

# Profit Complementarities in the Adoption of Electronic Medical Records by U.S. Hospitals\*

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## Abstract

A \$35 billion program was passed by the federal government to promote the adoption of Electronic Medical Records (EMR). However, billions of incentive payments were flowing out without clear evidence of effective implementation. This paper tries to understand hospitals' adoption choice of EMR vendors, particularly to evaluate choosing the locally market-leading vendor. Hospitals benefit from using the market-leading technology due to profit complementarities, but also worry about losing patients to competitors that share the same vendor. I construct a dynamic oligopoly model of technology adoption to assess the value of selecting the leading vendor. Using a nationwide sample of U.S. hospitals from 2006 to 2010, I apply the methodology developed by Aguirregabiria and Mira (2007) to recover the model primitives. The primary finding is that, on average, the per-period profit from choosing the locally market-leading vendor is increased by almost 51% as opposed to that from using any other technology. However, the impact moderates as compared with the sunk cost of implementation. From the counterfactual analysis I find if hospitals were incentivized to choose the locally market-leading vendor, it would help improve the market coordination substantially.

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# 1 Introduction

This paper seeks to explore profit complementarities in adopting Electronic Medical Records (EMR) by stand-alone hospitals in the U.S. In particular, the study focuses on profit complementarities in choosing the market-leading vendor. EMR allow health care providers to store, retrieve, and exchange health information using computers instead of paper records. The advancement of this technology holds the promises to improve the efficiency of the health care system. In 2009, Congress passed legislation devoting \$35 billion to promote the adoption of EMR, with the ultimate goal to allow seamless exchange of patient information. Almost four years and \$12 billion later, data sharing, however, has proven very difficult to achieve. Recently, the government agency—Centers for Medicare and Medicaid Services (CMS)—announced its intention to change the timeline and revise the rulemaking for the last stage in the program, in order to accelerate information sharing. The purpose of my analysis is to provide some valuable inputs on the benefits of market coordination.

The definition of profit complementarities vary by context. In this case, it describes a situation in which a hospital can benefit from choosing a vendor that is also chosen by its neighbors. EMR systems are not interoperable. The system from one vendor cannot communicate with that from another. Hospitals may be more likely to extract profit complementarities if they use products from the same supplier. This paper looks specifically into profit complementarities from the local market-leading technology. There could be various sources. A vendor well-established in the local market may have developed a better relationship with local providers and payers. When hospitals process and submit claims, it will bring in great cost efficiency if its platform is compatible with the system of the payer. The leading supplier may also be able to provide sufficient expertise in the implementation of similar technologies. All of such could be translated into a cost advantage when the hospital purchases from the largest vendor.

A hospital choosing the most popular product can benefit from profit complementarities, but interoperability is not necessarily beneficial to a hospital. As indicated in an article by Kellermann and Jones (2013), health care providers have little incentive to “acquire and develop interoperable HIT systems” but would rather “lock

in” their patients to “enforce brand loyalty.” These two competing forces make it hard to theoretically determine the sign of using the market-leading technology. The objective of this paper is to examine which force dominates and to evaluate the effect of the market-leading technology on profits. By understanding this, regulators will be better positioned to expand the use of health IT and help hospitals make sound choices.

In 2009, the Health Information Technology and Economic and Clinical Health (HITECH) Act, a \$35 billion program of grants and incentive payments, was passed as part of the American Recovery and Reinvestment Act (ARRA). The goal of this program was to establish a Nationwide Health Information Network (NwHIN) where patient information can be exchanged freely across diverse entities. Nearly four years after the enactment of the HITECH act, \$12.7 billion has been paid out, but seamless transfer of health information is still out of reach. In the current incentive program, a hospital will be subsidized as long as it meets the specified requirements of meaningful use. The program doesn’t set up any standard for interoperability nor impose any restriction on the choice of vendors. Thus, on one hand, hospitals are free to choose any vendor in the market. But on the other hand, since the products from different suppliers cannot talk with each other, the resulting information silos go against the original objective of the program and make the establishment of the NwHIN even more difficult. The government agency recently delayed the rulemaking for the last stage of the program and sought input on potential policy to accelerate information exchange across providers. At this moment when the policy makers reconsider the strategies needed to ensure interoperability, information about the value of the market-leading technology becomes important. If profit complementarities dominate the countervailing competition effect, promoting such a technology can not only bring in cost efficiency but is also helpful to improve coordination at the regional level. If the competition effect devaluates this technology, the government needs to take a closer look into the incentive behind hospitals’ choices of vendors.

This paper contributes to studies on the adoption decision of EMR, most of which involve network externalities (Miller and Tucker (2009), Lee, McCullough and Town (2012)). The variable of interest, in all such studies, is the number of adopting hospitals nearby, to assess the extent to which the technology has permeated into the

network. However, since EMR is not compatible, the presence of two adopting hospitals does not necessarily imply that both belong to the same network unless they are using the system from the same vendor. This paper addresses this issue by using the information of the identity of EMR vendors to define a network. In addition, it is the first study applying a dynamic framework to investigate the adoption choice of EMR vendors. In order to recover the value of using the market-leading technology, I develop a dynamic oligopoly model in the tradition of Maskin and Tirole (1988) and Erison and Pakes (1995). In this model, hospitals simultaneously make adoption decisions and the market evolves as hospitals adopt or switch to a new system in response to variation in the economic environment. The choice of vendors is a dynamic decision due to the following reasons. Large hospitals may have incentives to adopt early so that their choices become predominant in the market. They can benefit later on as more and more neighbor hospitals follow their choices. Small hospitals may hold up the current adoption decision, waiting to see which technology is optimal. Missing the dynamic element will omit all of these incentives. This is the first study making use of the information of the identity of EMR vendors to study the dynamics in hospitals' choice of vendor.

Using a nationwide sample of U.S. hospitals from 2006 to 2010, my estimation method follows the approach developed by Aguirregabiria and Mira (2007). I find that hospitals extract positive profits in selecting the market-leading vendor. On average, a hospital's profit from adopting EMR increases by almost 51% if it chooses the locally market-leading vendor. However, the effect moderates as compared with the substantial amount of the sunk cost. The gain is asymmetric between large and small hospitals. Profits generated from using the market-leading technology is higher for large hospitals, due to greater profit complementarities and less competitive pressure for these hospitals. I also find that both large and small hospitals have to bear a significant amount of switching cost when switching HIT vendors but large hospitals spend less in switching. A potential explanation is that large hospitals are capable of internalizing the cost of consulting and IT system management when switching. It dramatically reduces the expense to set up a different system since external consultancy and project management constitute the largest cost contributor.

With all the structural estimates, I am able to carry out the counterfactual anal-

ysis. I consider two types of subsidy programs. One is the subsidy for any type of EMR adoption, which attempts to mimic the current incentive program where the standard on interoperability is almost blank. The other one provides subsidies toward hospitals only if they choose the locally market-leading vendor. The outcome variable of interest is the rate of coordination in adopting EMR. The results suggest that encouraging the adoption of the market-leading technology could improve the market coordination substantially. I also compare the effect from the two programs in a new market, where the adoption rate is close to zero, and in a mature market, where almost all hospitals have adopted EMR but with almost zero communication. I find the targeted subsidy towards the most popular technology is much more effective in a new market. It is worthwhile to point out that promoting such a technology is just one way to set up the standard of interoperability. The key message is that the outcome is likely to have been better if the requirement on interoperability was explicitly incorporated at the earlier stage of the incentive program.

The rest of the paper proceeds as follows: Section 2 presents literature related to this topic. Section 3 provides basic information and institution background about EMR. Section 4 describes the datasets applied in this study. Section 5 provides reduced-form evidence on the value of using the market-leading technology. Section 6 presents the structure model characterizing the adoption decision of hospitals. Section 7 describes the estimation strategy. Section 8 shows the estimation results. Section 9 runs counterfactual experiments and discusses the potential policy implications. The last section concludes and points out the future directions.

## **2 Relation to Literature**

Empirical studies examining the adoption decision of EMR usually involves network externalities. Miller and Tucker (2009) studied the relationship between privacy protection policy and technology diffusion. By comparing the states with and without the policy, their results suggested that privacy regulation inhibited the adoption of EMR by suppressing the network externalities. Another paper by Lee, McCullough and Town (2012) focused on the impact of Health Information Technology on hospital productivity and found little evidence of the network effect. Wang (2012) tried

to disentangle the network externalities from the countervailing competitive effect by separately examining different adoption levels of EMR. She found that the basic level adoption yields a positive network effect while the advanced EMR application suggests a competitive effect. As indicated earlier, I define networks at the vendor level, unlike these studies.

A study by Dranove et al. (2012), from a different perspective, looked into the relationship between the hospital operational cost and EMR adoption. Their results indicate that hospitals benefit from EMR adoption when the necessary complements are in place; hospitals in a less favorable location undergo an increase in costs even after several years of installation. The supply condition of local complementary assets can help hospitals realize more profits from the adoption of EMR and hence they must be accounted for in the adoption decision. This paper emphasizes the role of the market-leading technology because one potential benefit from choosing such a product is that the vendor is more likely to supply sufficient complementary resources to its clients. This paper is also complementary to the empirical literature on network externalities. Tucker (2008) identified the network externalities from individual adoption of a video-messaging technology in an investment bank. Gowrisankaran and Stavins (2004) examined the extent of network externalities for automated clearing house (ACH). A follow-up study by Ackerberg and Gowrisankaran (2006) constructed an equilibrium model and structurally estimated the magnitude and sources. This paper incorporates the dynamic structure into a model in which a network is defined by using the technology from the same vendor.

A dynamic oligopoly model is constructed to characterize hospitals' adoption decision. There is a growing literature on estimating the dynamic models (Rust (1987); Hotz and Miller (1993); Hotz, Miller, Sanders and Smith (1994); Aguirregabiria and Mira (AM) (2003, 2007); Bajari, Benkard and Levin (2007); Pakes, Ostrovsky and Berry (POB) (2007); Arcidiacono and Miller (2011)). The seminal paper by Rust introduced the Nested Fixed Point (NXFP) algorithm for single-agent dynamic programming (DP) problems. It is a full solution method in the sense that the DP problem is solved for every trial value of the parameters. Moreover, under the assumption of the model, it gives the MLE that is asymptotically efficient. This method can be extended to estimate the dynamic oligopoly problem by assuming all the shocks are

purely private information (Aguirregabiria and Mira (2007)). However, the limitation of the NXFP algorithm is the computational burden due to repeated full solution to the DP problem. Hotz and Miller (1993) observed the existence of the inverse mapping between the choice-specific probability and the difference in the choice-specific value functions. They proposed the Conditional Choice Probability (CCP) estimation method in which it is unnecessary to solve the DP problem even once to get the structural estimates. The key idea is to substitute the future values with future actions that can be nonparametrically estimated from the data. Aguirregabiria and Mira (2002) showed the asymptotic efficiency of the CCP estimator and suggested a recursive CCP algorithm to correct the possible inconsistency from the one-step CCP estimator. Arcidiacono and Miller (2011) extended the CCP framework from the model with a terminal state to a much wider set of dynamic problems.

