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

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This draft: January 24, 2016

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. 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 with even lower expense on subsidy payments. Moreover, more generous assistance to small hospitals is more effective in achieving market integration than supporting large hospitals.

*I am deeply indebted to Gautam Gowrisankaran for the continuous guidance and support. I have benefited from conversations with Keith Joiner, Mo Xiao, Ashley Langer, Mauricio Varela, Tiemen Woutersen and Benjamin Sperisen. I also thank the workshop and seminar participants for valuable suggestions and comments. I acknowledge HIMSS Analytics for providing the data used in this study. All the errors are my own.

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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 local market-leading vendor, which has the highest local market share. 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 enable 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 varies 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." Miller and Tucker (2014) studied the relation between health information exchange and the size of hospitals. They showed that

larger hospitals are more likely to exchange information internally but less willing to share information externally with nearby hospitals, reflecting a tendency to create information silos. By examining heterogenous effects from organizaitional size on data exchange, they provided some evidence that the reluctance of information sharing can be linked to hospitals' strategic concern. For instance, facilitating data outflow could cause potential loss of patients. These two competing forces, the profit complementaries and countervailing competition effect, make it hard to theoretically determine the sign of using the market-leading technology. The first objective of this paper is to examine which force dominates and to assess the value of adopting the market-leading technology. 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. 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. It is also likely that 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' choices of vendors.

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 sunk costs. The gain is asymmetric between large and small hospitals. Profits generated from using the market-leading technology are higher for large hospitals, probably 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 costs when switching HIT vendors but large hospitals spend less in switching. A potential explanation is that large hospitals are capable of internalizing the costs of consulting and IT system management in changing vendors. 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 analysis. I first consider two types of subsidy programs. One is the subsidy for any type

of EMR adoption, which attempts to mimic the element of 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, defined by the percentage of local hospitals choosing the market-leading technology. The results suggest that encouraging the adoption of the market-leading technology could improve the market coordination with even lower expenditure on subsidy payments. I do the same comparison in both new markets, in which the adoption rate is close to zero, and in mature markets, where a lot of adoption has already occurred but with almost zero communication. I find targeted subsidies 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 was likely to have been better if the requirement on interoperability was explicitly incorporated at the earlier stage of the incentive program.

Another counterfactual analysis seeks to understand the potential outcome if the amount of subsidies differ according to hospital size. I consider the following two programs: targeted subsidies towards large hospitals and targeted subsidies towards small hospitals. In either of them, only large or small hospitals will get subsidized if they choose the local market leader. I find targeted subsidies for small hospitals play a more effective role in achieving market coordination. A possible explanation is that large hospitals are more advantageous in procuring Health IT and thus financial assistance seems less vital for them than for small hospitals. In addition to reducing the financial barrier, targeted subsidies towards small hospitals also provide them guidance on what is the more "appropriate" technology. Consequently, given a fixed amount of budget, offering more generous supports to these small organizations could have led to a better outcome than that in the present world where the amount of subsidies is proportional to the size of a hospital.

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 directions for future work.

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. (2014), 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 (2003) 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 ahd 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 serve functions that paper records cannot deliver. According to the Healthcare Information and Management Systems Society (HIMSS), a solid EMR 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 have evolved from the early days being a silo system—in which the digital records from each ancillary department were 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 (2008), the average implementation cost for a 250-bed hospital 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 con-

sultancy, 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 being 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 adoption 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 practices. She used the multi-state inpatient discharge data to examine the relationship and found that the share of patients coded to higher-pay DRGs increased 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 local 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 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 the one chosen 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 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 implementation 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' incentives. 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 num-

ber 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 technology 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 the 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). A 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 2010. Another thing to note is that the market for EMR is fairly concentrated. Although there are more than 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 the major vendors with the group "others", these 12 options form 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 make 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 if they choose the market-leading technology. A hospital is categorized as large if its number of beds is more than the mean size. The results suggest 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 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 despite of varying magnitudes, suggesting 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 preferences over some particular vendors due to their specific 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 characteristics at the market level, such as market-wise promotion or special preferences of local physicians, affecting the formation of the leading technology and the choice of vendors at the same time. For instance, a vendor based in this market may provide promotion to all local hospitals. The leading vendor becomes mostly-adopted simply because of the promotion rather than the benefit from coordination. To address this issue, I employ the observations of affiliated hospitals belonging to multi-region hospital chains. More specifically, I create the instruments by averaging the indicator of market dominance for each vendor across the outside associated markets. Consider a market M_1 with three hospitals A (stand-alone), B (affiliated) and

