eligible for Medicare is also expected. Hospitals in the market with more people who are eligible for

Medicare, are more likely to adopt. This may be that the Medicare programs are usually under a prospective payment system, and the incentive to avoid duplicate tests and control costs through EMR is greater.

In my data, in a median market, an academic and general hospital with 200 staffed beds will increase its revenue by 10.4 units per period from the adoption of level 1, and 16.6 units by adopting level 2. If this hospital adopts level 2, with a discount rate of 0.95, the discounted present value of expected payoff stream would be 332 units. I use this scenario to quantify the different effects generated by level 1 and level 2 adoption. First, the presence of one more level 1 adopter in the market will increase the revenue of level 1 for this hospital by 2.6%, while the revenue of level 2 is increased by 2%, keeping other variables constant. If one non-adopter decides to adopt level 2, the revenue for level 1 will decrease by 1% and the revenue of level 2 will fall by 0.7%. If there is one level 1 adopter upgrading to level 2, this would reduce the revenue of level 1 by 1.7% and reduce the payoffs of level 2 by 2.5%.

Table 2.4 reports the cost estimation results. For the hospital in the above case, the costs of adopting level 1 are 200.34 units, while adopting level 2 costs an additional 106.7 units. If the hospital is a level 1 adopter, the upgrade costs would be 107.3 units. Note that the discounted present value of adopting level 2 for this hospital is 332 units, thus adopting level 2 will generate a profit of 24.6 units. Information about installation costs is not publicly observable.

The structural parameters show the presence of both cooperation and competition in this adoption process. I use these estimated parameters to perform the counterfactual experiments in the next section, and later discuss the strategic effects in detail.

## 2.7 Experiments

After all the structural parameters are recovered, I proceed to the counterfactual experiments using the underlying theoretical model. The main findings for the above estimation are that level 1 Installed Base has a complementary effect on neighboring adoptions, while the level 2 Installed Base has a competitive effect. The different externalities across different adoption levels are the primary interest of the counterfactual experiments. I perform two types of experiments in this paper. The first compares hospitals' different adoption behaviors in monopoly and duopoly markets. I find that network effects and strategic interactions are important in the duopoly market: the probability of adoption depends greatly on the others' adoption levels; hospitals may preempt in the adoption game of higher-level EMR in order to deter the other's adoption; non-adopters adopt EMR earlier in the monopoly markets than in the duopoly market, while level 1 adopters adopt level 2 earlier in the duopoly market. I then examine the government's incentive programs for EMR by performing a policy experiment. The primary finding is that a cost reduction would greatly stimulate the adoption of EMR.

### 2.7.1 Methods

This section describes the method used in the counterfactual experiments. I solve the equilibrium using Pakes and McGuire (1994, 2001) algorithm. The state vector is denoted by $s = \{n_1, n_2, n, z, f, \epsilon\}$, with $n_1, n_2$ changing endogenously and $z$ changing exogenously. By discretizing the continuously changing market variables $z$, as well as discrete variables $n_1, n_2, n$, I get the state space for each hospital. I then compute the Bellman functions and solve the MPNE, using the estimates of the structural model.

Specifically, let $V_0(s)$, $V_1(s)$, and $V_2(s)$ denote the value functions for non-adopters, level 1 adopters, and level 2 adopters respectively. Using the aggregation properties of the extreme value distribution of private shock $\epsilon$, the Bellman equations for these value functions can be simplified as follows:

$$\begin{aligned} V_0(s) \quad &= \ln\Bigg\{\exp\left[\beta\sum_{s'} V_0(s')Prob(s'|s)\right] \\ &+ \exp\left[-C_0^1 + \beta\sum_{s'} V_1(s')Prob(s'|s)\right] \quad + \exp\left[-C_0^2 + \beta\sum_{s'} V_2(s')Prob(s'|s)\right]\Bigg\} \end{aligned} \tag{2.22}$$

$$\begin{aligned} V_1(s) \quad &= \ln\Bigg\{\exp\Bigg[R_1(s)+\beta\sum_{s'}V_1(s')Prob(s'|s)\Bigg] \\ &+\exp\Bigg[R_1(s)-C_1^2+\beta\sum_{s'}V_2(s')Prob(s'|s)\Bigg]\Bigg\} \end{aligned} \tag{2.23}$$

$$V_2(s) = R_2(s) + \beta \cdot \sum_{s'} V_2(s')Prob(s'|s) \tag{2.24}$$

From these value functions, I get the probabilities of each decision, conditional on the adoption level and state.

$$p_{L=0}(a=k|s) = \frac{\exp\left[-C_0^a + \beta\sum_{s'}V_a(s')Prob(s'|s)\right]}{\exp\left(V_0(s)\right)} \qquad (k=0,1,2) \tag{2.25}$$

$$p_{L=1}(a=k|s) = \frac{\exp\left[R_1(s) - C_1^a + \beta\sum_{s'}V_a(s')Prob(s'|s)\right]}{\exp\left(V_1(s)\right)} \qquad (k=1,2) \tag{2.26}$$

Note that $C_0^0 = 0, C_1^1 = 0$. These choice probabilities of active hospitals are used to get the state transition $Prob(s'|s)$. I then apply a fixed-point algorithm in order to compute the value functions as well as the probabilities of each choice. The procedure is:

1. Guess a set of initial values for probabilities of each choice $p_L^0(a|s)$.

2. Use probabilities of each choice to get the state transition matrix, then plug them into Bellman equations to compute the value functions for hospitals at different adoption levels.

3. Using the computed value functions from step 2, get a new set of probabilities of each choice for the active hospitals $p_L^1(a|s)$ .

4 Repeat steps 2 and 3, until the probabilities of each choice $p_L(a|s)$ converge.

I examine the equilibrium behaviors by comparing monopoly and symmetric duopoly markets in my study. I assume these hypothetical markets all have a population of 60, 000, and 10% of them are eligible for Medicare. The hospital in my experiment is an academic, general hospital with 190 staffed beds. While I focus on the strategic interactions between homogenous hospitals and in small markets, this model can be extended to capture heterogeneous hospitals and larger markets. The market variables $z = \{Pop, Med\}$ are assumed to be constant over years. I compute the value functions and the probabilities of each choice across states. The results are presented in Table 2.5, which I will interpret in the next section..[3]

After the recovery of the probabilities of each choice in monopoly and duopoly markets, I further examine the adoption behaviors by simulation. Specifically, I simulate one monopoly market with hospital 1, one monopoly market with hospital 2 and one duopoly market with both hospitals 1 and 2 in it. Hospitals 1 and 2 are identical hospitals (they are both academic and general hospitals with 190 staffed beds), except for the private shocks which are uniformly distributed i.i.d. across hospitals, times, and simulations. The hospitals are initially nonadopters. For each simulation, I simulate hospitals' adoption behavior for 100 periods using the probabilities of adoption in Table 2.5 (each period is one year.). All the hospitals adopt level 2 during each simulation, since the time span is 100 periods long. The number of simulations is 10,000, and I then get the average adoption time. The results are reported in Table 2.6, and will be discussed in detail later.

I then perform a policy experiment that aims to examine the effects of an incentive program for EMR adoption. In 2009, the U.S. started the Medicare and Medicaid EMR/EHR Incentive Programs, which provide incentives for EMR adoption. Eligible professionals can receive up to $44,000 through the Medicare program and up to $63,750 through the Medic-

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[3] In the monopoly case, the state is constant, yielding one set of value functions: $V_0(s), V_1(s)$ and $V_2(s)$. In the symmetric duopoly market, the changing state variables are $n_1$, $n_2$, which depend on the two hospitals' adoption levels. Thus the different states are described by $(Li, L-i)$, $(Li, L-i = 0, 1, 2)$, where $Li$ denotes hospital $i$ 's adoption level, and $L-i$ denotes the other hospital's level. Thus there are 9 different states in total, depending on the hospitals' adoption stages. The value functions for hospital i are: $V_0(0,0), V_0(0,1), V_0(0,2), V_1(1,0), V_1(1,1), V_1(1,2).$,and $V_2(2,0), V_2(2,1), V_2(2,2)$.

aid program, and hospitals can receive incentive payments totaling some \$2 million or more. I perform an experiment to study the effects of a cost reduction on adoption behavior, which may offer some policy implications. I assume the costs of EMR adoption are reduced by 5% in this experiment. The method and configurations of markets are the same as the above experiments, except for the cost parameters. The results are presented in Tables 2.8 and 2.9.

### 2.7.2 Results

#### Monopoly and Duopoly Markets

In Table 2.5, I present the results of value functions, probabilities of each action, revenue and cost across states in monopoly and duopoly markets. In the duopoly market, I find that the probabilities of each action vary significantly across states. For both non-adopters and level 1 adopters, the likelihoods of adopting are much lower when the other hospital is a level 2 adopter, compared to the case when the other one is a non-adopter or level 1 adopter, which demonstrates the competitive effect of level 2 adoption. For example, if hospital $i$ is a nonadopter, its likelihood to adopt level 1 is 10% lower when the other hospital is a level 2 adopter, than when the other one is level 1 adopter. The adoption probabilities in the duopoly market might either be higher or lower than in the monopoly market, depending on the other hospital's adoption level. From the data, I observe similar adoption rates and hazard rates for monopoly and duopoly markets, which are shown in Figures 2.2 and 2.3. Failing to consider the different externalities yielded by adoption levels, may conclude the lack of strategic interactions in these markets. However, these counterfactual experiments show that these similar adoption rates might be the outcome of strategic interaction between hospitals, as the duopoly markets may be in different states.

Table 2.6 presents the simulation results of hospitals' adoption times. Note that the differences in level 2 adoption times between monopoly markets and duopoly market might indicate the presence of preemption. Because of the competitive effect of level 2 adoption, hospitals have the incentives to preempt, and deter other hospitals' adoptions. It takes

4.62 years for the first of the two hospitals in the duopoly market to adopt level 2, and it takes a little bit longer (4.98 years) for the first of the two hospitals in monopoly markets to adopt level 2. Then it takes 12.93 years for the last of the two hospitals in the duopoly market to adopt level 2, which is 1.43 years longer than the time in monopoly markets. To further study the preemptive effect in the adoption game of level 2, I perform another simulation by assuming hospitals are level 1 adopters initially. The results are presented in Table 2.7. The first of the two hospitals in the duopoly market adopts level 2 EMR about half a year earlier than the first of the two hospitals in monopoly markets. As a result of this preemption, it takes a little bit longer for the last of the two hospitals in the duopoly market to adopt level 2. Therefore the preemptive effect is present in the duopoly market.