Similar to Hotz and Miller's (1993) idea, Bajari, Benkard and Levin (2007) (BBL) provided a method for estimating the dynamic game models which also circumvents the needs to solve the Markov-perfect Nash Equilibrium (MPNE). The estimator proceeds in two steps. The first step is to estimate the policy function and the law of motion for state variables. In the second step, the structural estimates are recovered by imposing the optimality conditions for equilibrium. Ryan (2012) applied BBL to evaluate the welfare costs of the environmental regulation in a model where firms make the decision of investment, entry and exit. Collard-Wexler (2013) used a similar method in his paper to assess the role of demand shocks in the ready-mix concrete industry. The estimation strategy in this paper is based on a two-step framework, following closely the approach developed by Aguirregabiria and Mira (2007) but also similar to that in Bajari, Benkard and Levin (2007) and Pakes, Ostrovsky and Berry (2007). Hospitals are assumed to have correct belief about the environment and competitors' behavior so the policy function can be estimated from the equilibrium that is actually played in the data. With the estimated policy function, I apply forward simulation to get the value function. The parameters are recovered by picking the values that are most probable to produce the observed behavior.

### 3 Industry Background

EMRs were invented in 1970s, but the acceptance to this technology had been very slow until recent years. In 2009, the American Recovery and Reinvestment Act (ARRA) has provided \$35 billion to promote Health Information Technology (HIT), in particular to encourage the adoption EMR. It is the first substantial commitment of federal resources to support the adoption of EMR and creates a strong push in the diffusion of HIT. As the cornerstone of the Affordable Care Act in improving quality and lowering cost, EMR serves functions that paper record cannot deliver. According to the Healthcare Information and Management Systems Society (HIMSS), a solid EMRs foundation should include the following key components: Clinical Data Repository (CDR), Clinical Decision Support Capabilities (CDS), and Computerized Physician/Provider Order Entry (CPOE). CDR is essentially a centralized database that collects, stores, accesses and reports health information. It is the backbone of the entire system. CDS assists clinicians in decision-making tasks namely determining the diagnosis or setting treatment plans. CPOE is a more advanced type of electronic prescribing. It can link to the adverse drug event (ADE) system to avoid potential medication errors.

EMR has evolved from the early days being a silo system—in which the digital records from each ancillary department was isolated—towards nowadays an integrated architecture allowing sharing of data across departments, also known as the enterprise EMR system. The implementation cost of an EMR system varies tremendously depending on the sophistication of the system built, amount of data conversion, level of customization, one-on-one assistance during training and on-going use and etc. According to a study conducted by the Congress Budget Office, the average implementation cost for a 250-bed hospital (about the mean size in my sample) ranges from \$3-\$16 million and the ongoing cost for subsequent upgrade and maintenance is approximately 20%-30% of the initial contract value per year, i.e., up to \$5 million annually afterwards. The rollout cost would even rocket to hundreds of million dollars for large hospitals. For example, in 2011 the medical center at the University of California, San Francisco spent \$150 million to have the EMR system in place. Such a large upfront payment involves a tangible part such as licence purchase, hardware investment, workflow consulting, project management and staff training. The



last three components—external consultancy, project management and human capital investment—constitute the largest contributor in the upfront cost. The intangible cost mainly comes from the productivity loss during initial implementation. There are various reasons for hospitals willing to spend millions of dollars on this expensive technology. Besides the strong push from the federal incentive program, the usage of EMR enables hospitals to engage in better documentation, lower the administrative cost, and streamline and automate their revenue practices. Digitizing medical records also help hospitals get adapted to the reform in the payment system as well as the new features of the Accountable Care Organization. Last but not the least, a qualified EMR system can bring in more efficiency and improve the quality of health care.

However, the evidence about the effect of EMR adoption has been mixed. McCullough et al. (2010) connected health care quality to the use of CPOE and discovered substantive improvement from using the technology. Miller and Tucker (2011) provided a careful analysis of the impact on neonatal outcomes from the adoptions of EMR and found that a 10% increase in basic EMR adoption would reduce neonatal mortality rates by 16 deaths per 100,000 live births. Agha’s job market paper (2011) investigated the impact of HIT on the quality and intensity of care delivered to Medicare patients but detected no significant improvement after the implementation. A more recent study by Li (2014) placed emphasis on the effect of EMR adoption on medical coding and billing practice. She used the multi-state inpatient discharge data to examine the relationship and found that the share of patients coded to a higher-pay DRGs increases significantly after EMR adoption.

The choice of EMR vendors relies on various factors such as the upfront and ongoing costs, the vendor-specific functionalities, individual hospital characteristics, payer impacts and local factors. In particular, the goal of this study focuses on profit complementarities from adopting the market-leading technology. The vendor with the highest local market share is defined as market-leading. In U.S., hospitals are divided into two categories according to the affiliation status: stand-alone hospitals that are independent organizations and affiliated hospitals that belong to a larger hospital chain. The analysis of this paper only concentrates on the sample of stand-alone hospitals while the adoption choice of affiliated hospitals is assumed to be exogenous

to the local market.

I examine these hospitals for several reasons. For hospital systems, most organizational decisions are made by the managing party, who usually faces the tradeoff between localization and consolidation, especially when the locally-leading vendor is not the same as the choice of the parent system. Also, due to the heterogeneity in hospitals systems, it is difficult to characterize their decision process with a relatively simple model. By focusing on stand-alone hospitals, I can examine a relatively simple adoption decision but still identify the impact of profit complementarities. The data provides somewhat evidence in supporting this argument. Conditional on first-time adoption, only 19 % of affiliated hospitals chose the market-leading vendor while the rest followed the choice of the parent system even when it was not most widely-adopted in the local market.

## 4 Data

The data is constructed by pooling information from various sources. The first primary dataset comes from Healthcare Information and Management Systems Society (HIMSS) Analytics Database, which is the most comprehensive national source of hospital information technology (HIT) adoption data. The database covers the majority of U.S. hospitals, and includes market share and purchasing plan data for over 90 software applications and technologies. It is an annual survey recording the time and the choice of a hospital's adoption decision. More specifically, the dataset contains the information about the year adoption, the component deployed, adoption status, and the identity of the product supplier, which enables a more realistic network definition.

There is no consensus on how to define adoption of EMR for a hospital. Jha et al. (2009) used a very comprehensive definition. From a list of 32 potential functionalities of an inpatient electronic health record, they asked an expert panel to define the functionalities that constitute a basic and comprehensive electronic system respectively. Miller and Tucker (2009) measured EMR adoption by whether a hospital is installing or has installed the enterprise EMR system. In my paper, a hospital is defined to adopt EMR if CDR is live and operational in the hospital. The imple-

mentation of CDR is the prerequisite for other applications. It implies the hospital's willingness to enter the market and it is often the case that other typical and common applications such as CDS and CPOE will be put in place soon after the installation of CDR. This paper tries to understand the factors that will affect hospitals' choice of vendors. The adoption of CDR may uncover some information about hospitals' incentive. The second row of Table 1 and 2 report the nationwide adoption rate derived from the sample. In 2006 49% of the hospitals deployed EMR and the number went up to 84% in 2009. The adoption rate for stand-alone hospitals is slightly lower than that in general. The fraction of using the market-leading technology by stand-alone hospitals is more than 60% in both years.

I complement the HIT data with the American Hospital Association (AHA) Annual Survey, using the Medicare provider number and geographic information to perform the linkage. The AHA data includes a rich set of hospital-specific features such as number of beds, system affiliation, profit status, indicator of academic medical center, percentage of Medicare and Medicaid discharge and etc. Table 1 and 2 provides a summary statistics for the main variables. In 2006, about 45% of hospitals are stand-alone hospitals and this ratio fell by 2% in 2009. Also, the distribution of profit status and bed size remained almost the same during the sample period.

In this paper, a market is equivalent to a health service area (HSA), a measure developed by Makuc et al. (1991). An HSA is one or more counties that are relatively self-contained with respect to the provision of routine hospital care. The location of each hospital can be directly linked to the corresponding HSA. There are around 921 HSAs in the sample, covering more than 95% of HSA in US. The final dataset contains 4,560 hospitals between the year 2006 and 2009. Another thing to note is that the market for EMR is fairly concentrated. Although there are more 2,000 certified EMR vendors, most of the products are supplied by a few large companies. Table 3 lists the top 11 vendors that account for about 92% of the national market share in 2006. All the other vendors are categorized into another group called "others." Combining with the major vendors, these 12 options forms a choice set available to all hospitals in the model.

## 5 Reduced-form Evidence

This section provides some reduced-form evidence on how the hospital evaluates the market-leading technology. The two competing forces makes the sign of the value uncertain. To address this question, I run a conditional logit regression by regressing the choice of vendors on a set of product characteristics and hospital features. Whether the vendor is market-leading in the local area becomes a product characteristic entering into the value function. If the gain outruns the potential loss of business, the hospital will expect positive returns in choosing the market-leading technology and hence the estimated coefficient will be positive. If instead the concern about losing patients is greater, the coefficient is expected to be negative. The estimation is based on the sample of first-time adoption to provide a cleaner setting. Table 4 shows the results of the conditional logit regression. The upper panel reports the coefficients for the product characteristics: whether the vendor is market-leading and its interaction with the dummy for a large hospital. The latter aims to capture the extra gain/loss for large hospitals. A hospital is categorized as large if its number of beds is more than the mean size. The results suggests hospitals benefit from using the market-leading technology, implying profit complementarities exceed the loss from competition.

The lower panel presents the coefficients for the hospital characteristics interacting with vendor dummies. Bed size influences the choice of vendors as the variable cost (savings) could vary by product. In particular, the coefficients for Vendor CPSI and Healthland are negatively significant, indicating lack of cost savings per unit of bed. This is consistent with the design of these two products as both of them mainly target at rural and critical access hospitals most of which are small hospitals. Hospitals with different profit status may behave systematically differently in the choice of vendors. All of the coefficients for not-for-profit hospitals are positive, implying that such hospitals are more likely to adopt EMR. Teaching hospitals are responsible for clinical training and education for new generation of physicians in addition to delivering medical services, and thus they may have special preference in some particular vendors due to the various difference in functionality. The results suggest some vendors are much more popular among teaching hospitals. There could be other variables also playing some role in the choice of vendors, but the coefficients for the variables of interest—the product characteristics—seem quite robust across different

specifications.

A potential concern about endogeneity may arise. There may exist some unobserved market characteristics affecting the formation of the leading technology and the choice of vendors at the same time. I use an outside market proxy as a cleaner measure. Consider a stand-alone hospital (called “ $A$ ”) in Chicago, which has, a competitor belonging to a hospital system for which most of the members locate in Phoenix. Instead of using the market structure in Chicago, I derive the product characteristic—whether a particular vendor is market-leading—from the market structure in Phoenix. The market condition in Phoenix is a clean measure in the sense that it is much less likely to be related to the market in Chicago, but it may have some association with the choice of Hospital  $A$ . The adoption decision of the hospital system may put some weight on the market in Phoenix, which will have impacts on the choice of its member in Chicago and further on Hospital  $A$ ’s decision. The idea here basically uses excluded variables from one system to identify another, similar to the strategy applied in the paper by Gowrisankaran and Stavins (2004). In order to apply this proxy, the sample is further restricted to the markets with both newly-adopting stand-alone hospitals and affiliated hospitals belonging to a multi-region system. This reduces the sample by one third. Table 5 reports the results in this specification. The market-leading dummy loses its significance, but its interaction with the large hospital dummy is positively significant. Large hospitals expect some gains from choosing the market-leading vendor.