C (affiliated). The endogenous variable for A is a vector with each entry denoting the market leadership in M_1 for the corresponding vendor. Suppose B is affiliated to a hospital chain $Beta$, most of whose members locate in outside markets M_2 and M_3, i.e., the majority of members are at these two markets and the number of members is the same in both of them. Both M_2 and M_3 are called the outside associated markets. Suppose C belongs to another hospital chain $Zeta$, whose majority members locate in M_1 and M_4. Thus, the instruments for A is the average of the market leader indicators across M_2, M_3 and M_4. This instrument is relevant in the sense that both the managing parties of $Beta$ and $Zeta$ may consider the market condition in these areas and thus affect the choice of B and C, which may have impacts on A's decision. It could be a clean measure as it is plausible that these outside markets have little relation with the unobservables in M_1. 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). It is important to note that the application of this set of instruments depends on the assumption that there are no spillovers across markets. 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 hospital system. This reduces the sample by one third.

I use the control function approach[1] to estimate the model. The model is estimated in two steps. The first step is a regression with the endogenous variable as the dependent variable and with the exogenous instruments as explanatory variables. Next, I estimate the choice model including the residuals estimated from the first step. The inclusion of the residuals "control" for the endogeneity in the original model. Table 5 reports the results from this specification. The market-leading dummy loses its significance, but its interaction with the large hospital dummy is positively significant, implying large hospitals expect some gains from choosing the market-leading vendor. In all, the results of this analysis suggest that profit complementarities outrun the negative impact from competition. The following is to construct a theoretical model and further pin down the value of this choice.

[1] I also apply other approaches such as ivprobit and 2SLS, from which the findings are quite similar.

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 $\forall m = 1, 2, ..., M$. 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 $s_i = j(j \in \mathcal{J} = \{1, 2, ..., J\})$ for using the product from Vendor j. $\mathcal{J} = \{1, 2, ..., J\}$ is a choice set which contains all EMR vendors available to hospitals, including the major vendors listed in Table 3 plus the additional group "others". 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 $\varepsilon = \{\varepsilon^0, \varepsilon^1, \varepsilon^2, ..., \varepsilon^J\}$ from some distribution. Conditional on a commonly observed vector of state variables s and their private shocks ε, 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 $\mathcal{J} = \{1, 2, ..., J\}$ 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 ζ^j plus the unobserved component ε^j. ζ^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 η. 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 provide some idea about the mean expense on switching. Staying with the original choice results in the corresponding unobserved shock, such as ε^0 for non-adopting. Let ε 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 τ. 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

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

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

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

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 s. γ_1 captures the profit complementarities if purchasing from the largest supplier and γ_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 γ_3 implies that the profit complementarities is increasing in the hospital's size. A 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

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

and the CSVF to stay with no EMR is

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

where β is the discount factor, ζ 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

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

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

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

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

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

η 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 η^{big} suggests that large hospitals have to bear a greater amount of switching cost. Similarly, the Bellman Equation is

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

To summarize, the structural parameters involves the sunk cost ζ^j, the switching cost η and η^{big}, and the marginal values γ_1, γ_2^j and γ_3. The cost parameters measure the net present value while the γ'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:

$$\sigma : (s, \varepsilon) \to a. \tag{9}$$

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 costs 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, ε 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 in more detail in the next section on the 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 rationalize 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:

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

where x^j is a vector of product characteristics that vary by vendor and z_i represents a group of hospital-specific features. α's and λ's measure the marginal value of those variables. Note that the λ'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 for a particular vendor. In the model, the decision of affiliated hospitals is assumed exogenous to the local market but can still be observed by stand-alone hospitals and thus enter the profit function. The evolution of these exogenous hospitals' choices is modeled analogously to that of stand-alone hospitals. The x^j for Hospital i is a

vector:

$$x^j = \begin{aligned} & [f(s,j),\ g(s,j),\ g(s,j) \times 1\{i \text{ is a large hospital}\}, \\ & l(j),\ l(j) \times 1\{i \text{ is a large hospital}\}] \end{aligned} \tag{11}$$

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 $g(\cdot) \times 1\{\text{i is a large hospital}\}$ 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

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

where $r(j)$ indicates whether j is the major supplier of EMR for the entire hospital chain. 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. Recall that the purpose of this part is to estimate the evolution of the market structure and thus to forward simulate the future path. 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 value