Another evidence for strategic interaction in Table 2.6 is that it takes 2.32 years for the first of the two non-adopters in monopoly markets to adopt level 1, and 2.51 years for the first of the two non-adopters in the duopoly market to adopt level 1. It takes a little bit longer in the duopoly market to first adopt level 1. In addition, It takes 8.20 and 8.27 years for the two hospitals in monopoly markets from non-adopters to level 2 adopters, while it takes about half a year longer for the hospitals in the duopoly market to finally adopt level 2. Thus nonadopters tend to adopt earlier in the monopoly markets. However, when the two hospitals are initially level 1 adopters, they tend to adopt level 2 earlier in the duopoly market, as shown in Table 2.7. It takes about 6.3 years for them in monopoly markets to adopt level 2, and about 6.2 years in the duopoly market. Although the difference is small, it shows the positive network effect of level 1 adoption.

### Policy Experiment

The high cost of EMR adoption is always a big concern for health care providers. To address this problem, federal and state governments enacted relevant regulations and laws to stimulate the adoption, including the Medicare and Medicaid EMR/EHR Incentive Programs that were started in 2009. These programs will give rewards to eligible health care providers who have installed certified EMR/EHR.

The policy experiment examined the effect of a 5% cost reduction on adoption behaviors. The results are reported in Table 2.8, which compares the simulation results from the original estimate and the case of a 5% cost reduction. The cost reduction speeds up the adoptions of both levels. It takes about one year less for the first of the hospitals in both monopoly and duopoly markets to adopt level 1, than the original case. The hospitals adopt level 2 EMR about 5 years earlier after the cost reduction. The results show the incentive program for EMR adoption will greatly boost the adoption.

However, the effects of the incentive program on adoption might vary across hospitals. I perform another experiment by examining the effects on a larger hospital. I assume this hospital is a general, academic hospital with 600 staffed beds. The results are shown in Table 2.9. This policy accelerates this hospital's adoption of level 2 by nearly half a year. Other hospitals' adoption behaviors can also be examined by this policy experiment. The result that the effects vary across hospitals may have policy implications, such as how to optimally allocate the incentive package.

To sum up, the first experiment compares the adoption behaviors in monopoly and duopoly markets, and analyzes the network effects and strategic interactions in the duopoly market. The policy experiment examines the effect of the government's incentive programs and finds their huge effects on accelerating adoption. The experiments can be extended to cover a larger market and examine other relevant policies as well.

## 2.8 Conclusion

This paper studies the multilevel adoption of Electronic Medical Record technology in U.S. hospitals, by separately examining the externalities yielded by different adoption levels. I develop a dynamic structural model to capture the strategic interactions among hospitals. Forward-looking hospitals make adoption decisions every period, by maximizing their discounted present value of expected profits. I apply the estimation method developed by Bajari, Benkard and Levin (2007) to recover the revenue and cost functions and find the presence of network effects in the adoption: there is a complementary effect of level

1 adoption and a competitive effect of level 2 adoption. The counterfactual experiments compare the monopoly and duopoly markets and demonstrate the importance of strategic interactions. I find that cooperation and competition are both present in this adoption game. A policy experiment examines the government's incentive programs and finds their huge effects. This study yields important insights into the diffusion of EMR technology and offers implications for the policy aiming to promote the nationwide adoption of EMR. This paper is the first, to my knowledge, to separate the different externalities of EMR adoption levels, by considering a multilevel adoption game and analyzing the strategic interactions in a dynamic pattern.