## 6 Model

I develop a simple oligopoly model built on the theoretical framework constructed by Maskin and Tirole (1988) and Erison and Pakes (1995). There are  $M$  regional markets, each of which has  $N_m$  stand-alone hospitals  $\forall m = 1, 2, \dots, M$ . Each market is fully described by an  $N_m$  state vector  $s = (s_i, s_{-i})$  where  $s_i$  and  $s_{-i}$  are Hospital  $i$ ’s and its rivals’ adoption status respectively, with  $s_i = 0$  corresponding to no EMR in place and  $s_i = j (j \in \mathcal{J} = \{1, 2, \dots, J\})$  for using the product from Vendor  $j$ .  $\mathcal{J} = \{1, 2, \dots, J\}$  is a choice set which contains all EMR vendors available to hospitals. Since all the vendors are serving the national market, the choice set is fixed for every

decision maker. Each hospital is assumed to capture a fixed portion of consumer surplus so oligopoly competition in medical care will not be explicitly considered in the model. For simplicity, I further assume there is no entry and exit in the market. Time is discrete and infinite. Each decision period is one year.

In each period, the sequence of events unfolds as follows: At the beginning of every period, each hospital receives a vector of private draws  $\varepsilon = \{\varepsilon^0, \varepsilon^1, \varepsilon^2, \dots, \varepsilon^J\}$  from some distribution. Conditional on a commonly observed vector of state variables  $s$  and their private shocks  $\varepsilon$ , all the hospitals simultaneously decide whether to adopt EMR and which vendor to choose. A hospital that has no EMR can either purchase from a choice set  $\mathcal{J} = \{1, 2, \dots, J\}$  or remains non-adopting. A hospital with some on-site system can either continue its own choice or switch to other vendors, but reversion is not allowed. A new purchase from Vendor  $j$  incurs a mean adoption cost  $\zeta^j$  plus the unobserved component  $\varepsilon^j$ .  $\zeta^j$  can be viewed as the net sunk cost of installing the software from Vendor  $j$ , which mainly includes the licence fee, upfront investment on hardware and human capital, resulting attrition and productivity loss. Switching from one vendor to another results in a switching cost  $\eta$ . It is modeled the same across vendors for identification and computational reasons. Switching did not occur very frequently during the sample period and inclusion of vendor-specific switching costs considerably increases the computational burden. A fixed amount of switching cost across all vendors may not be flexible enough to capture the vendor heterogeneity, but it is able to provides some idea about the mean expense for switching. Staying with the original choice results in the corresponding unobserved cost shock, such as  $\varepsilon^0$  for non-adopting. Let  $\varepsilon$  terms be *i.i.d.* and have type I extreme value distributions. I assume it takes one period until the technology becomes operational within the organization. Thus, the action takes effect at the start of the following period and then the market evolves.

Consider Hospital  $i$  that has no EMR makes the purchase from Vendor  $j$  at period  $\tau$ . At  $t < \tau$ , the per-period payoff is  $\pi_{it}^0(s) = \varepsilon_{it}^0$ . At the time of purchase  $t = \tau$ , the per-period payoff is

$$\pi_{it}^j(s) = -\zeta^j + \varepsilon_{it}^j. \quad (1)$$

When  $t > \tau$ , if Hospital  $i$  keeps using product  $j$ , the per-period payoff becomes

$$\pi_{it}^j(s) = \gamma_1 g(s, j) + \gamma_2^j \text{beds}_i + \gamma_3 g(s, j) \times 1\{i \text{ is a large hospital}\} + \varepsilon_{it}^j \quad (2)$$

where  $g(s, j)$  is an indicator of whether Vendor  $j$  is market-leading at period  $t$  which can be calculated from the contemporary industry structure.  $\gamma_1$  captures the profit complementarities if purchasing from the largest supplier and  $\gamma_2^j$  measures the vendor-specific cost savings per unit of bed. The term  $\gamma_3 g(s, j) \times 1\{i \text{ is a large hospital}\}$  captures the extra gain/loss for large hospitals if they choose the market-leading vendor. A positive  $\gamma_3$  implies that the profit complementarities is increasing in the hospital's size. The hospital is viewed as large if the number of beds is greater than the mean size in the sample. Now I exposit Hospital  $i$ 's decision problem in terms of the choice-specific value function (CSVF)  $\delta^j(s)$ . The choice-specific values represent the value of choosing each option absence of the unobservable component. Therefore, the CSVF for Hospital  $i$  to choose Vendor  $j$  is

$$\delta^j(s) = -\zeta^j + \beta \sum_{s'} P(s'|s, a(s) = j) EV(s') \quad (3)$$

and the CSVF to stay with no EMR is

$$\delta^0(s) = \beta \sum_{s'} P(s'|s, a(s) = 0) EV(s') \quad (4)$$

where  $\beta$  is the discount factor,  $\zeta$  is the sunk cost of adoption,  $EV(s')$  is the ex-ante future value function and  $a(s)$  denotes the action chosen at state  $s$ . The transition probability,  $P(\cdot|\cdot)$ , depends on the firm's own behavior and equilibrium actions of its rivals. Therefore, the Bellman Equation for a hospital that has no EMR before is

$$V(s, \varepsilon) = \max_{j \in \{0\} \cup \mathcal{J}} \{\delta^j(s) + \varepsilon^j\}. \quad (5)$$

$V(s, \varepsilon)$  is the value function given the market state  $s$  and the private shocks  $\varepsilon$  faced by the hospital. By the same logic, I can write down the CSVF for Hospital  $i$  with

product  $k$  chooses to continue its current choice

$$\begin{aligned} \delta^k(s) = & \gamma_1 g(s, k) + \gamma_2^k \text{beds} + \gamma_3 g(s, k) \times 1\{i \text{ is a large hospital}\} \\ & + \beta \sum_{s'} P(s'|s, a(s) = k) EV(s') \end{aligned} \quad (6)$$

while the CSVF for the hospital already with product  $k$  but deciding to switch to Vendor  $j$  is

$$\begin{aligned} \delta^j(s) = & -\zeta^j - \eta - \eta^{\text{big}} \times 1\{i \text{ is a large hospital}\} + \gamma_1 g(s, k) + \gamma_2^k \text{beds} \\ & + \gamma_3 g(s, k) \times 1\{i \text{ is a large hospital}\} + \beta \sum_{s'} P(s'|s, a(s) = j) EV(s'). \end{aligned} \quad (7)$$

$\eta$  measures the mean switching cost and the term  $\eta^{\text{big}} \times 1\{i \text{ is a large hospital}\}$  captures the extra gain/loss from switching for large hospitals. A positive  $\eta^{\text{big}}$  suggests that large hospitals have to bear a greater amount of switching cost. Similarly, the Bellman Equation is

$$V(s, \varepsilon) = \max_{j \in \mathcal{J}} \{\delta^j(s) + \varepsilon^j\}. \quad (8)$$

To summarize, the structural parameters involves the sunk cost  $\zeta^j$ , the switching cost  $\eta$  and  $\eta^{\text{big}}$ , and the marginal values  $\gamma_1$ ,  $\gamma_2^j$  and  $\gamma_3$ . The cost parameters measure the net present value while the  $\gamma$ 's serve the flow pay off. Hospitals are assumed to play symmetric and Markovian strategies, i.e., the adoption choice only conditions on the current market state and the private shocks. Each hospital's adoption strategy is a mapping from state vectors and private shocks to the action:

$$\sigma : (s, \varepsilon) \rightarrow a. \quad (9)$$

Hospitals must weigh the benefits of using the new product against the adoption cost, the sum of the mean cost and the private draw. A purchase will not occur unless the sum of them is sufficiently low. The Markov-perfect Nash Equilibrium (MPNE) requires each hospital's adoption choice to be optimal given the strategy profiles of all rivals for all  $s$ ,  $\varepsilon$  and all possible alternative choices  $\tilde{\sigma}(s, \varepsilon)$ . At least one MPNE exists according to the Brouwer fixed-point theorem. Pesendorfer and Schmidt-Dengler (2008) offered a nice proof of the existence. However, the uniqueness of the equilibrium is not guaranteed, which will be discussed more in the next session



on empirical approach.

## 7 Empirical Strategy

The empirical strategy follows closely to the methodology developed by AM (2007), and it is also close to the approach in BBL (2007) and POB (2007). The first step is to estimate the equilibrium policy function. Assuming agents hold correct belief and play optimally, this step attempts to characterize hospitals' actions as a function of state variables. It avoids computing the equilibrium as the policy function is estimated from the equilibrium actually played in the data. The second step finds the parameters that rationalizes the observed policy function as the optimal choice given the underlying theoretical model. There are no guarantees that the equilibrium is unique. I impose the following assumption in order to group all the markets together in estimating the policy function.

Assumption 1: The same equilibrium is played in all markets.

This assumption is critical to obtain consistent estimates in the first step. Suppose there are two equilibria played in the data:  $\sigma_1(s, \varepsilon)$  and  $\sigma_2(s, \varepsilon)$ . The estimated policy can be a convolution of both and therefore the imposition of the MPNE will generally not produce consistent estimates for the primitives. Under Assumption 1, I can group the markets together to recover the policy function.

### Step One: Estimating the policy function

Hospitals make decisions about whether to adopt and which vendor to choose. The option actually picked should give the highest payoff. The probability for Hospital  $i$  to purchase from Vendor  $j$  is characterized using a logit regression:

$$P_i(a(s) = j) = \frac{\exp(x^j \alpha + z_i \lambda^j)}{\sum_{k=0}^J \exp(x^k \alpha + z_i \lambda^k)} \quad (10)$$

where  $x^j$  is a vector of product characteristics that vary by vendor and  $z_i$  represents a group of hospital-specific features.  $\alpha$ 's and  $\lambda$ 's measure the marginal value of those variables. Note that the  $\lambda$ 's vary across vendors. For example, if  $z_i$  includes the

number of beds, the corresponding coefficient informs the marginal value per unit of bed from a particular vendor. In the model, the decision of affiliated hospitals is assumed to be exogenous to the local market but will also be observed by the stand-alone hospitals and thus enter the profit function. The evolution of these exogenous hospitals' choice is modeled analogously to that of the stand-alone hospitals. The  $x_j$  for stand-alone hospitals is a vector:

$$x_j = [f(s, j), g(s, j), g(s, j) \times 1\{i \text{ is a large hospital}\}, l(j), l(j) \times 1\{i \text{ is a large hospital}\}] \quad (11)$$

where  $f(s, j)$  measures the market share of Vendor  $j$ ;  $g(s, j)$ , defined as earlier, indicates whether Vendor  $j$  is the most popular in the local market; and  $l(j)$  represents whether  $j$  is the same as the previous choice if Hospital  $i$  has already installed EMR. Both  $f(\cdot)$  and  $g(\cdot)$  are measures of the popularity for Vendor  $j$ .  $l(\cdot)$  helps capture the inertia in adoption choice. Inclusion of  $f(\cdot)$ ,  $g(\cdot)$  and  $g(\cdot) \times 1\{i \text{ is a large hospital}\}$  helps to capture the transition of market states. As the number of possible states is more than the data points, I use those functions as approximation. Similarly, the  $x_j$  for affiliated hospitals includes

$$x_j = [r(j), l(j), l(j) \times 1\{i \text{ is a large hospital}\}] \quad (12)$$

where  $r(j)$  indicates whether  $j$  is the major supplier for the entire hospital system.  $z_i$  could be different for both types of hospitals with different adoption status. According to the literature, important variables that affect the choice of vendors include environment factors like local competition levels, and hospital characteristics such as profit status, the number of beds, outpatient visits, inpatient admissions, full-time physicians, the percentage of Medicare and Medicaid discharges and whether the hospital is a teaching hospital. Which variables are included in the estimation depends on economic significance and model predictability. A market corresponds to a HSA and year combination. By assuming the errors to be *i.i.d.* across years and hospitals, I pool all the observations together for estimation.