Figure 2.1: Hazard Rates

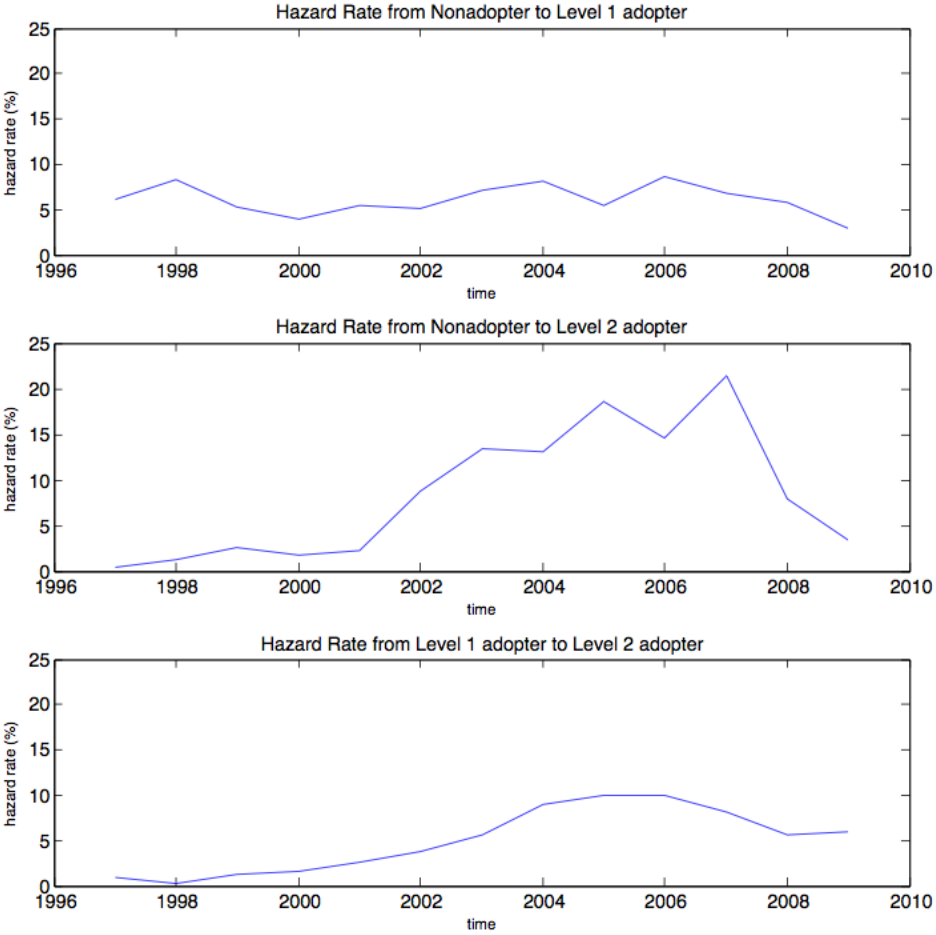


Figure 2.2: Adoption Rates for Monopoly and Duopoly Markets

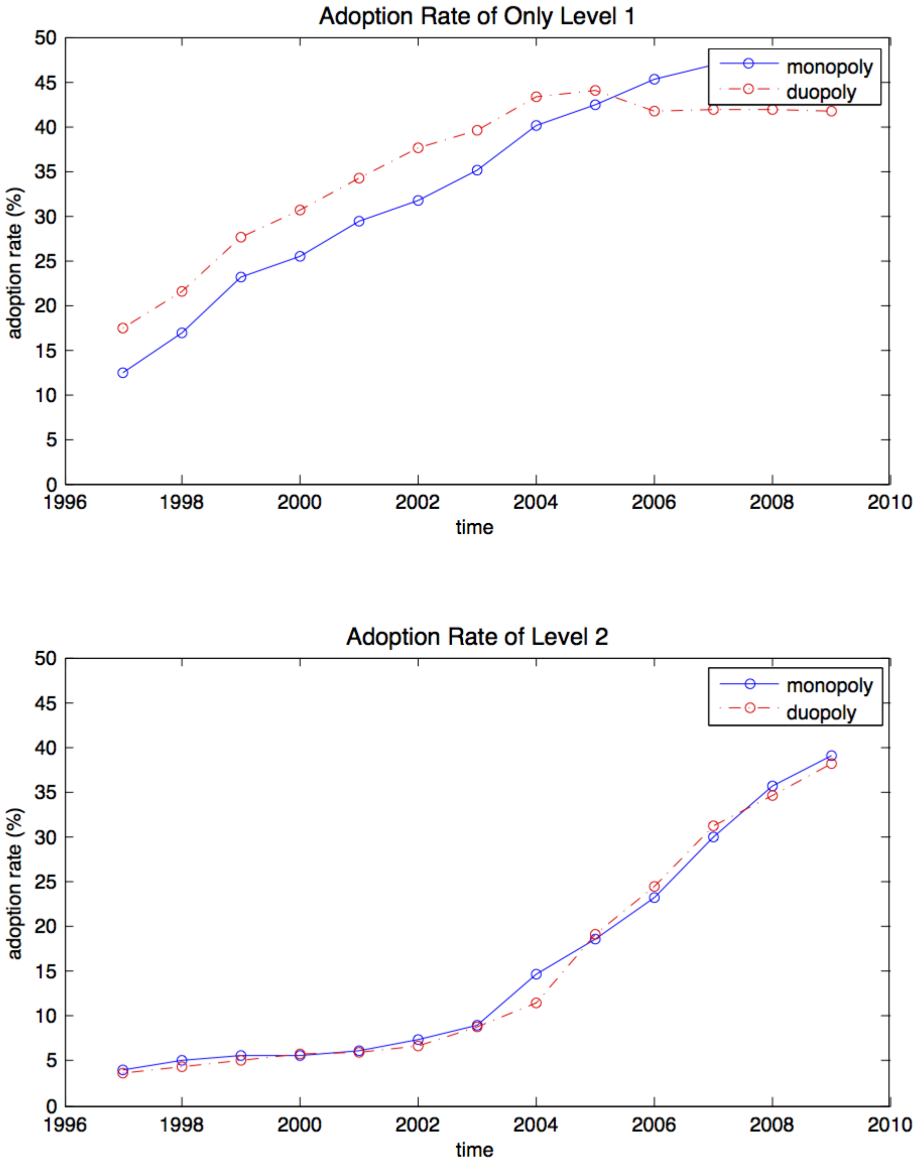


Figure 2.3: Hazard Rates for Monopoly and Duopoly Markets

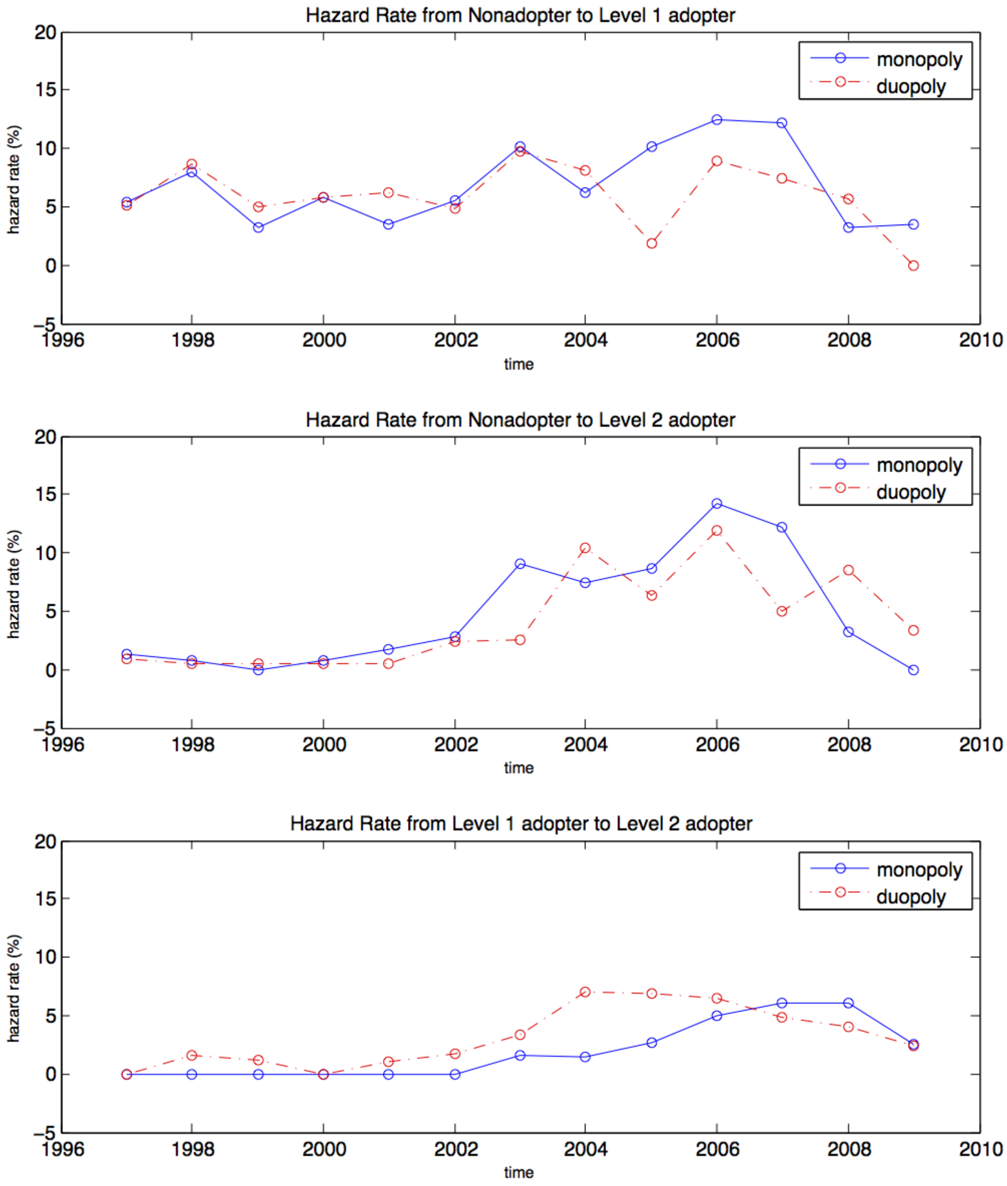
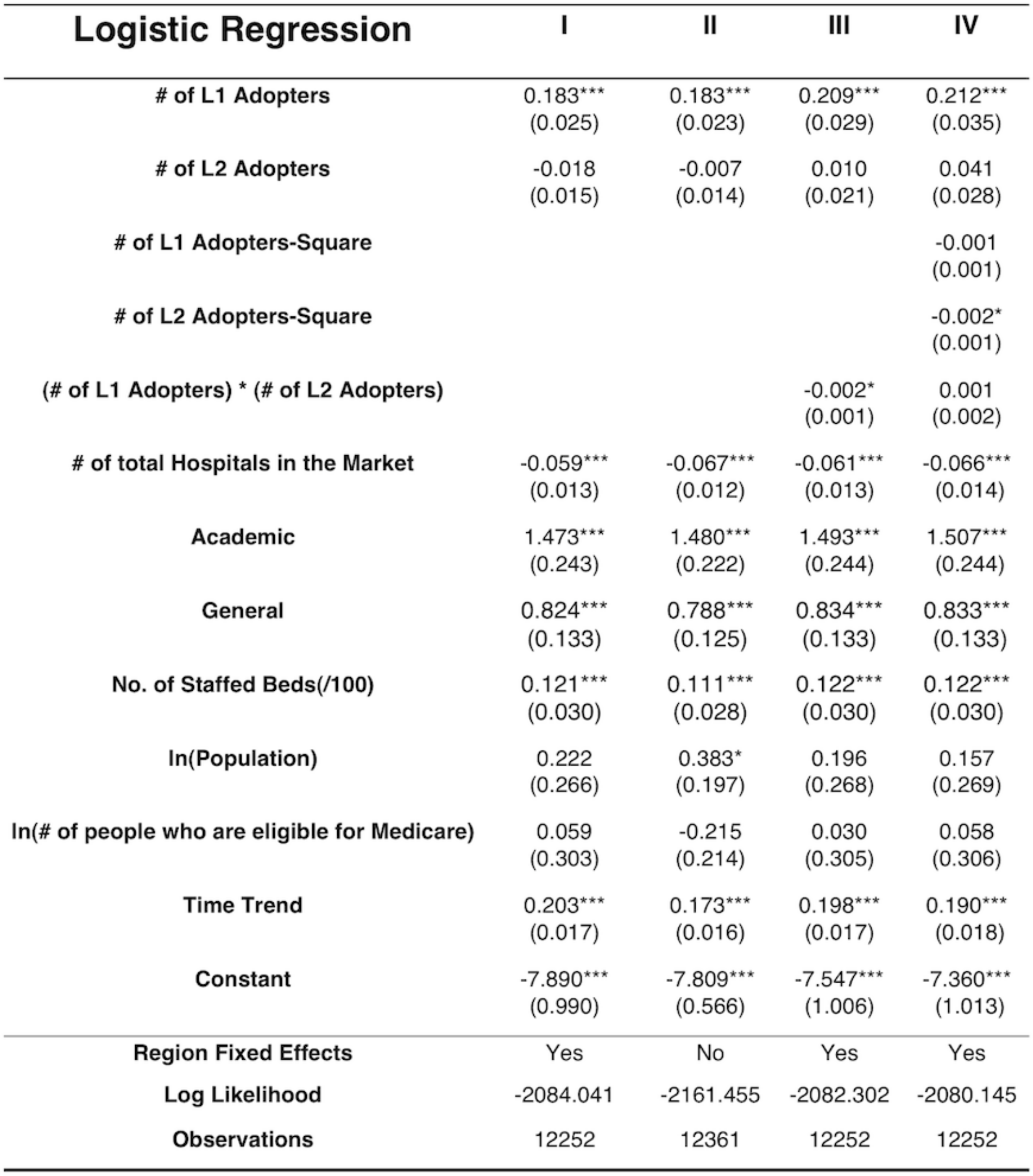


Table 2.1 : Adoption Policy Results for Non-adopters

| | **Multinomial Logistic** | **I** | **II** | **III** | **IV** |
|---|---|---|---|---|---|
| **Adopt Level 1** | **# of L1 Adopters** | 0.012 | 0.029* | 0.002 | 0.038 |
| | | (0.016) | (0.015) | (0.017) | ( 0.026) |
| | **# of L2 Adopters** | 0.013 | 0.016 | -0.007 | -0.018 |
| | | (0.012) | (0.012) | (0.019) | (0.023) |
| | **# of L1 Adopters-Square** | | | | 0.003* |
| | | | | | (0.001) |
| | **# of L2 Adopters-Square** | | | | -0.001 |
| | | | | | ( 0.001) |
| | **(# of L1 Adopters) * (# of L2 Adopters)** | | | 0.001 | 0.004* |
| | | | | (0.001) | (0.002) |
| | **# of total Hospitals in the Market** | -0.010* | -0.023*** | -0.010 | -0.008 |
| | | (0.006) | (0.005) | (0.006) | (0.006) |
| | **Academic** | -0.291 | -0.216 | -0.291 | -0.283 |
| | | (0.196) | (0.189) | (0.196) | (0.196) |
| | **General** | -0.079 | -0.005 | -0.086 | -0.080 |
| | | (0.081) | (0.0771) | (0.081) | (0.082) |
| | **No. of Staffed Beds(/100)** | 0.039 | 0.049* | 0.039 | 0.040 |
| | | (0.028) | (0.027) | (0.028) | (0.028) |
| | **ln(Population)** | -0.347 | -0.606 | -0.350 | -0.355 |
| | | (0.192) | (0.158) | (0.192) | (0.293) |
| | **ln(# of people who are eligible for Medicare)** | 0.444** | 0.773*** | 0.469** | 0.458** |
| | | (0.217) | (0.173) | (0.217) | (0.218) |
| | **Time Trend** | 0.037*** | 0.019* | 0.040*** | 0.040*** |
| | | (0.011) | (0.011) | (0.011) | (0.011) |
| | **Constant** | -3.021*** | -3.174*** | -3.152*** | -3.120*** |
| | | (0.646) | (0.335) | (0.652) | (0.653) |
| **Adopt Level 2** | **# of L1 Adopters** | 0.012 | 0.002 | 0.029 | 0.009 |
| | | (0.016) | (0.015) | (0.018) | (0.025) |
| | **# of L2 Adopters** | -0.026** | -0.009 | -0.002 | -0.043* |
| | | (0.010) | (0.010) | (0.015) | (0.022) |
| | **# of L1 Adopters-Square** | | | | 0.001 |
| | | | | | (0.001) |
| | **# of L2 Adopters-Square** | | | | -0.002*** |
| | | | | | (0.001) |
| | **(# of L1 Adopters) * (# of L2 Adopters)** | | | -0.002** | 0.001 |
| | | | | (0.001) | (0.001) |
| | **# of total Hospitals in the Market** | -0.019*** | -0.016*** | -0.019*** | -0.025*** |
| | | (0.007) | (0.006) | (0.007) | (0.007) |
| | **Academic** | 0.535*** | 0.420** | 0.538*** | 0.544*** |
| | | (0.191) | (0.181) | (0.191) | (0.192) |
| | **General** | 0.932*** | 0.768*** | 0.946*** | 0.961*** |
| | | (0.102) | (0.093) | (0.103) | (0.103) |
| | **No. of Staffed Beds(/100)** | 0.201*** | 0.221*** | 0.202*** | 0.204*** |
| | | (0.025) | (0.023) | (0.025) | (0.025) |
| | **ln(Population)** | 0.354 | -0.090 | 0.365 | 0.334 |
| | | (0.224) | (0.174) | (0.225) | (0.225) |
| | **ln(# of people who are eligible for Medicare)** | 0.026 | 0.429** | -0.031 | 0.001 |
| | | (0.254) | (0.192) | (0.256) | (0.257) |
| | **Time Trend** | 0.388*** | 0.335*** | 0.382*** | 0.374*** |
| | | (0.014) | (0.013) | (0.015) | (0.015) |
| | **Constant** | -9.677*** | -8.807*** | -9.394*** | -9.213*** |
| | | (0.779) | (0.411) | (0.792) | (0.793) |
| | **Region Fixed Effect** | Yes | No | Yes | Yes |
| | **Log Likelihood** | -7069.060 | -7239.233 | -7065.671 | -7059.081 |
| | **Observations** | 17714 | 17714 | 17714 | 17714 |

Table 2.2 : Adoption Policy Results for Level 1 Adopters



| **Logistic Regression** | **I** | **II** | **III** | **IV** |
|---|---|---|---|---|
| **# of L1 Adopters** | 0.183***<br>(0.025) | 0.183***<br>(0.023) | 0.209***<br>(0.029) | 0.212***<br>(0.035) |
| **# of L2 Adopters** | -0.018<br>(0.015) | -0.007<br>(0.014) | 0.010<br>(0.021) | 0.041<br>(0.028) |
| **# of L1 Adopters-Square** | | | | -0.001<br>(0.001) |
| **# of L2 Adopters-Square** | | | | -0.002*<br>(0.001) |
| **(# of L1 Adopters) * (# of L2 Adopters)** | | | -0.002*<br>(0.001) | 0.001<br>(0.002) |
| **# of total Hospitals in the Market** | -0.059***<br>(0.013) | -0.067***<br>(0.012) | -0.061***<br>(0.013) | -0.066***<br>(0.014) |
| **Academic** | 1.473***<br>(0.243) | 1.480***<br>(0.222) | 1.493***<br>(0.244) | 1.507***<br>(0.244) |
| **General** | 0.824***<br>(0.133) | 0.788***<br>(0.125) | 0.834***<br>(0.133) | 0.833***<br>(0.133) |
| **No. of Staffed Beds(/100)** | 0.121***<br>(0.030) | 0.111***<br>(0.028) | 0.122***<br>(0.030) | 0.122***<br>(0.030) |
| **ln(Population)** | 0.222<br>(0.266) | 0.383*<br>(0.197) | 0.196<br>(0.268) | 0.157<br>(0.269) |
| **ln(# of people who are eligible for Medicare)** | 0.059<br>(0.303) | -0.215<br>(0.214) | 0.030<br>(0.305) | 0.058<br>(0.306) |
| **Time Trend** | 0.203***<br>(0.017) | 0.173***<br>(0.016) | 0.198***<br>(0.017) | 0.190***<br>(0.018) |
| **Constant** | -7.890***<br>(0.990) | -7.809***<br>(0.566) | -7.547***<br>(1.006) | -7.360***<br>(1.013) |
| **Region Fixed Effects** | Yes | No | Yes | Yes |
| **Log Likelihood** | -2084.041 | -2161.455 | -2082.302 | -2080.145 |
| **Observations** | 12252 | 12361 | 12252 | 12252 |

Standard errors are reported in parentheses below estimate. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Table 2.3: Structural Parameters: Revenue Functions

| | **Revenue of Level 1** | **SE** | **Revenue of Level 2** | **SE** |
|---|---|---|---|---|
| **Constant** | -2.0559 | 0.7087 | 2.2405 | 0.5679 |
| **# of L1 Adopters** | 0.2679 | 0.0895 | 0.3160 | 0.1065 |
| **# of L 2 Adopters** | -0.1081 | 0.0454 | -0.1127 | 0.0196 |
| **# of Hospitals** | -0.0920 | 0.0197 | -0.1199 | 0.0228 |
| **Academic** | 0.8912 | 0.2069 | 0.8379 | 0.1847 |
| **General** | 0.7228 | 0.1790 | 0.6343 | 0.1691 |
| **ln(No. of Staffed Beds)** | 0.5968 | 0.1080 | 1.0778 | 0.3180 |
| **ln(Population)** | 0.4461 | 0.2862 | 0.1694 | 0.1040 |
| **ln(# of people who are eligible for Medicare)** | 0.3390 | 0.1397 | 0.6293 | 0.2813 |

Table 2.4: Structural Parameters: Cost Functions

| | **Constant** | **SE** | **ln(Number of Beds)** | **SE** |
|---|---|---|---|---|
| Cost of Level 1 | 198.1600 | 30.8460 | 0.4118 | 0.1126 |
| Cost of Level 2 | 305.0852 | 60.9652 | 0.4118 | 0.1126 |
| Upgrade Cost | 105.0901 | 26.7895 | 0.4118 | 0.1126 |

The three cost functions have the same parameter for ln(Number of Beds).

Table 2.5: Counterfactual Experiment

| | V0 | V1 | V2 | P(a=0\|L=0) (%) | P(a=1\|L=0) (%) | P(a=2\|L=0) (%) | P(a=0\|L=1) (%) | P(a=1\|L=1) (%) | Revenue of Level 1 | Revenue of Level 2 |
|---|---|---|---|---|---|---|---|---|---|---|
| **Monopoly** | 7.52 | 217.32 | 328.45 | 68.63 | 24.92 | 6.45 | 84.31 | 15.69 | 10.69 | 16.42 |
| **Duopoly (i's level, -i's level)** | | | | | | | | | | |
| **(0, 0)** | 4.91 | | | 70.55 | 22.6 | 6.84 | | | | |
| **(0, 1)** | 4.76 | | | 67.15 | 24.96 | 7.88 | | | | |
| **(0, 2)** | 3.82 | | | 82.59 | 14.27 | 3.14 | | | | |
| **(1, 0)** | | 214.54 | | | | | 82.13 | 17.87 | 10.60 | |
| **(1, 1)** | | 214.76 | | | | | 81.54 | 18.46 | 10.87 | |
| **(1, 2)** | | 212.84 | | | | | 86.35 | 13.65 | 10.49 | |
| **(2, 0)** | | | 325.83 | | | | | | | 16.30 |
| **(2, 1)** | | | 326.19 | | | | | | | 16.61 |
| **(2, 2)** | | | 323.80 | | | | | | | 16.19 |
| **Cost of Level 1** | 200.32 | | | | | | | | | |
| **Cost of Level 2** | 307.25 | | | | | | | | | |
| **Cost of Upgrade** | 107.25 | | | | | | | | | |

Market-level Characteristics: a population of 60,000, 10% of them are eligible for Medicare
Hospital-level Characteristics: academic, general, with 190 staffed beds.
Discount Rate 0.95
$V0$ : value function of non-adopters
$V1$ : value function of level 1 adopters
$V2$ : value function of level 2 adopters

Table 2.6: Simulation Results of Hospitals Starting from L=0

| **Adoption Time** | | **2 Monopoly Markets** | **1 Duopoly Market** |
|---|---|---|---|
| | | **(with hospital 1 and hospital 2 respectively)** | **(with both hospital 1 and hospital 2)** |
| **First to Adopt L1** | Time when the first of the two hospitals adopts level 1 | 2.32 | 2.51 |
| **First to Adopt L 2** | Time when the first of the two hospitals adopts level 2 | 4.98 | 4.62 |
| **Last to Adopt L2** | Time when the last of the two hospitals adopts level 2 | 11.49 | 12.93 |
| **L2 Adoption for hospital 1** | Time when hospital 1 adopts level 2 | 8.20 | 8.79 |
| **L2 Adoption for hospital 2** | Time when hospital 2 adopts level 2 | 8.27 | 8.76 |
| **Time Span(Years)** | | 100 | |
| **Number of Simulation** | | 10000 | |

Table 2.7: Simulation Results for Hospitals Starting from L=1

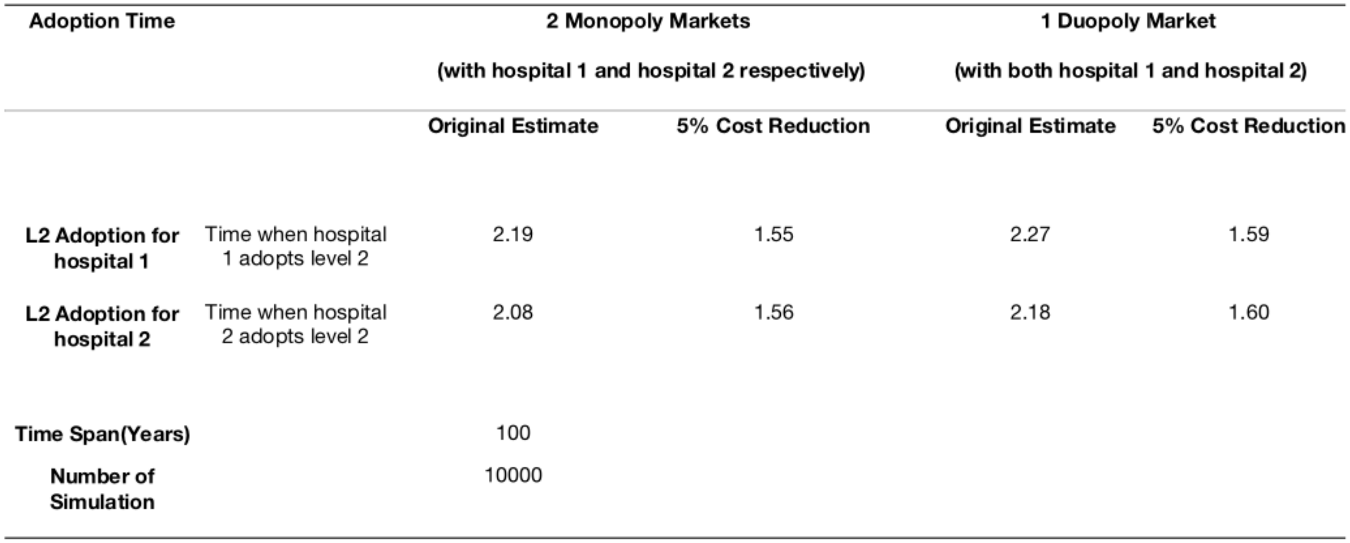
| **Adoption Time** | | **2 Monopoly Markets** | **1 Duopoly Market** |
|---|---|---|---|
| | | **(with hospital 1 and hospital 2 respectively)** | **(with both hospital 1 and hospital 2)** |
| **First to Adopt L 2** | Time when the first of the two hospitals adopts level 2 | 3.42 | 2.97 |
| **Last to Adopt L2** | Time when the last of the two hospitals adopts level 2 | 9.26 | 9.50 |
| **L2 Adoption for hospital 1** | Time when hospital 1 adopts level 2 | 6.35 | 6.21 |
| **L2 Adoption for hospital 2** | Time when hospital 2 adopts level 2 | 6.32 | 6.25 |
| **Time Span(Years)** | | 100 | |
| **Number of Simulation** | | 10000 | |