## Step Two: Recovering the structural parameters

The estimated policy function from the previous step describes how the state evolves over time and allows me to simulate the value of different choices which can be used to recover the model primitives. Starting with the actual state, I simulate the future market configurations for each action the hospital might take. States evolve according to the policy function estimated from the first stage. The simulated future paths will be long enough in order to approximate the infinite horizon problem (Here I use 100 periods). The value associated with a particular action will be the discounted values along the entire future path, i.e., the discounted sum of the expected per-period payoff from all future periods where the expected per-period payoff function is

$$\begin{aligned}
 E_{\varepsilon_{it}} \pi_{it}(s) = & [\gamma_1 g(s, k) + \gamma_2^k \text{beds} + \gamma_3 g(s, k) \times 1\{i \text{ is a large hospital}\}] \times 1\{\text{with } k \text{ in place}\} \\
 & - \zeta^j \times 1\{\text{purchase from } j\} - \eta \times 1\{\text{switching from } k \text{ to } j\} \\
 & - \eta^{\text{big}} \times 1\{i \text{ is a large hospital}\} \times 1\{\text{switching from } k \text{ to } j\}
 \end{aligned} \tag{13}$$

Another computational simplification in AM is that one doesn't have to do the forward simulation for every trial value of the parameters. Define

$$\begin{aligned}
 W(s_t; \sigma(s)) = & E_{\sigma(s)} \sum_{\tilde{t}=0}^{\infty} \beta^{\tilde{t}} [1\{\text{purchase from } j\}, 1\{\text{switching from } k \text{ to } j\}, \\
 & g(s_{t+\tilde{t}}, k) \times 1\{\text{with } k \text{ in place}\}, \text{beds} \times 1\{\text{with } k \text{ in place}\}].
 \end{aligned} \tag{14}$$

In my model, all the unknown parameters enter linearly into the payoff function. The value function is then

$$\begin{aligned}
 V(s_t; \sigma(s), \theta) = & W(s_t; \sigma(s)) \cdot [-\zeta^j, -\eta - \eta^{\text{big}} \times 1\{i \text{ is a large hospital}\}, \\
 & \gamma_1 + \gamma_3 \times 1\{i \text{ is a large hospital}\}, \gamma_2^{k'}]
 \end{aligned} \tag{15}$$

where  $\theta$  denote the set of structural parameters to be estimated. By repeating such a simulation process for multiple times, the expected discounted value is the average across all the repetitions. Then I can write down the CSVF and hence the probability of each action. The structural parameters are estimated by maximizing the probability of observed actions.

## 8 Empirical Results

### 8.1 Policy function

The estimation of the policy function is essentially a multinomial logit regression and the main purpose is for forward simulation. Since hospitals that have no EMR have an extra option than those with an existing system, and since endogenous and exogenous hospitals have different policy functions governing the movement of their states, I run the logit regression on four different subsets of the sample: stand-alone hospitals without EMR, stand-alone hospitals with EMR, affiliated hospitals without EMR and affiliated hospitals with EMR. As in Equation 11, the product characteristics  $x_j$  facing stand-alone hospitals contain the market share, whether a particular vendor is market-leading and its interaction with a large hospital dummy. The first two variables are different measures to reflect the popularity of each vendor and the last one helps capture the extra gain/loss for the large hospitals choosing the market-leading technology. The key role played by the policy function is to represent the transition across the states. The state space in this model can be enormous. The transition matrix for a market with 3 stand-alone hospitals (each with 13 options) is a  $2137 \times 2137$  matrix, let alone the markets with more than 10 stand-alone hospitals. As the number of possible states is more than the data points, I use  $x_j$  as approximation. I also included into  $x_j$  other functions of the market states, such as whether it is the second or third leading technology and the interaction between all of them. The reported specification provides the best sample fit.

Table 6 displays the estimates of the policy function based on the sample of all stand-alone hospitals without EMR. The upper panel reports the coefficients for product characteristics and the lower presents the results for the hospitals characteristics interacting with vendor dummies. What hospitals features are included depends on economic significance and sample predictability. Vendors with higher market share seem to be more attractive to new adopters and using the market-leading technology is beneficial to large hospitals. The specification in this section is similar to that in the reduced-form estimation except that the sample applied here includes all stand-alone hospitals without EMR while the previous one is only a subset. The finding here is somewhat consistent with that in the previous specification with outside proxy. Ac-

According to the lower panel, the probability of choosing a particular vendor increases with the bed size for most of the vendors except for CPSI and Healthland. This also confirms the previous finding that the products from these two suppliers are better fit in smaller hospitals. All the vendor dummies are negatively significant, implying that new adopters are confronting substantial barriers in adopting the technology. Table 7 reports the results for the sample of stand-alone hospitals with EMR. In order to characterize the inertia of choices I add two more variables into the product characteristics: whether a particular vendor is chosen and its interaction with the large hospital dummy. The latter seeks to capture whether large hospitals behave differently than small ones. The last two columns in the upper panel show hospitals tend to be very “loyal” to the vendor they chose although large hospitals have a slightly higher chance to switch. A potential source of this “loyalty” may stem from a large amount of switching cost, which will be estimated in the second stage. The first three columns suggest that being the leading vendor plays a minor role in affecting the choice of hospitals with existing systems. The variables in the lower panel are somewhat different from that in the previous sample. What to include is again based on economic significance and model predictability.

The choices of affiliated hospitals evolves exogenously to the local market. However, their choices are part of the state variable and thus affect the adoption decision of stand-alone hospitals. I simulate the future choices of affiliated hospitals based on the “exogenous” product characteristics: an indicator of the hospital’s system-wise dominant vendor and its previous choice. Specifically, the product characteristic for affiliated hospitals without EMR only involves an indicator of whether a particular vendor is dominant inside the hospital system. The upper panel in Table 8 provides the estimate of this variable and it is suggested member hospitals are more inclined to follow the choice of the parent system. The finding is robust for the set of affiliated hospitals with EMR, as shown in Table 9. This provides supportive evidence for the assumption that their decisions are exogenous to the local market. For the group of affiliated hospitals with EMR, I also include the two variables to capture the inertia and find that the previous choice plays a significant role in the adoption choice.

## 8.2 Structural Estimates

The policy function estimated from the first stage allows me to simulate the future states for all actions the hospital might take. The length of the future path is set to be 100 periods such that the discounted presented value of the last period is sufficiently small. I derive the value function by summing up all the future payoffs associated with each action and the probability is given by the assumed distribution of the unobserved shocks. Table 10 reports the estimates for the model primitives. The upper panel presents the value of using the market-leading technology, the switching cost as well as both interacting with the large hospital dummy. All of them are positively significant. Hospitals benefit from choosing the market-leading vendor and the gain is asymmetric between large and small hospitals. On average, profit generated from using the market-leading technology is 73.7% ( $= 0.0157/0.0213 \times 100\%$ ) higher for large hospitals. There are two possible reasons: greater profit complementarities and less competitive pressure. A large hospital tends to interact more intensively with local payers and providers, and therefore using a compatible technology saves a lot of trouble. It is also more likely for them to get favorable pricing since they are often the preferred customers to vendors. When patients are able to switch between health care providers easily, a large hospital will expect inflow of patients given the advantage in technology and services. Both large and small hospitals bear a significant amount of switching cost but large hospitals spend 38.3% ( $= 0.72/1.88 \times 100\%$ ) less in switching. External consultancy and system management are most expensive in implementation of EMR. As a result, large hospitals will set up their own department for IT support. If the hospital has to switch to a different vendor, the established IT team can be “recycled” to serve another system. However, this is not realistic for small hospitals, which instead has to keep hiring third-party consulting.

The lower panel in Table 10 presents the estimates of vendor-specific sunk cost and cost saving per 100 beds. The adoption of EMR incurs a considerable amount of sunk cost, regardless of which vendor to choose. The amount of sunk cost varies a lot by vendor. The lowest sunk cost is less than 40% ( $= 2.71/6.80 \times 100\%$ ) of the highest one. If I roughly equate the median sunk cost (4.43) to the median implementation cost (\$9.5 million according to the study by the Congress Budget Office) for a hospital with 250 beds, one unit of sunk cost represents about \$2.2 ( $= 9.5/4.43$ ) million. It

is a very rough estimate since the sunk cost also includes the potential production loss which may not be accounted for in the pecuniary value. The third column in the lower panel in Table 10 lists the estimated cost savings for each vendor, most of which are positively significant except for the three vendors: CPSI, Healthland and HMS. It is consistent with the reduced-form evidence. For a hospital with 250 beds, adoption of EMR increases the per-period profit by 0.042 units from the cost-saving by bed size. If the EMR adopted is the market-leading technology, the hospital can further boost up its profit by 0.0213 units. Therefore, choosing the market-leading vendor can increase the per-period profit from adoption by 50.7% ( $= 0.0213/0.042 \times 100\%$ ) as opposed to other vendors. Although the market-leading technology brings in much higher payoff at each period, it is only 0.47% of the average sunk cost. Note that both the parameters for the market-leading technology and cost savings are based on one single period while the sunk cost measures the net discounted costs to implement the technology. In order to make the comparison more sensible, I adjust them into the net present values. Consistent with the discounted factor used in the estimation  $\beta = 0.95$ , a life-time payoff from using the market-leading technology is 0.43 ( $= 0.0213/(1 - \beta)$ ) units, which accounts for 9.4% of the average sunk cost. The net gain from using the market-leading technology is moderate compared with the substantial cost barriers. The last two columns in the upper panel of Table 10 reveals the mean switching cost, which is almost 43% of the average sunk cost. This also explains why not everybody chooses the market-leading technology despite the potential benefit. At the moment of purchase, not all the hospitals have the perfect sense about which technology will be market-leading. If a hospital picked a choice that turns out to be suboptimal in the market, it would probably get stuck given the high switching cost. Note that all the analysis above are made for hospitals in general. Large hospitals would be probably in a more favorable position.

## 9 Counterfactual Analysis

Estimating a structural model allows me to simulate counterfactual experiments since I know the underlying primitives. My primary interest is to assess the impact on the adoption outcome across different policy regimes. To achieve this, I compute the MPNE of the theoretical model with the estimated parameters. The outcome vari-

able is defined to be the rate of market coordination. It is the fraction of stand-alone hospitals that choose the market-leading technology which, additionally, is adopted by more than one hospitals. This extra requirement emphasizes the will of policy makers to coordinate hospitals' adoption choices. Consider a market with three hospitals, each installing a different system. Each hospital is using the market-leading technology, but no market coordination is occurring from the standpoint of the policy makers. It should be emphasized that this measure does not perfectly match the level of market coordination. Consider a different market with four hospitals. Two of them use the same product and the remaining share another one. In terms of this measure, the rate of coordination is 100% but in fact information cannot be exchanged freely in this market. The results should be interpreted in such a way that the emergence of this type of coordination reflect a certain level but not full degree of market coordination.

I should have solved out the full solution for each market in the data, but I only take the markets with three stand-alone hospitals into the analysis due to the computational constraints. It should be a reasonable measure as three active hospitals in a market is the average size in the data. Figure 1 compares the trend of adoption rate computed from the actual data with the in-sample prediction. The blue line shows the pattern generated from the data while the red line depicts the path predicted by the estimated model primitives. The model is doing a reasonable job for the in-sample prediction.

## 9.1 Too many choices?

This subsection explores a potential explanation for failure in market coordination. There are eleven major vendors plus hundreds of small ones available to hospitals, but each of them is not compatible with each other. In order to find out whether too many choices is one possible reason for poor coordination, I reduce the number of choices and compare the resulting rates of coordination. In the conducted experiment, I shut down all the vendors except for the six most popular ones and simulate the markets ten years forward. Figure 2 shows how the rate of market coordination evolves across time. The blue line describes the trend for the market with the full



choice set while the red line for the experiment in which only six options are available. Both cases start with 18% of market coordination. Ten years later, it increases to 48% in the case of 6 choices while the markets with the original choice set have 34% coordination. The gap between two lines expands across time, implying having fewer options is helpful to improve the market coordination.

## 9.2 Subsidy in new markets

The previous experiment provides some evidence that the number of choices has impacts on the level of coordination. I now perform counterfactual experiments under different policy regimes in new markets where most of the hospitals have no EMR. The first policy experiment involves the subsidy towards all adoption. As long as the hospital chooses to adopt, regardless of which vendor to pick, it will obtain a certain amount of subsidy. This unconditional subsidy program tries to mimic the element in the actual incentive program where no restriction is imposed on the choice of vendors. Given the fact that different products cannot communicate, the standard on interoperability is essentially blank under such a program. Another experiment considers a subsidy program in which hospitals have to choose the locally market-leading technology in order to get the reimbursement. It imposes an extra requirement, specially encouraging the adoption of the most popular technology in the local region. In each experiment, I derive the relationship between the amount of subsidy and the rate of market coordination across time. Due to the computation constraint, I restrict the available choices to be the six most popular vendors.

Figure 3 presents the relations under two policy regime. This is a 3-D graph with  $X$  axis being the amount of subsidy measured by the percentage of the median sunk cost,  $Y$  axis representing year and  $Z$  axis denoting the rate of market coordination. Both the left and right graphs represent the same figure from different perspectives. Particularly, the right one is the overlook of the graph. The green surface describes the evolution under the unconditional program and the red one presents that for the targeted subsidies. Whichever goes above represents greater market coordination. Taking a closer look at both graphs, I find the red surface slope goes steeper than the green one over time, implying that the targeted subsidies are even more effective over

time. As time goes by, later adopters, who prefer to wait and see competitors' choices, will have better sense about which is the best technology in the market. Targeted subsidies towards the most popular technology make the choices for them even more obvious. Therefore, the market becomes increasingly integrated across time, hence widening the gap between the red and green surfaces.

However, the impact is not that obvious at the early stage. In the first two years, when the amount of subsidies is below 10 percent or between 38 to 58 percent of the median sunk cost, the unconditional subsidy program results in slightly better coordination. Intuitively, what distinguishes the targeted subsidies from the other lies in the fact that it forces hospitals to be more careful in the choice of vendors. Under such a program, early adopters tend to think twice about their choices so that the local leading vendor is likely to show up earlier. For later adopters, this extra requirement increases their option value of waiting and thus delays their action. The higher amount of subsidies is set, the more delay there will be. This is consistent with the finding that during the early years, the adoption rate under the unconditional subsidy program is increasingly higher in the amount of subsidies (shown in Figure 4).

When the amount of targeted subsidies is very low and during the first few years of the program, early adopters behave very much like they were in the program subsidizing any type of technology, and later adopters tend to delay their adoption just a little bit. Therefore, the targeted subsidies will not function very well and the outcome could be even worse than the other. As the amount of subsidies increases, early adopters are more careful in choosing the "right" vendor such that the local leading vendor "stands out" quickly. In the meantime, later adopters will not wait for too long and as a result, the market coordination in the presence of targeted subsidies catches up pretty soon and even outruns the other very early. When the amount of subsidies reaches a certain level where the sunk cost is no longer as a big concern as before, more and more hospitals are willing to adopt early in the case where any type of adoption gets subsidized. However, the generous subsidies will instead defer the adoption decision of even more hospitals in the targeted program. Therefore, early clustering is more likely to happen in the program offering unconditional subsidies when the amount of subsidies is rather high.

The graph on the right in Figure 3 shows the targeted subsidies to the locally leading technology dominates the other throughout the entire simulated period if the amount of subsidy is between 10% to 38% or more than 58% of the median sunk cost, which is between \$0.97 to \$3.90 million or more than \$5.85 million from the back-of-the-envelope calculation introduced earlier<sup>1</sup>. The red surface goes beyond the green one after 3 years as long as the amount of subsidies is more than 10% of the median sunk cost. In the actual incentive program, an eligible hospital with an average size (with 250 beds, 10,000 total discharge per year and 30% medicare discharge) can get \$1.2 million.<sup>2</sup> Assuming the amount from the model is a plausible estimate, the government is likely to have performed better with the same amount of expense. Promoting the market-leading technology is only one of the many measures to encourage a regional standard on interoperability. The comparison of these two experiments aims to illustrate the importance of stressing the requirement about compatibility. In order to apply IT to health care effectively, the government should not only provide payments to purchase new technology, but can also take advantage of the profit complementarities to achieve interoperability. It is worthwhile to point out that I use the level of coordination as the outcome variable since the main policy concern is market integration. But hospitals' profits show similar results due to the fact that hospitals gain benefit from coordination. As shown in Figure 5, hospitals' profits are higher in the presence of targeted subsidies and the difference in profits becomes increasingly larger over time.

### 9.3 Subsidy in mature markets

This subsection evaluates the outcome from different types of subsidy in mature markets. Special attention is placed to markets with high adoption rate but almost no coordination. I design in the first experiment an unconditional subsidy towards all switching. Any hospital that switches can get a payment equal to the mean switching cost. The counterpart experiment imposes an additional requirement that hospitals

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<sup>1</sup>For a hospital with 250 beds, one unit of sunk cost is equivalent to \$2.2 million.

<sup>2</sup>A simpler version of the official formula is that the incentive payment equals the product of the initial amount, percentage Medicare share discharge and transition factor. The initial amount is the sum of \$2 million plus \$200 per discharge for the 1,150th–23,000th discharge. The payment lasts for 5 years and I only use the subsidy in the first year so the transition factor is 1.

will not get reimbursed unless they switch to the market-leading technology. Similarly, the latter experiment promotes the usage of the market-leading technology. I simulate ten years forward for both policy regimes and compare how the rates of market coordination change across time. Figure 6 plots the evolution for the case without subsidy, with unconditional subsidy and with subsidy towards special technology. All of them start with no market coordination. The rate of market coordination only increases to 24% after 10 years in the markets without any financial assistance from the government. In the first four years, both subsidy programs perform the same, but the one requiring extra condition outruns the other after then. The effect on mature markets is not as obvious as that in new markets. However, the government has to pay a higher price—the mean adoption cost is more than 40% of the mean sunk cost.

## 10 Conclusion and future work

This paper tries to understand the dynamics behind hospitals' adoption decision in the choice of EMR vendors. In particular, I focus on the sample of stand-alone hospitals which are considering whether to choose the technology leading the local market. On the one hand, hospitals gain profit complementarities from using the market-leading technology. However on the other hand, they are worried about losing patients when it is easier for them to switch between health care providers. The goal of this study is to estimate which force dominates and whether the policy makers can take advantage of this special property to improve market coordination.

I develop a dynamic oligopoly model to characterize hospitals' adoption decision. Whether a particular vendor is market-leading becomes a product characteristic goes into the profit function. Based on a national sample of U.S. hospitals, I estimate the structural parameters following the approach by Aguirregabiria and Mira (2007). It is found that hospitals expect positive returns from adopting the market-leading technology, i.e., profit complementarities exceeds the countervailing competitive effect. The gain is asymmetric between large and small hospitals. On average, choosing the market-leading vendor increases the per-period profit from adoption by almost 51% compared with other choices. However, the impact is moderate when it is compared with the amount of sunk cost in implementing the technology. Hospitals also have to

bear a considerable amount of switching cost, about 43% of the average sunk cost, when they change vendors and small hospitals suffer even more. Consequently, it is important for the government to provide financial subsidy in assisting new purchase. However, the diffusion of HIT will be more effective if the government stresses the requirement of interoperability and one way is to incentivize the adoption of the market-leading technology. By recognizing the value of such a technology, the policy makers will play a significant role in helping hospitals make sound choices to improve market coordination.

The policy design in the current analysis is nondiscriminatory—a constant amount towards all hospitals. Considering the different magnitude in profit complementarities and switching costs between large and small hospitals, one can even go further by configuring some discriminatory payment mechanism to maximize the effect of the financial subsidy given the limited budget. I also consider modeling potential penalties, as percentage of total Medicare reimbursement, to hospitals which fail to demonstrate meaningful use of Health IT. It is believed that penalties in Medicare reimbursement could have even greater impacts on hospitals' incentive of adoption. Counterfactual experiments involving policy regimes with richer structure is part of the future plan for this project. I also consider including the supply side into the analysis. The current study models the hospital profit directly derived from adopting EMR without considering the vendors' behavior. The main reason is due to lack of data on the supply side. This part requires more extensive search in data and the literature.

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Table 1: Summary statistics in the sample of 2006

| Variable  | Obs  | Mean   | Std. Dev. | Min | Max  |
|---|------|--------|-----------|-----|------|
| EMR adoption for all hospitals                            | 4560 | 0.49   | 0.50      | 0   | 1    |
| EMR adoption for stand-alone hospitals                    | 2060 | 0.41   | 0.49      | 0   | 1    |
| % for stand-alone hospitals to use market-leading product | 844  | 0.67   | 0.47      | 0   | 1    |
| Number of hospitals in a HSA                              | 4560 | 4.95   | 6.49      | 1   | 90   |
| Number of stand-alone hospitals in a HSA                  | 2060 | 2.24   | 2.66      | 0   | 33   |
| Number of competitors in a local market                   | 4560 | 3.95   | 6.49      | 0   | 89   |
| Ratio of competitors adopting EMR                         | 4560 | 0.37   | 0.37      | 0   | 1    |
| Number of beds for stand-alone hospitals                  | 2060 | 142.04 | 160.62    | 6   | 1558 |
| For-profit stand-alone hospital                           | 2060 | 0.04   | 0.20      | 0   | 1    |
| Not-for-profit stand-alone hospital                       | 2060 | 0.58   | 0.49      | 0   | 1    |
| Academic medical center                                   | 2060 | 0.06   | 0.23      | 0   | 1    |
| % of Medicare discharge for stand-alone                   | 2060 | 0.50   | 0.15      | 0   | 0.99 |
| % of Medicaid discharge for stand-alone                   | 2060 | 0.16   | 0.11      | 0   | 0.84 |