Table 2.8: Policy Experiment: 5% cost reduction

| **Adoption Time** | | **2 Monopoly Markets** | | **1 Duopoly Market** | |
|---|---|---|---|---|---|
| | | **(with hospital 1 and hospital 2 respectively)** | | **(with both hospital 1 and hospital 2)** | |
| | | **Original Estimate** | **5% Cost Reduction** | **Original Estimate** | **5% Cost Reduction** |
| **First to Adopt L1** | Time when the first of the two hospitals adopts level 1 | 2.32 | 1.35 | 2.51 | 1.39 |
| **First to Adopt L 2** | Time when the first of the two hospitals adopts level 2 | 4.98 | 2.04 | 4.62 | 2.06 |
| **Last to Adopt L2** | Time when the last of the two hospitals adopts level 2 | 11.49 | 4.64 | 12.93 | 4.89 |
| **L2 Adoption for hospital 1** | Time when hospital 1 adopts level 2 | 8.20 | 3.35 | 8.79 | 3.47 |
| **L2 Adoption for hospital 2** | Time when hospital 2 adopts level 2 | 8.27 | 3.33 | 8.76 | 3.48 |
| **Time Span(Years)** | | 100 | | | |
| **Number of Simulation** | | 10000 | | | |

Hospital-level Characteristics: academic, general, with 190 staffed beds.

Table 2.9: Policy Experiment: 5% cost reduction (a large hospital)



| **Adoption Time** | | **2 Monopoly Markets**<br>**(with hospital 1 and hospital 2 respectively)** | | **1 Duopoly Market**<br>**(with both hospital 1 and hospital 2)** | |
|---|---|---|---|---|---|
| | | **Original Estimate** | **5% Cost Reduction** | **Original Estimate** | **5% Cost Reduction** |
| **L2 Adoption for hospital 1** | Time when hospital 1 adopts level 2 | 2.19 | 1.55 | 2.27 | 1.59 |
| **L2 Adoption for hospital 2** | Time when hospital 2 adopts level 2 | 2.08 | 1.56 | 2.18 | 1.60 |
| **Time Span(Years)** | | 100 | | | |
| **Number of Simulation** | | 10000 | | | |

Hospital-level Characteristics: academic, general, with 600 staffed beds.

# Chapter 3

## Agglomeration in Certification: the Case of LEED (Leadership in Energy & Environmental Design) Certification, *with Marc Rysman*

### 3.1 Introduction

This chapter studies the adoption of LEED (Leadership in Energy & Environmental Design) certification, which is an internationally recognized building certification system that evaluates environmental impact. We focus on the study of potential strategic interactions when these buildings get certified and choose the certification level. We are interested in examining whether there is agglomeration or dispersion in certification levels, in order to study the potential presence of network effects, competitive effects or other neighborhood effects.

LEED is a third-party green building certification system developed and administered by the U.S. Green Building Council (USGBC) in 1993. It aims to measure building sustainability, including the metrics such as sustainable sites, energy savings, water efficiency, CO2 emissions reduction and improved indoor environmental quality, etc. It addresses both commercial and residential building types, working throughout the building lifecycle design and construction, operations and maintenance, and even for the neighborhood development. It is accepted in the United States and in a number of other countries around the world, encompassing more than 20,000 member organizations and 120,000 LEED accredited professionals. LEED points are awarded and credits are weighted to reflect their potential environmental impacts. The credits accrued mainly in the following categories: sustainable sites, water efficiency, energy and atmosphere, materials and resources and indoor environmental quality.

The adoption of LEED certification and green building technology can protect the environment. In addition, the adoption of LEED can also help business, in the sense that green buildings may seem attractive to buyers and tenants who prefer lower operating costs and healthier indoor environments and so on. As we can see in our dataset later, most of the buildings that registered for LEED belong to for-profit organizations. Other than the choice of getting certified, it's also important to think about which level to get. LEED offers four levels of certifications: Certified, Silver, Gold and Platinum, to indicate different standards of environmental impact. Would the buildings choose the certification level independently? If not, would the buildings agglomerate at some certain levels, or disperse across various levels within market? As a result of locally network or competitive effects, it's highly possible that the certified buildings might agglomerate at some levels, or try to differentiate from others, rather than the independent random choice would predict. On the one hand, the presence of market characteristics, network effects and socially transmitted neighborhood effects may cause the buildings to agglomerate. On the other hand, the buildings in the same market may try to compete by differentiating from each other on the certification levels, as the model of product differentiation would predict.

The data we use here covers 33,189 LEED registrations all over the world (mainly in the U.S.) from 2000 to July, 2010. We observe data including the buildings' certification levels and locations, which allow us to study the certification allocation, that is, whether buildings agglomerate or disperse on certification levels. We apply a set of methods, including simulation and Multinomial Test of Agglomeration and Dispersion (MTAD) developed by Rysman & Greenstein (2005). By the method of simulation, we observe intuitively that buildings agglomerate locally, compared to the national adoption rate. In addition, we use Multinomial Test of Agglomeration and Dispersion to further study this agglomeration. MTAD is based on the likelihood function from a multinomial distribution, which examines not only whether to reject the hypothesis of independent random choice, but also whether the data are agglomerated or dispersed. The result of MTAD is consistent with the result from simulation, which is the data are characterized by agglomeration arrangement. A further study shows that this result doesn't vary across markets with different number of certified buildings.

Section 3.2 talks about the background and the industry. Section 3.3 describes the data we use here. Section 3.4 covers the methods used here to analyze the adoption pattern, and also shows the results. Section 3.5 concludes.

## 3.2 Background

LEED (Leadership in Energy and Environmental Design) is a third-party green building certification system developed and administered by the U.S. Green Building Council (USGBC) in 1993. It aims to measure building sustainability, including the metrics such as sustainable sites, energy savings, water efficiency, CO2 emissions reduction and improved indoor environmental quality, etc. It addresses both commercial and residential building types, working throughout the building lifecycle design and construction, operations and maintenance, and even for the neighborhood development. It applies to almost all project types including healthcare facilities, schools, homes and even entire neighborhoods.

The benefits of getting LEED certification include lowering operating costs, increasing asset value, reducing waste sent to landfills, conserving energy and water, reducing harmful greenhouse gas emissions, qualifying for tax rebates and so on. LEED would also help business, in the sense that green buildings may seem attractive to buyers and tenants who prefer lower operating costs and healthier indoor environments. This gives the owners of for-profit buildings incentives to gain LEED certification, trying to attract tenants, increase the occupancy, and raise the rent.

LEED certification mainly involves the following five steps: the first step is to choose which rating system to use. The rating system almost applies to all projects types, including New Construction (NC), Existing Buildings (EB), Commercial Interiors (CI), Schools, Homes and so on; the second step is to get registered and by doing this the project will be accessible in LEED online; the next step is to submit the certification application; after the application is submitted and the review fee is paid, the review would begin but the processes differ slightly for each project type; the final step is to receive the certification decision, which can either be accepted or appealed.

How are the reveiw decisions made? Projects earn points to satisfy green building requirements. The credits accrued mainly in the following categories: sustainable sites, water efficiency, energy and atmosphere, materials and resources and indoor environmental quality. For commercial buildings and neighborhoods, to earn LEED certification, a project must satisfy all LEED prerequisites and earn a minimum 40 points on a 110-point LEED rating system scale. Homes must earn a minimum of 45 points on a 136-point scale. According to the rating system, the LEED rating system offers four certification levels - Certified, Silver, Gold and Platinum.[1]

The cost structure of LEED certification includes registration fees and certification fees. The registration fee is a flat fee paid up front at the time of registration. Certification fees vary by project size and the average cost is \$2,000.

## 3.3 Data

The dataset used in this paper is from the U.S. Green Building Council (USGBC). It covers 33,189 registrations in LEED all over the world (mainly in the U.S.) from 2000 to July, 2010. The dataset contains information about the registered buildings' registration dates, certification dates, certification levels, and buildings' characteristics including ownership types and locations.

Figure 3.1 shows the number of projects registered each year, from 2000 to 2010. There are vey few registrations in the early periods and the number starts to take off around year 2007. This fact is consistent with previous evidence about technology adoption, which is the number of adopters is a upward-convex curve in the early periods. Among these registrations, 6331 (19.08%) of them had been certified by July, 2010. However we have information about certification date only for 3113 certified projects. We compute the review

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[1] There was a "bronze" level in the original rating system, but merged with "certified" level in the later system.

time as the time span between registration date and certification date, and we find that on average, it takes two years to get the review decision after submitting the registration application.

Table 3.1 shows the ownership type of these registrations. Among the 22,161 registrations which have this information, 42% of them are for-profit projects, and 33% of them are government-owned. The high ratio of for-profit projects indicates that the great potential benefits of LEED to bring in business really motivate the for-profit organizations to get certified. Table 3.2 shows the rating systems that these registration choose. 60% of the 32,151 registrations belong to "New Construction & Major Renovations", which addresses design and construction activities for both new buildings and major renovations of existing buildings. It can be applied to offices, libraries, churches, hotels and government buildings. This fact may be explained as it is relatively less troublesome for new constructions to adopt green technology, compared to existing buildings.

As we talked before, 6331 projects in our dataset had been certified by July, 2010. If a project gets certified, it will be attributed to cerntain certification level according to the credits it has earned. LEED offers four levels of certification: Certified, Silver, Gold and Platinum. Figure 3.2 shows the certification levels of 5747 certifications which have this information. Most of them get Silver or Gold, which are the medium levels. Figure 3.3 shows the certification levels they got by year. In the first a few years, the four certification levels increased slowly and evenly. Up to year 2004, most of them belonged to level Certified. Level Silver and Level Gold grew rapidly starting from 2006. In 2008, most of the projects got level Gold. We can see that throughout the whole periods, very few projects get Level Platinum that indicates the highest standards.