Table 2: Summary statistics in the sample of 2009

| Variable  | Obs  | Mean   | Std. Dev. | Min | Max  |
|---|------|--------|-----------|-----|------|
| EMR adoption for all hospitals                            | 4560 | 0.84   | 0.37      | 0   | 1    |
| EMR adoption for stand-alone hospitals                    | 1969 | 0.77   | 0.42      | 0   | 1    |
| % for stand-alone hospitals to use market-leading product | 1517 | 0.64   | 0.48      | 0   | 1    |
| Number of hospitals in a HSA                              | 4560 | 4.95   | 6.49      | 1   | 90   |
| Number of stand-alone hospitals in a HSA                  | 1969 | 2.14   | 2.64      | 0   | 34   |
| Number of competitors in a local market                   | 4560 | 3.95   | 6.49      | 0   | 89   |
| Ratio of competitors adopting EMR                         | 4560 | 0.67   | 0.41      | 0   | 1    |
| Number of beds for stand-alone hospitals                  | 1969 | 140.04 | 166.38    | 4   | 2095 |
| For-profit stand-alone hospital                           | 1969 | 0.05   | 0.22      | 0   | 1    |
| Not-for-profit stand-alone hospital                       | 1969 | 0.56   | 0.50      | 0   | 1    |
| Academic medical center                                   | 1969 | 0.06   | 0.23      | 0   | 1    |
| % of Medicare discharge for stand-alone                   | 1969 | 0.50   | 0.15      | 0   | 0.96 |
| % of Medicaid discharge for stand-alone                   | 1969 | 0.17   | 0.11      | 0   | 0.77 |

Table 3: Top 11 EMR vendors and their market share among in 2006

| Vendor                         | Market share |
|--------------------------------|--------------|
| Healthland                     | 1.91%        |
| EPIC                           | 2%           |
| Healthcare Mngt. Systems (HMS) | 2.31%        |
| GE Healthcare                  | 3.33%        |
| Eclipsys                       | 3.87%        |
| CPSI                           | 5.69%        |
| Self-developed (SD)            | 7.69%        |
| Cerner                         | 11.73%       |
| Siemens                        | 11.87%       |
| McKessons                      | 12.67%       |
| Meditech                       | 28.98%       |
| sum                            | 92.04%       |

Table 4: Reduced-form evidence—the existence of profit complementarities

| market-leading        | market-leading × big |  |
|-----------------------|----------------------|--|
| 0.6198***<br>(0.1256) | 0.0761<br>(0.230)    |  |

|                | Cerner                 | CPSI                  | Healthland            | Eclipsys               | EPIC                   | GE                     |
|----------------|------------------------|-----------------------|-----------------------|------------------------|------------------------|------------------------|
| Bed size       | 0.0049<br>(0.0076)     | -0.0166**<br>(0.0077) | -0.0190**<br>(0.0081) | 0.0120<br>(0.0075)     | 0.0053<br>(0.0078)     | 0.0113<br>(0.0079)     |
| Not-for-profit | 1.1884<br>(0.8864)     | 0.6452<br>(0.8258)    | 0.5785<br>(0.8371)    | 2.1430*<br>(1.2343)    | 1.9251*<br>(1.0416)    | 2.3711*<br>(1.2731)    |
| Teaching       | 15.1531***<br>(1.6325) | -0.2143<br>(1.4762)   | -0.1803<br>(1.5045)   | -1.7297<br>(1.8380)    | 16.1781***<br>(1.5973) | 13.7384***<br>(2.1080) |
| Constant       | -0.1101<br>(0.6959)    | 3.5495***<br>(0.6157) | 3.1470***<br>(0.6293) | -3.0334***<br>(1.1744) | -1.6027 **<br>(0.8097) | -3.8790***<br>(1.0267) |

|                | HMS                   | McKessons              | Siemens                | Meditec                | Others                 |
|----------------|-----------------------|------------------------|------------------------|------------------------|------------------------|
| Bed size       | -0.0109<br>(0.0081)   | 0.0065<br>(0.0075)     | 0.0074<br>(0.0075)     | 0.0003<br>(0.0074)     | 0.0012<br>(0.0075)     |
| Not-for-profit | 0.2397<br>(0.8715)    | 0.9105<br>(0.8379)     | 1.8690**<br>(0.8848)   | 1.1484<br>(0.8149)     | 1.1492<br>(0.8318)     |
| Teaching       | 0.0367<br>(1.5123)    | 12.6544***<br>(1.8003) | 13.4320***<br>(1.6478) | 12.3908***<br>(1.7802) | 14.6913***<br>(1.5387) |
| Constant       | 2.1529***<br>(0.6425) | 0.8840<br>(0.6347)     | -0.4512<br>(0.7322)    | 2.3388***<br>(0.6182)  | 1.5688 **<br>(0.6393)  |

N=9768

Table 5: Reduced-form evidence—the existence of profit complementarities (using control function)

| market-leading     | market-leading×big    |
|--------------------|-----------------------|
| 0.0846<br>(0.5007) | 2.6721***<br>(0.8264) |

|          | Cerner                | CPSI                  | Healthland            | Eclipsys             | EPIC                  | GE                 |
|----------|-----------------------|-----------------------|-----------------------|----------------------|-----------------------|--------------------|
| Constant | 1.1231***<br>(0.4058) | 2.5824***<br>(0.3669) | 2.0422***<br>(0.3753) | 0.41<br>(0.4566)     | 0.5092<br>(0.4492)    | -0.281<br>(0.5394) |
|          | HMS                   | McKessons             | Siemens               | Meditec              | Others                |                    |
| Constant | 1.4356***<br>(0.3933) | 1.8076***<br>(0.3811) | 1.3749***<br>(0.3939) | 2.5006***<br>(0.379) | 2.0302***<br>(0.3756) |                    |
| N=6780   |                       |                       |                       |                      |                       |                    |

Table 6: Estimates of the policy function (Stand-alone, w/o EMR)

| market share          | market-leading     | market-leading×big   |
|-----------------------|--------------------|----------------------|
| 0.7122***<br>(0.2453) | 0.0044<br>(0.1947) | 0.4071**<br>(0.1904) |

|                | SD                      | Cerner                 | CPSI                    | Healthland              | Eclipsys                | EPIC                   |
|----------------|-------------------------|------------------------|-------------------------|-------------------------|-------------------------|------------------------|
| Bed size       | 0.0029<br>(0.0043)      | 0.0039***<br>(0.0015)  | -0.0081***<br>(0.0017)  | -0.0097***<br>(0.0024)  | 0.0092***<br>(0.0010)   | 0.0030<br>(0.0022)     |
| Not-for-profit | -0.3980<br>(0.8363)     | 0.6693*<br>(0.4063)    | 0.3075*<br>(0.1748)     | 0.2335<br>(0.2215)      | 1.6830**<br>(0.8505)    | 1.3250*<br>(0.7686)    |
| Teaching       | -13.8569***<br>(1.6132) | 0.9334<br>(0.9720)     | -13.3599***<br>(0.3572) | -13.3339***<br>(0.4449) | -14.5723***<br>(0.7770) | 2.1994**<br>(0.9278)   |
| Constant       | -5.6129***<br>(0.4253)  | -5.1636***<br>(0.3077) | -2.3821***<br>(0.1196)  | -2.8037***<br>(0.1586)  | -7.6426***<br>(0.8595)  | -6.4284***<br>(0.4848) |

|                | GE                     | HMS                     | McKessons              | Siemens                | Meditec                | Others                 |
|----------------|------------------------|-------------------------|------------------------|------------------------|------------------------|------------------------|
| Bed size       | 0.0086***<br>(0.0021)  | -0.0039<br>(0.0025)     | 0.0059***<br>(0.0008)  | 0.0062***<br>(0.0010)  | 0.0018**<br>(0.0007)   | 0.0023**<br>(0.0010)   |
| Not-for-profit | 1.6069<br>(0.9951)     | -0.1314<br>(0.3494)     | 0.4959**<br>(0.2528)   | 1.4263***<br>(0.3613)  | 0.7558***<br>(0.1527)  | 0.7334***<br>(0.2237)  |
| Teaching       | -0.6056<br>(1.3673)    | -13.3982***<br>(0.5704) | -2.0211**<br>(1.0385)  | -1.3320<br>(0.8674)    | -2.0329*<br>(1.0846)   | 0.0326<br>(0.7409)     |
| Constant       | -8.2930***<br>(0.6505) | -3.6769***<br>(0.1962)  | -4.2640***<br>(0.1874) | -5.4798***<br>(0.3508) | -3.1045***<br>(0.1244) | -3.8352***<br>(0.1829) |

N=39624

Table 7: Estimates of the policy function (Stand-alone, w/ EMR)

| market share       | market-leading     | market-leading×big | same_as_previous     | same_as_previous×big |
|--------------------|--------------------|--------------------|----------------------|----------------------|
| 0.3027<br>(0.3872) | 0.0802<br>(0.2388) | 0.019<br>(0.2773)  | 5.8852***<br>(0.182) | -0.4140*<br>(0.2235) |

|            | Cerner                | CPSI                   | Healthland              | Eclipsys               | EPIC                  | GE                     |
|------------|-----------------------|------------------------|-------------------------|------------------------|-----------------------|------------------------|
| Bed size   | 0.0013<br>(0.0011)    | -0.0129***<br>(0.0022) | -0.0196***<br>(0.0031)  | 0.001<br>(0.0016)      | 0.0016<br>(0.0013)    | 0.0023*<br>(0.0014)    |
| For-profit | -1.3010**<br>(0.6575) | 0.5389<br>(0.4868)     | -1.5226***<br>(0.462)   | -1.4885***<br>(0.5538) | -2.6347***<br>(0.693) | 0.1332<br>(0.8156)     |
| Teaching   | 0.3018<br>(0.8891)    | -10.5295***<br>(0.777) | -10.6777***<br>(0.7898) | 1.0249<br>(0.9378)     | 0.8907<br>(0.918)     | 0.8781<br>(0.87)       |
| Constant   | 0.8503**<br>(0.4173)  | 2.7640***<br>(0.4343)  | 3.0426***<br>(0.5161)   | 0.3158<br>(0.5835)     | 1.0952**<br>(0.4712)  | -1.7326***<br>(0.6666) |

|            | HMS                     | McKessons              | Siemens             | Meditec                | Others              |
|------------|-------------------------|------------------------|---------------------|------------------------|---------------------|
| Bed size   | -0.0136***<br>(0.0042)  | 0.0003<br>(0.0014)     | 0.0015<br>(0.0012)  | -0.0009<br>(0.0012)    | -0.0005<br>(0.0013) |
| For-profit | -1.2161*<br>(0.686)     | -2.2365***<br>(0.7165) | -0.6236<br>(0.4669) | -2.4632***<br>(0.9237) | -0.0096<br>(0.4624) |
| Teaching   | -10.1295***<br>(0.9406) | 0.2218<br>(0.961)      | 0.1521<br>(0.8238)  | -1.4998*<br>(0.8419)   | 0.734<br>(1.0517)   |
| Constant   | 1.9324***<br>(0.4937)   | 1.0681**<br>(0.508)    | 0.0895<br>(0.4849)  | 2.3956***<br>(0.4163)  | -0.388<br>(0.4505)  |

N=60324

Table 8: Estimates of the policy function (Affiliated, w/o EMR)

| system dominating |                        |                        |                        |                        |                        |                        |
|-------------------|------------------------|------------------------|------------------------|------------------------|------------------------|------------------------|
|                   | 2.0853***              |                        |                        |                        |                        |                        |
|                   | (0.0884)               |                        |                        |                        |                        |                        |
|                   | Self-developed         | Cerner                 | CPSI                   | Healthland             | Eclipsys               | EPIC                   |
| Bed size          | 0.0019***<br>(0.0007)  | 0.0021***<br>(0.0006)  | -0.0069**<br>(0.003)   | -0.0143***<br>(0.0042) | 0.0020*<br>(0.0012)    | 0.0012*<br>(0.0007)    |
| Not-for-profit    | -0.8441**<br>(0.3774)  | 0.4582**<br>(0.2226)   | -0.5896*<br>(0.3348)   | -0.0908<br>(0.3563)    | 1.6677**<br>(0.7533)   | 3.2469***<br>(0.7101)  |
| %Medicare         | -1.2401*<br>(0.6365)   | -1.6060**<br>(0.686)   | 1.4855<br>(1.2944)     | 0.0684<br>(1.2139)     | -2.1646<br>(1.9756)    | -1.5231*<br>(0.8769)   |
| Constant          | -3.5953***<br>(0.429)  | -3.0245***<br>(0.4199) | -3.9492***<br>(0.8509) | -2.9596***<br>(0.809)  | -5.3726***<br>(1.2677) | -5.5964***<br>(0.8697) |
|                   | GE                     | HMS                    | McKessons              | Siemens                | Meditec                | Others                 |
| Bed size          | 0.0024***<br>(0.0009)  | -0.0026*<br>(0.0015)   | 0.0020***<br>(0.0005)  | 0.0004<br>(0.0007)     | 0.0005<br>(0.0006)     | 0.0014*<br>(0.0008)    |
| Not-for-profit    | 2.2271***<br>(0.7336)  | -1.4520***<br>(0.3466) | 0.7611***<br>(0.2035)  | 0.0887<br>(0.2075)     | 1.2992***<br>(0.1911)  | 0.7282**<br>(0.3312)   |
| %Medicare         | -0.8437<br>(1.2326)    | -2.3751***<br>(0.5267) | -1.3543**<br>(0.6567)  | -3.9831***<br>(0.5953) | -1.1476*<br>(0.6338)   | -1.5962<br>(0.9959)    |
| Constant          | -6.1285***<br>(1.1405) | -1.4750***<br>(0.3537) | -3.3206***<br>(0.3795) | -1.5589***<br>(0.2993) | -3.8481***<br>(0.4008) | -3.8598***<br>(0.6114) |
| N=34944           |                        |                        |                        |                        |                        |                        |



Table 9: Estimates of the policy function (Affiliated, w/ EMR)

| system dominating     | same_as_previous      | same_as_previous×big |
|-----------------------|-----------------------|----------------------|
| 1.3089***<br>(0.0957) | 4.8336***<br>(0.0987) | -0.2557*<br>(0.1345) |

|           | Cerner                 | CPSI                   | Healthland            | Eclipsys               | EPIC                  | GE                    |
|-----------|------------------------|------------------------|-----------------------|------------------------|-----------------------|-----------------------|
| Bed size  | 0.0019***<br>(0.0007)  | -0.0044***<br>(0.001)  | -0.0073**<br>(0.003)  | 0.0028***<br>(0.0007)  | 0.0028***<br>(0.0006) | 0.0017**<br>(0.0007)  |
| %Medicare | 3.7011***<br>(1.0458)  | 4.3433***<br>(1.0596)  | 5.4168***<br>(1.7236) | 3.4056**<br>(1.5248)   | 3.1445***<br>(1.0454) | 2.193<br>(1.4086)     |
| %Medicaid | 2.5690*<br>(1.5042)    | 3.2605**<br>(1.4944)   | 1.9818<br>(3.9046)    | 1.1805<br>(2.3911)     | -2.0057<br>(1.8089)   | -0.3332<br>(1.7571)   |
| Constant  | -2.1377***<br>(0.6027) | -2.3350***<br>(0.6464) | -3.4792**<br>(1.4056) | -2.6049***<br>(0.9931) | -1.1816*<br>(0.6655)  | -1.8963**<br>(0.8419) |

|           | HMS                    | McKessons              | Siemens                | Meditec                | Others                 |
|-----------|------------------------|------------------------|------------------------|------------------------|------------------------|
| Bed size  | -0.0049***<br>(0.0013) | 0.0011<br>(0.0008)     | 0.0002<br>(0.0007)     | 0.0001<br>(0.0007)     | 0.0012<br>(0.001)      |
| %Medicare | 3.9610***<br>(1.4713)  | 3.8027***<br>(1.3155)  | 1.7096<br>(1.1398)     | 3.7860***<br>(1.1509)  | 6.1945***<br>(1.5661)  |
| %Medicaid | 4.4903**<br>(1.7558)   | 4.3568**<br>(1.7312)   | 2.0883<br>(1.6912)     | 3.1581*<br>(1.738)     | 5.1797***<br>(1.8224)  |
| Constant  | -2.3549**<br>(0.9196)  | -2.8050***<br>(0.8024) | -1.9669***<br>(0.7314) | -2.2121***<br>(0.6859) | -4.9706***<br>(0.9676) |

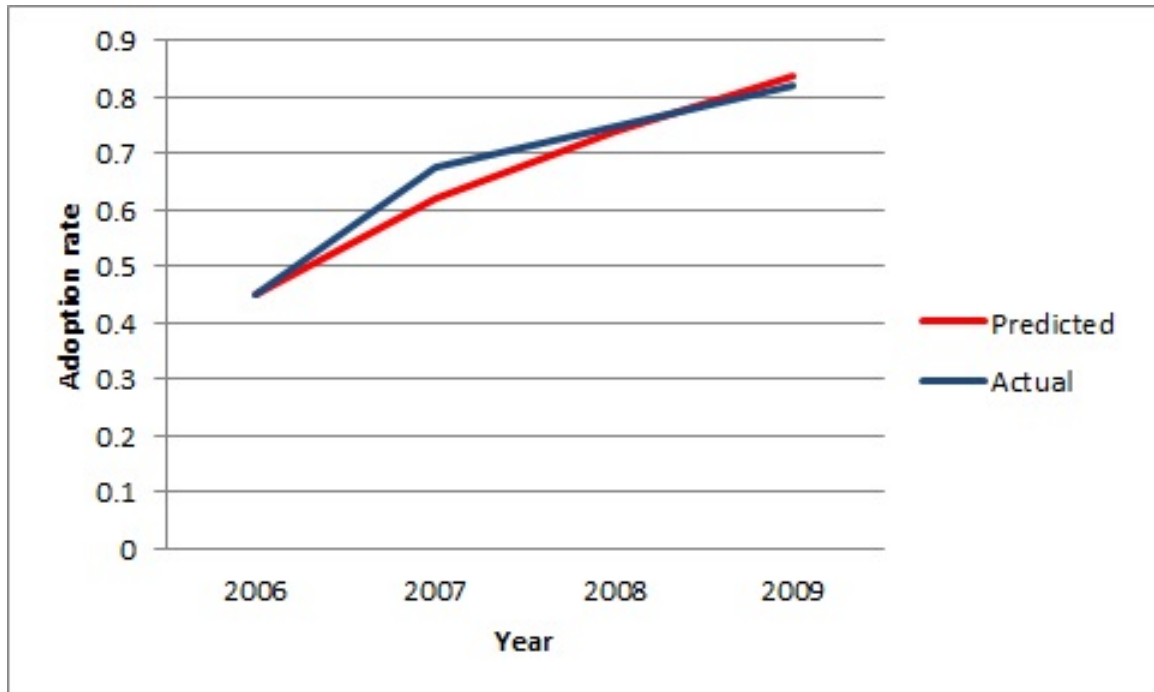
N=89724

Table 10: Structural estimates for the dynamic model

| market-leading       | market-leading×big  | switching cost      | switching cost×big     |
|----------------------|---------------------|---------------------|------------------------|
| 0.0213***<br>(0.005) | 0.0157*<br>(0.0082) | 1.8834***<br>(0.14) | -0.7199***<br>(0.1738) |

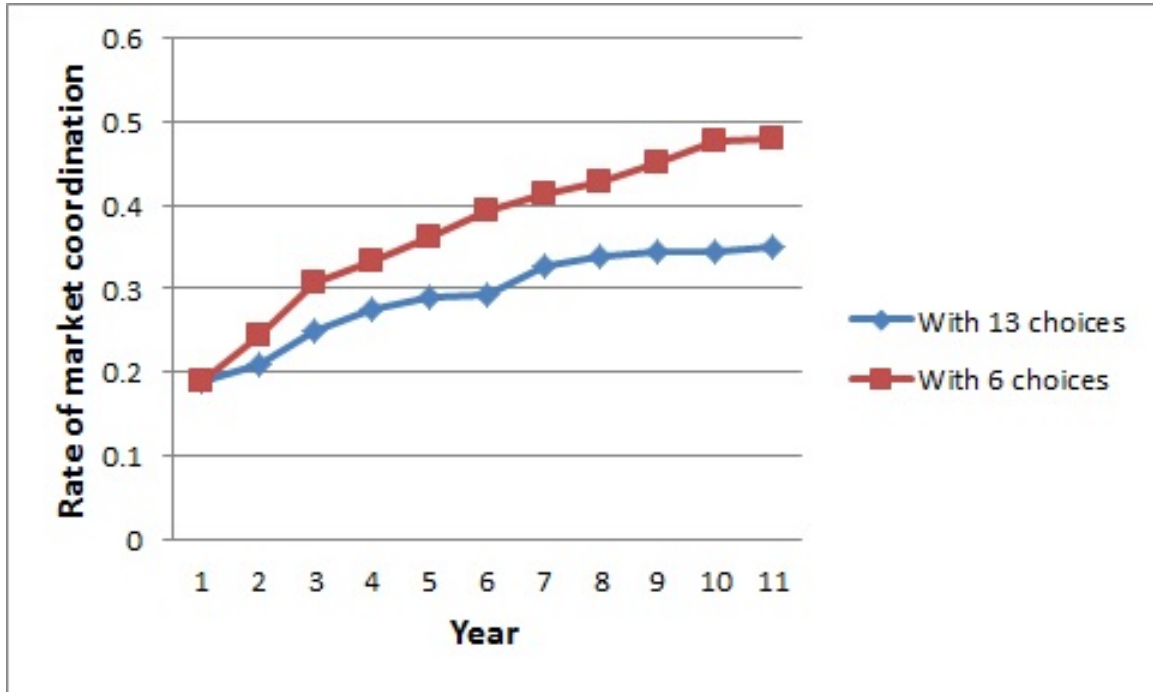
|                | Sunk cost             | Cost saving per 100 beds |
|----------------|-----------------------|--------------------------|
| Self_developed | 5.8169***<br>(0.2945) | 0.018***<br>(0.0041)     |
| Cerner         | 5.2462***<br>(0.2452) | 0.0362***<br>(0.0047)    |
| CPSI           | 2.7055***<br>(0.1338) | -0.0158<br>(0.0103)      |
| Healthland     | 3.0657***<br>(0.1724) | -0.0303*<br>(0.016)      |
| Eclipsys       | 5.6912***<br>(0.3177) | 0.0374***<br>(0.0042)    |
| EPIC           | 5.5308***<br>(0.2661) | 0.0418***<br>(0.0039)    |
| GE             | 6.8015***<br>(0.475)  | 0.0406***<br>(0.0049)    |
| HMS            | 4.0098***<br>(0.2219) | -0.0152<br>(0.0161)      |
| McKessons      | 4.1194***<br>(0.1627) | 0.0299***<br>(0.0034)    |
| Siemens        | 4.7431***<br>(0.1902) | 0.0301***<br>(0.0036)    |
| Meditec        | 3.0472***<br>(0.13)   | 0.0199***<br>(0.0039)    |
| Others         | 3.5761***<br>(0.1267) | 0.0101***<br>(0.0031)    |