This paper focuses on the allocation of certification levels in the US. We are interested in studying whether the allocation is more agglomerated or more dispersed, than what it would be under an independent random choice model, so we study only the projects that get certified in the US from now on. First we define the market according to the first three digits in zip code, and we assume that the agents interact only within markets. By this way we have 4794 certifications in 631 distinct markets in the US. Figure 3.4 shows the number of certifications by market. 157 (24.88% of the 631 markets) markets have only 1 certification, and 114 (18.07% of 631 markets) markets have 2 certifications. 80% of the markets have fewer than 60 certifications. In order to study the possible strategic interactions within markets, we will focus on markets with at least two certifications, and there are 474 such markets with 4637 certifications in them.

## 3.4 Methods and Results

We apply a set of methods here to study the allocation of certification levels. The goal is to show that whether the certified projects agglomerate or differentiate on certification levels, which may indicate the presence of network effects or socially transmitted neighborhood effects. The idea of these methods is to compare the national rates of certification levels to the local rates. We first compute the national rates for different certification levels. We then assume the agents make independent random choices using the national rates as the probabilities to choose the certification level, and compare this scenario to the data. By studying how these two scenarios differ from each other, we show whether the allocation is agglomerated or dispersed.

Subsection 3.4.1 uses the method of simulation to show how these rates differ. Subsection 3.4.2 describes how we use Multinomial Test of Agglomeration and Dispersion (MTAD) to further study the allocation of certification levels.

### 3.4.1 Simulation

Let $\{n_i^c, n_i^s, n_i^g, n_i^p\}$ be the numbers of of certifications in market $i$ that are level Certified, Silver, Gold and Platinum, and $n_i$ be the number of all the certifications in market $i$, that is, $n_i = n_i^c + n_i^s + n_i^g + n_i^p$. In order to study the possible strategic interactions, we ignore the markets with only one certification.

We first study the adoption pattern of level Certified. The adopotion rate of level Certified in market $i$ is calculated as $n_i^c/n_i$ , where $n_i > 1$. The national adoption rate of level Certified is 25%. If the agents make independent random choices, that is, the agents in each market would choose level Certified with probability 25%, and other levels with probability 75%. We simulate what would have happened in this scenario, and compare the result to the data. Figure 3.5 presents a histogram graph of adoption rates of level Certified. The black bars represent the observed adoption rates, while the grey bars represent the simulated results. This figure shows only the results from considering markets with more than five certifications, since we don't observe significant results from markets with fewer than five certifications. Note the national adoption rate of level Certified is 25%, and if highly differentiated markets are defined as the markets with adoption rate between 20% and 30%, we find that the grey bar is much higher than the black bar, which indicates that the independent random choice model would predict much more markets with adoption rates between 20% and 30%. The simulation puts much more weight around adoption rate 25%, and thus in reality the agents are agglomerating on the tails of the distribution.

Similarly, we look at the adoption rates of level Certified&Silver, and level Platinum. The national adoption rate of level Certified&Silver is 59%, that is, 59% of the certified buildings choose either level Certified or Silver. We simulate what would have happened if all the agents in each market independently choose level Certified or level Silver with probability 59%. Figure 3.6 shows the results from the simulation and the data. If we define the highly differentiated markets as the markets with the adoption rates between 50% and 70%, and we then see that the grey bars are higher than the black bars in this range. This indicates that the independent random choices would predict more markets with adoption rate between 50% and 70%. Therefore the agents are also agglomerating in this case.

Let's move on to look at the adoption pattern of level Platinum. Figure 3.7 shows the results. This case is different from the previous ones, in the sense that we can't observe significant difference between simulation and the data. This result indicates the possibility that there is no agglomeration or differentiation when the agents choose whether to get level Platinum, but it is also possible that there are so few observations about this level Platinum that we can't draw any information from them.

### 3.4.2 Multinomial Test of Agglomeration and Dispersion (MTAD)

In this subsection we test whether the hypothesis of independent random choice can be rejected and whether the arrangement of certification levels is more agglomerated or more dispersed, by the Multinomial Test of Agglomeration and Dispersion (MTAD) developed by Rysman and Greenstein (2005)[2].

MTAD is based on the likelihood function from a multinomial distribution. It computes the likelihood of observed allocation as well as the expected likelihood if the allocation were actually generated by independent random choice. The appendix presents the details. The intuition of this test can be explained using the combinatoric statistic. We assume there are 4 projects which will make choices about whether to get level Certified. Consider the combinatoric expression $\begin{pmatrix} 4 \\ x \end{pmatrix}$, where $x$ is the number of projects that choose level Certified. If they make independent random choices, that is, they would choose level Certified with probability 25%, and other levels with probability 75% (note that the national adoption rate of level Certified is 25%), the expected value of the combinatoric expression would be 3.46. The dispersed arrangement generates $\begin{pmatrix} 4 \\ 2 \end{pmatrix} = 6$ , and the agglomerated arrangements generate $\begin{pmatrix} 4 \\ 0 \end{pmatrix} = \begin{pmatrix} 4 \\ 4 \end{pmatrix} = 1$. That is, whether the value is above or below the expected value would indicate whether the arrangement is dispersed or agglomerated, than what would have happened under independe random choice model.

Table 3.3 shows the results of MTAD. Row 1 presents the results when the agents are offered four choices: Certified, Silver, Gold and Platinum. We report the log-likelihood of the observed data from a multinomial distribution averaged over markets, as well as the expected log-likelihood and the standard deviation that would arise if the data were generated by independent random choices. We find that the expected likelihood is significantly

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[2] Other similar methodologies include the dartboard index of Ellison and Glaser(1997). We use MTAD here, as it examines not only whether to reject the hypothesis of independent random choice, but also the choice pattern - whether it is agglomerated or dispersed

higher than the observed likelihood, which indicates that the data are characterized by agglomeration arrangement.

Row 2 shows the results when the agents make choices about whether to get certification level Certified, and Row 3 shows the results of the case in which the agents make choices about whether to get any certification level below Silver (including Silver) or above Silver. We find the agglomeration arrangement for these two circumstances again.

Row 4 presents the result when the agents make choices about whether to get level Platinum. This time we can't observe any significant difference between observed likelihood and expected likelihood, and we can not reject the hypothesis that the data is generated by independent random choice. Note all the results are consistent with the results in subsection 4.1. We find the agglomeration allocation for the lower levels, but not the Platinum level.

Another important issue to consider is whether the arrangement would vary across markets with different number of certifications. Thus we compute the values of MTAD for markets with different number of certifications. The values of MTAD are calculated as the difference between the observed and expected log-likelihood, normalized by the standard deviation, and we consider the case in which the agents are offered four choices including Certified, Silver, Gold and Platinum. If the value of MTAD is smaller than -1.96, it means that there is statistically significant agglomeration characterizing the data. Figure 3.8 shows the MTAD for markets with different number of certifications. We observe that almost all the markets are characterized by agglomeration, except for the markets with number of certifications between 50 and 60, which account for only a small ratio of all the markets. This result indicates the agglomerated allocation characterize most of the markets, even when we control the number of certifications in the markets.

## 3.5 Conclusion

The third chapter studies the adoption of LEED (Leadership in Energy & Environmental Design) certification, which is an internationally recognized building certification system that evaluates environmental impact. Competition may affect not only certification adoption but also the adoption of quality standards. LEED offers four levels of certification to indicate the different standards of environmental impact. The agents in each market may interact strategically when choosing which level to adopt. On the one hand, the presence of market characteristics, network effects and socially transmitted neighborhood effects may cause the buildings to agglomerate. On the other hand, the buildings in the same market may try to compete by differentiating from each other on the certification levels, as the model of product differentiation would predict. We apply a set of methods, including simulation and Multinomial Test of Agglomeration and Dispersion (MTAD), and we find that the allocation of certification levels are characterized by agglomeration, rather than what would have happened under independent random choices.

## 3.6 Appendix

Testing for Agglomeration and Dispersion. (Marc Rysman, Shane Greenstein 2004)

Suppose there are M markets each populated by $n_m$ agents ($\underline{n} < n_m < \overline{n}$ ). The variable $n_m$ is distributed as discrete distribution $f(n_m)$ . In each market, the agents can choose from C options, and the unconditional probability of observing option c is $p_c$ . Actually the umber of agents choosing option c is denoted by variable $x_m^c$. If the agents make choices independently, the average log-likelihood of observing the outcome $x_m^1, ..., x_m^c$ in for M markets is

$$l(X,n,P) = \frac{1}{M}\sum ln(\begin{pmatrix} n_m \\ x_m^1, ..., x_m^c \end{pmatrix}) + x_m^1 ln(p_1) + ... + x_m^c ln(p_c)$$

Consider the likelihood value if the data were actually generated by independent random choice. Let the random variable $l(f,p)$ be distributed according to the distribution $l(X,n,p)$ if X was actually drawn from a multinomial distribution and $n_m$ was drawn from $f$ .

$$E[l(f,p)] = \sum_{n=\underline{n}}^{\overline{n}} \sum_{z\in\Sigma(n_m)} (ln(( \begin{matrix} n_m \\ z^1, ..., z^c \end{matrix} )) + z^1 ln(p_1) + ... + z^c ln(p_c)) L(z, n_m, p) f(n_m),$$

Where $\Sigma(n_m)$ is the set of all possible choice configurations of $n_m$ agents.

Then the statistic, $t(X,n,p) = l(X,n,p) - E[l(f,p)]$ is distributed asymptotically normal.

Figure 3.1: Number of Registrations by Year

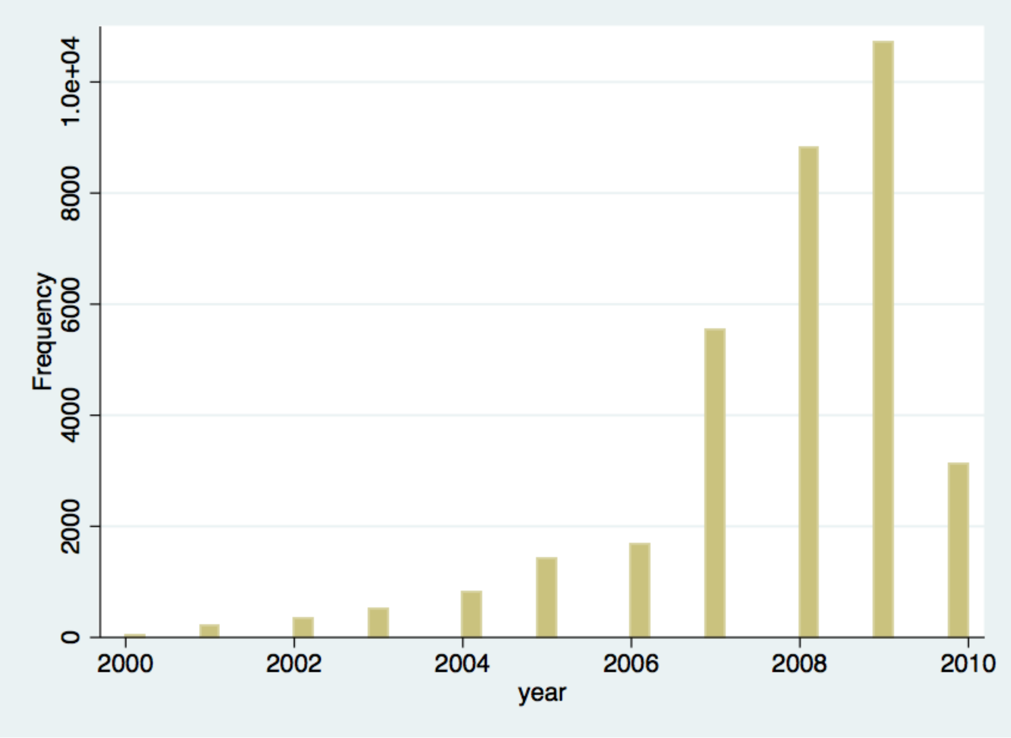

Figure 3.2: Certification Levels

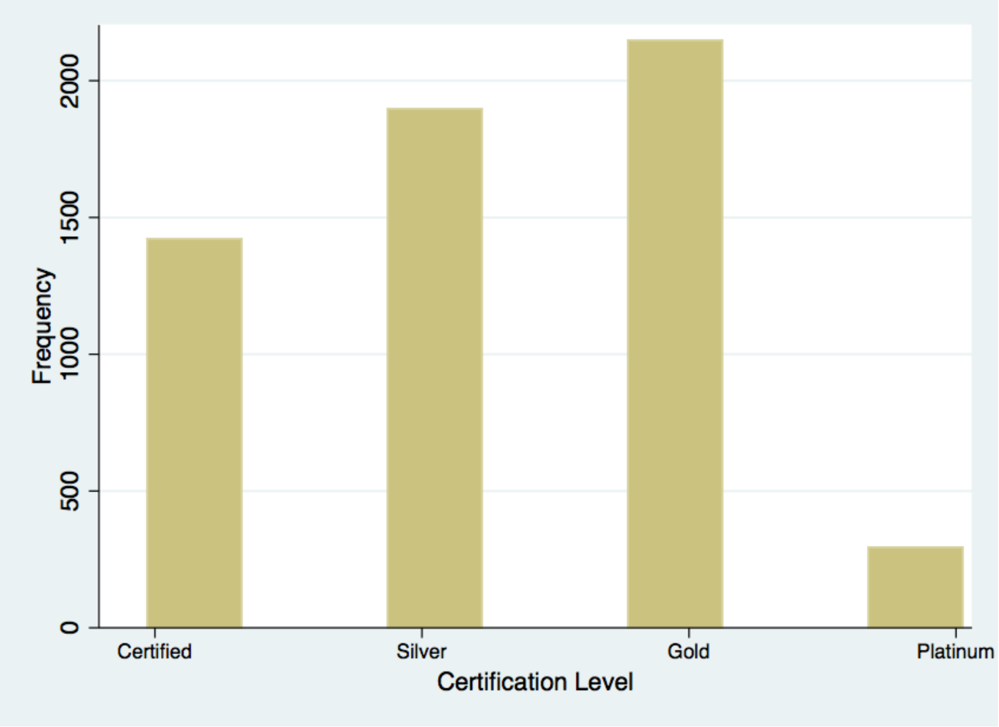

Figure 3.3: Certification Levels by Year

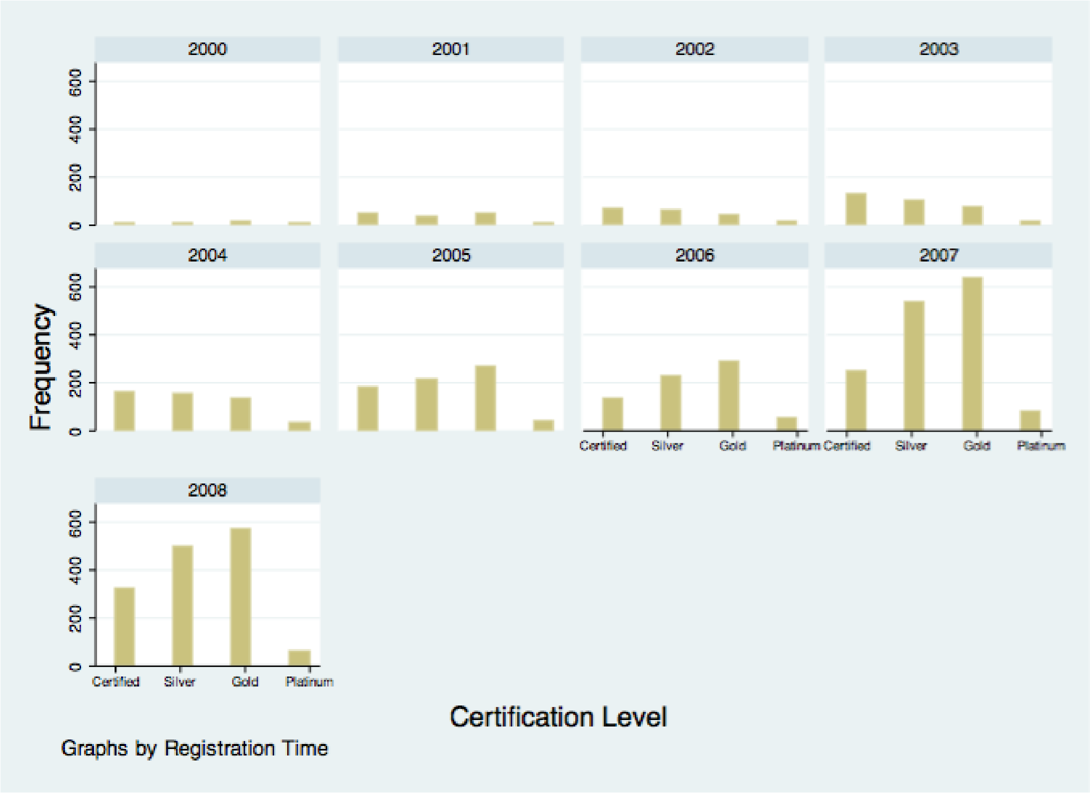

Figure 3.4: Number of Certifications in each Market

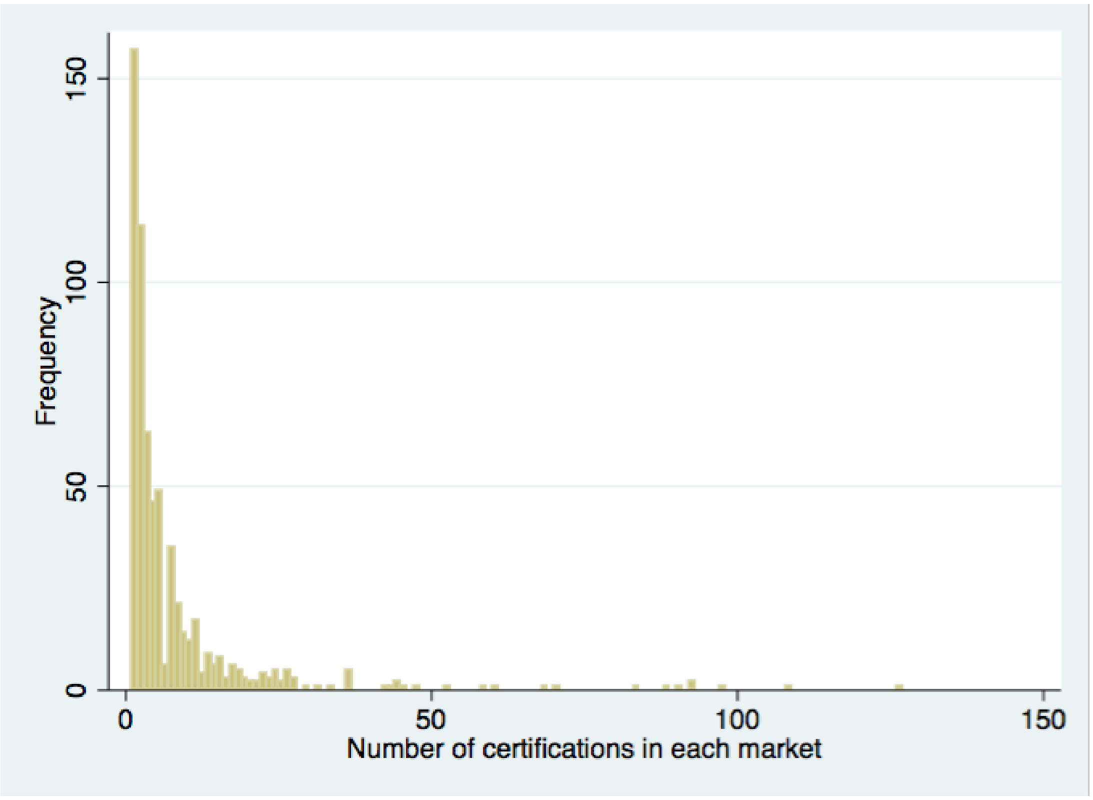

Figure 3.5: Adoption of Level Certified

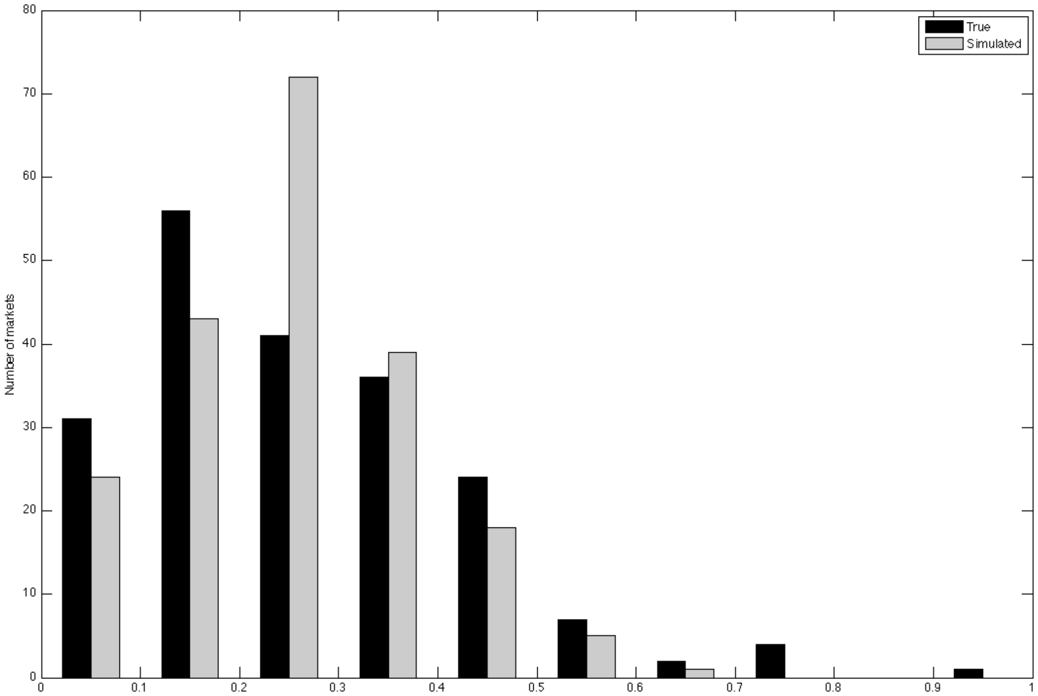

Figure 3.6: Adoption of Level Certified&Silver

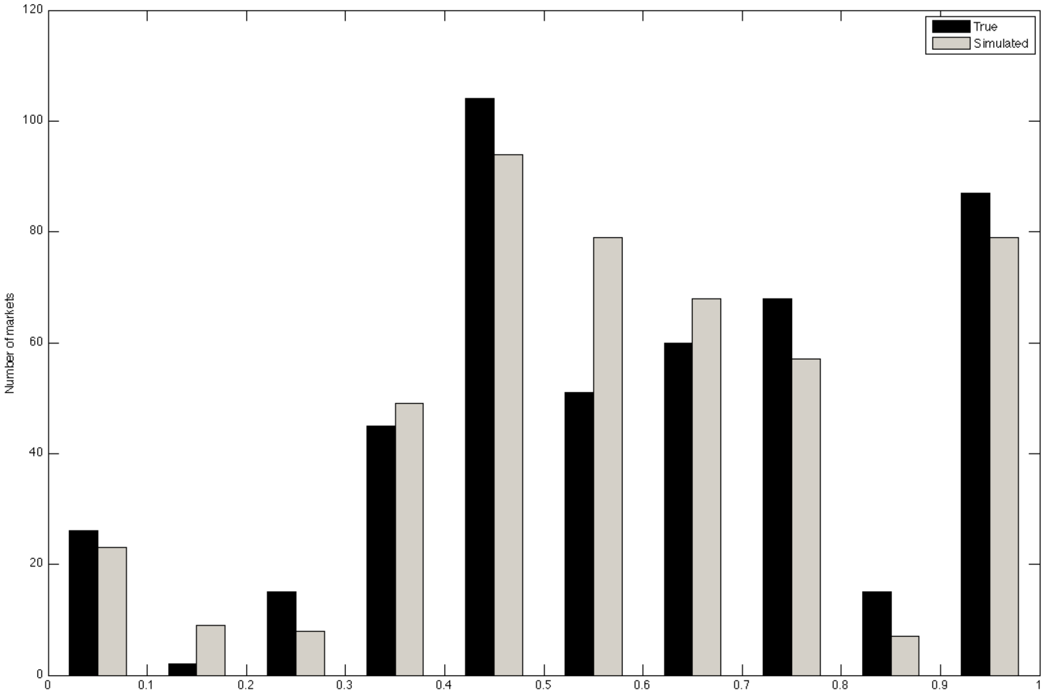

Figure 3.7: Adoption of Level Platinum

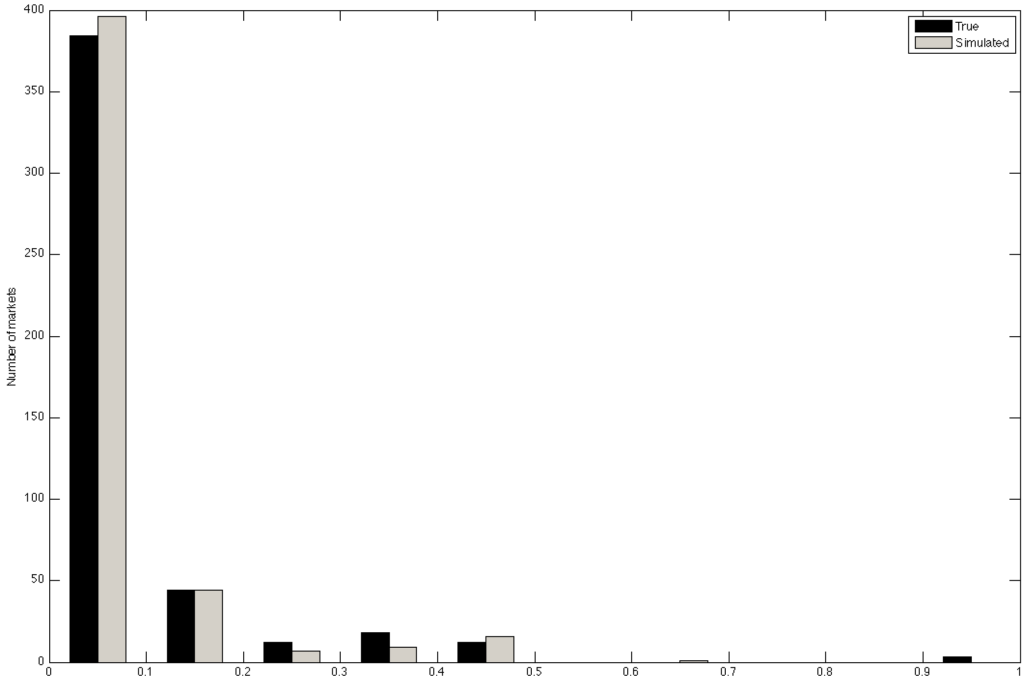

Figure 3.8: MTAD Values

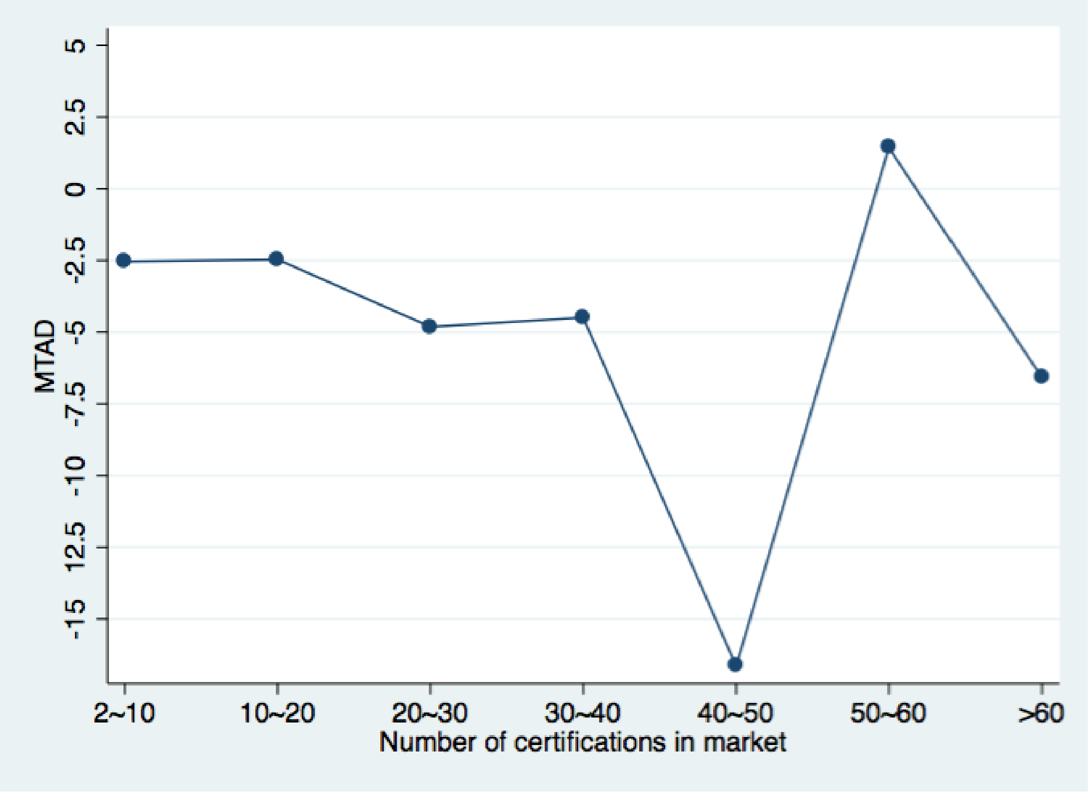

Table 3.1: Ownership Type

| | Freq | Percent |
|---|---|---|
| Profit Org. | 9341 | 42.15 |
| Non-Profit Org. | 3026 | 13.65 |
| Federal Government | 2941 | 13.27 |
| Local Government | 2672 | 12.06 |
| State Government | 1717 | 7.75 |
| Individual | 1045 | 4.72 |
| Other | 1419 | 6.4 |
| Total | 22161 | 100 |

Table 3.2: Rating System

| | Freq. | Percent |
|---|---|---|
| NC(New Construction) | 19266 | 59.92 |
| Retail NC | 144 | 0.45 |
| EB (Existing Buildings) | 4565 | 14.2 |
| CS (Core Shell) | 3374 | 10.49 |
| CI (Commercial Interiors) | 3061 | 9.52 |
| Retail CI | 238 | 0.74 |
| School | 1249 | 3.88 |
| ND (Neighborhood Development) | 254 | 0.79 |
| Total | 32151 | 100 |

Table 3.3: Results of the MTAD

| Description | Observed Likelihood | Expected Likelihood | Standard Deviation |
|---|---|---|---|
| Certified vs. Silver vs. Gold vs. Platinum | -3.262 | -2.94 | 0.03 |
| Certified vs. above Certified | -1.513 | -1.201 | 0.022 |
| Certified&Silver vs. Gold&Platinum | -1.508 | -1.341 | 0.019 |
| below Platinum vs. Platinum | -0.641 | -0.619 | 0.031 |

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