Figure 1: In-sample prediction of adoption rate



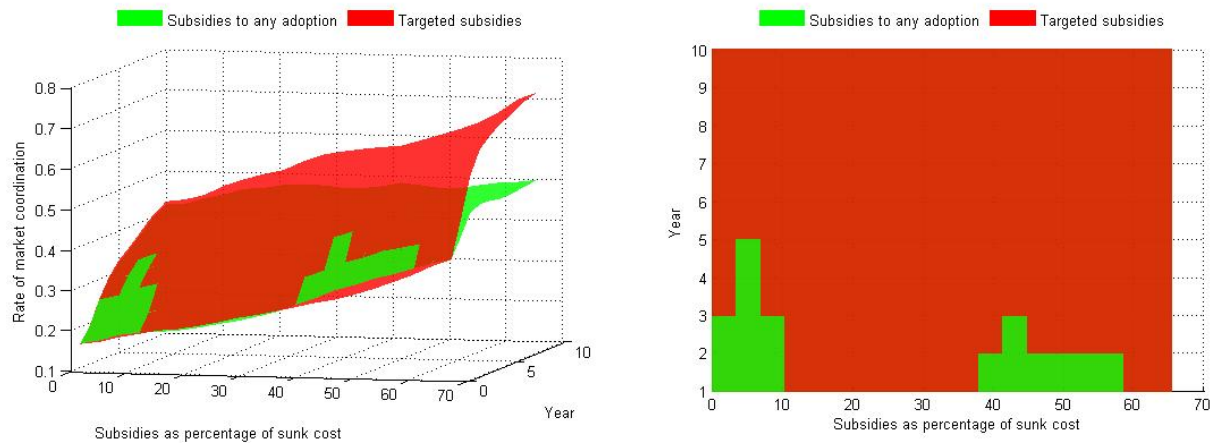
Note: Figure 1 compares the trend of adoption rate computed from the actual data with the in-sample prediction. The blue line shows the pattern generated from the data while the red line depicts the path predicted by the estimated model primitives. The model is doing a reasonable job for the in-sample prediction.

Figure 2: Market coordination between different choice sets



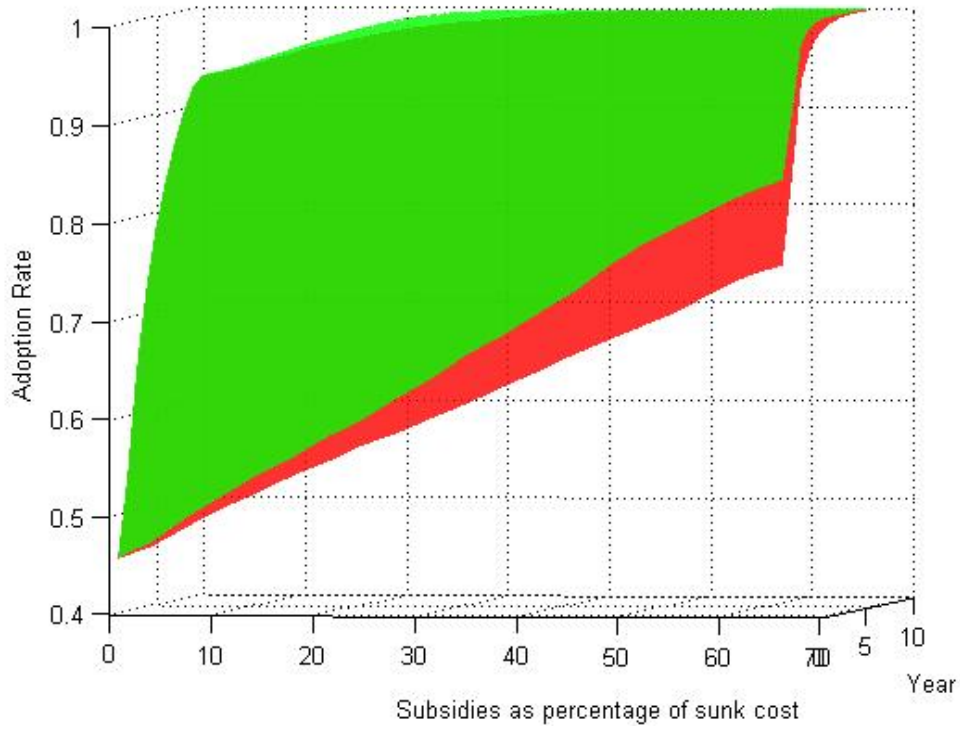
Note: Figure 2 shows how the rate of market coordination evolves across time. The blue line describes the trend for the market with the full choice set while the red line for the experiment in which only six options are available. Both cases start with 18% of market coordination. Ten years later, it increases to 48% in the case of 6 choices while the markets with the original choice set have 34% coordination. The gap between two lines expands across time, implying having fewer options is helpful to improve the market coordination.

Figure 3: Market coordination under different subsidy regime—new markets



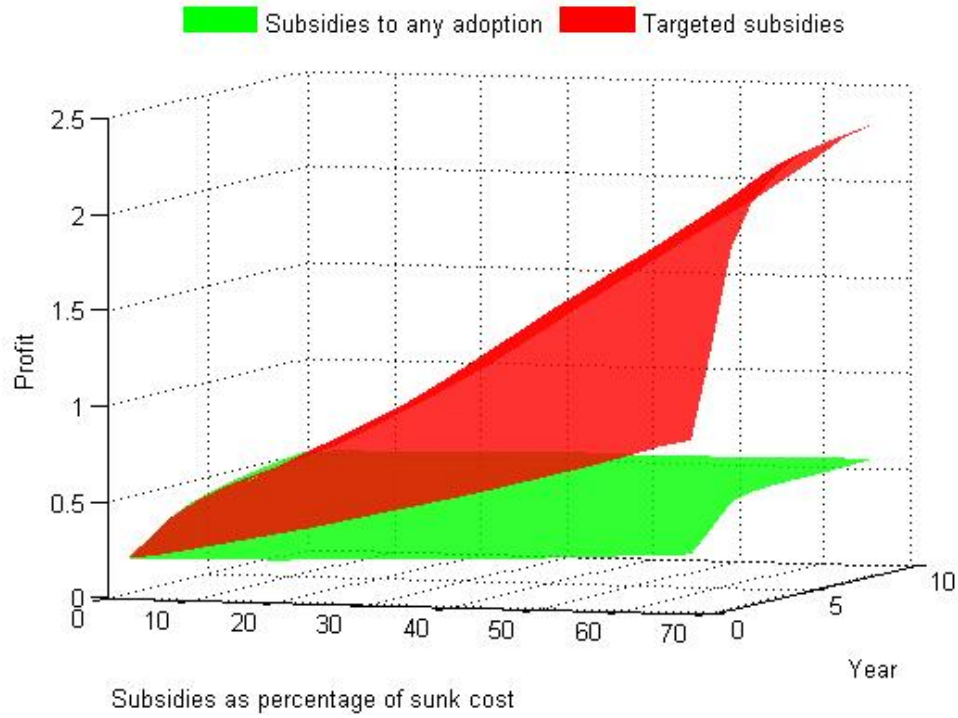
Note: Figure 3 presents the relations under two policy regime. This is a 3-D graph with  $X$  axis being the amount of subsidy measured by the percentage of the median sunk cost,  $Y$  axis representing year and  $Z$  axis denoting the rate of market coordination. Both the left and right graphs are the same figure from different perspectives. Particularly, the right one is the overlook of the graph. The green surface describes the evolution under the unconditional program and the red one presents that for the targeted subsidies. Whichever goes above represents greater market coordination.

Figure 4: Adoption rate under different subsidy regime—new markets



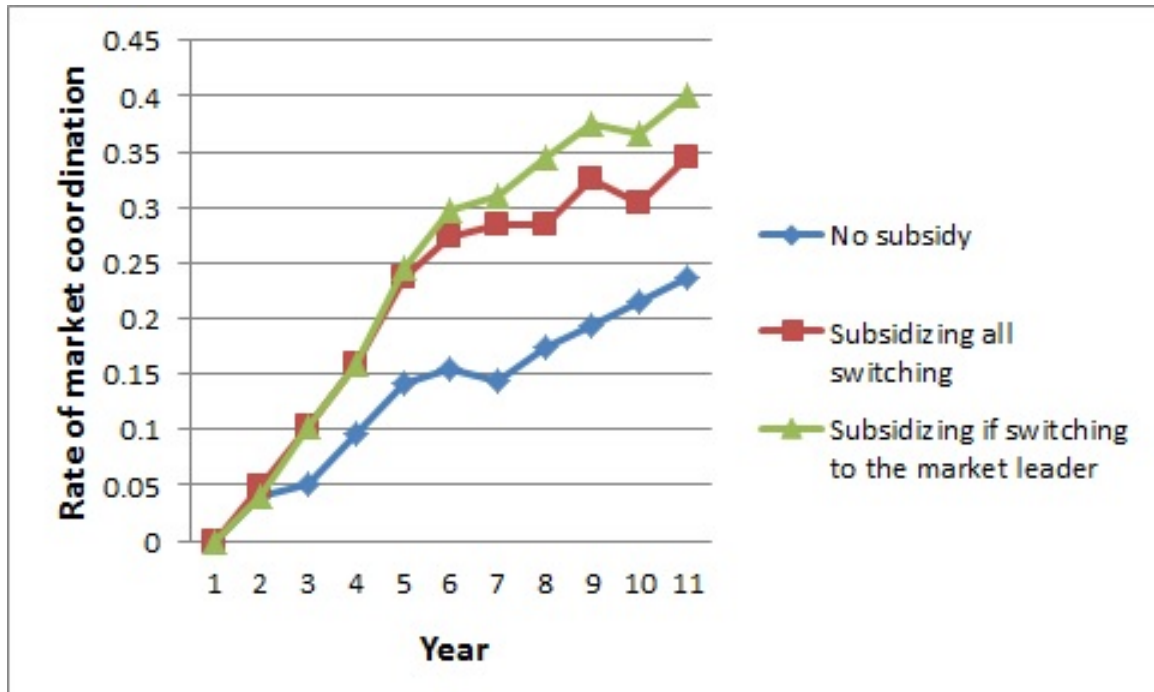
Note: Figure 4 presents the relations under two policy regime. This is a 3-D graph with  $X$  axis being the amount of subsidy measured by the percentage of the median sunk cost,  $Y$  axis representing year and  $Z$  axis denoting the adoption rate in the market. The green surface describes the evolution under the unconditional program and the red one presents that for the targeted subsidies. Whichever goes above represents higher adoption rate.

Figure 5: Profits under different subsidy regime—new markets



Note: Figure 5 presents the profits under two policy regime. This is a 3-D graph with  $X$  axis being the amount of subsidy measured by the percentage of the median sunk cost,  $Y$  axis representing year and  $Z$  axis denoting profits in the market. The green surface describes the evolution under the unconditional program and the red one presents that for the targeted subsidies. Whichever goes above represents higher profits.

Figure 6: Market coordination under different subsidy regime—mature markets



Note: Figure 6 plots the evolution for the case without subsidy, with unconditional subsidy and with subsidy towards special technology. All of them start with no market coordination. The rate of market coordination only increases to 24% after 10 years in the markets without any financial assistance from the government. In the first four years, both subsidy programs perform the same, but the one requiring extra condition outruns the other after then.