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 $\forall k \neq j$

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

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

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

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

$$V(s_t;\sigma(s),\theta) = \; W(s_t;\sigma(s)) \cdot [-\zeta^j,\; -\eta,\; -\eta^{\text{big}},\; \gamma_1,\; \gamma_2^k,\; \gamma_3]' \tag{15}$$

where θ 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 conditional 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 conditional 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 vendors' market share, market leader status 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 large hospitals choosing the market-leading technology. The key role played by the policy function is to present the transition across 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 2137×2137 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 include into x^j other functions of the market states, such as whether Vendor j 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 hospital characteristics interacting with vendor dummies. What hospital 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 a set of first-time adopters. The finding is somewhat consistent with the reduced-form evidence. 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 supplier 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 product characteristics: whether a particular vendor was already 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 the substantial amount of switching costs, 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 evolve 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. 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 affecting the current decision.

8.2 Structural Estimates

The policy function estimated from the first stage allows me to simulate the future states for all actions a 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. Choosing the market-leading vendor enhances the profit from adoption 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 the implementation of EMR. Large hospitals are capable of setting 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 costs 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 the 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 saving for each vendor, most of which are positively significant except for the three vendors: CPSI, Healthland and HMS. It is somewhat consistent with the reduced-form evidence. For a hospital with 250 beds, adoption of EMR, on average, increases the per-period profit by 0.042 ($= \frac{\sum_{j\in\mathcal{J}} \hat{\gamma}_2^j}{12} \times 250$) units from the cost-saving by bed size. If the product adopted is the market-leading technology, it 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% ($= \frac{0.0213}{(\sum_{j\in\mathcal{J}} \hat{\zeta}_1^j)/12}$) 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% ($= \frac{0.43}{(\sum_{j\in\mathcal{J}} \hat{\zeta}_1^j)/12} \times 100\%$) 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 reveal

the mean switching cost, which is almost 42% ($= \frac{1.8834}{(\sum_{j \in \mathcal{J}} \hat{\xi}_1^j)/12}$) of the average sunk cost. This also explains why not every hospital 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 turned 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 for each market with the estimated parameters. The outcome variable 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 hospital. This extra requirement (of being adopted by multiple local hospitals) 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 reflects 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 constraint. 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 the 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 with that in the presence of the full choice set. 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 over 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 49% in the case of 6 choices while the markets with the original choice set have 36% coordination. The gap between two lines expands over time, implying having fewer options is helpful to improve the market coordination.

9.2 Subsidy in new markets

Targeted subsidies vs. untargeted subsidies

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 over 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 regimes. 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 but 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 more effective over time. As time goes by, later adopters, who prefer to wait and see neighbor hospitals' 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 under such a program, and the gap is widened between the red and green surfaces during the later years.

The graph on the right in Figure 3 shows that targeted subsidies to the locally leading technology dominate the other program throughout the entire simulated period if the amount of subsidy is between 8% and 11% or between 19% and 21%, or more than 39% of the median sunk cost, which is between \$0.78 million and \$1.07 million, or between \$1.85 million and \$2.05 million, or more than \$3.80 million from the back-of-the-envelope calculation introduced earlier.[2] The red surface goes beyond the green one after 3 years as long as the amount of subsidies is more than 16% 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,[3] which is about 12.3% of the estimated median sunk cost. Figure 4 shows the two-dimensional profile of Figure 3 along this amount of subsidy, with the X axis being the year and Y axis the level of market coordination. The red line represents the outcome under the targeted-subsidy program while the green one de-

[2]For a hospital with 250 beds, one unit of sunk cost is equivalent to \$2.2 million.

[3]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 to 23,000th discharge. The payment lasts for 5 years and I use the amount of the subsidy in the first year so the transition factor is 1.

scribes the situation when any adopter is subsidized. Starting from the fourth year, the red line goes beyond the green one, implying that financial supports towards the leading technology result in a higher level of market coordination.

I further compare the outlay of incentive payments between two programs. Figure 5 displays the total expenditure of both programs over time given different amounts of subsidies. The left panel describes the relation in a 3-dimension space and the right one presents a cross section of the left-hand side surfaces when the subsidies are 12.3% of the median sunk cost. Subsidizing any adopters leads to larger expenditure than the targeted subsidies throughout the entire simulated period. Particularly if the amount of reimbursement is close to what is received by an average hospital in the actual program, the difference can go up by 27% at the end of the simulated period. Assuming the amount calculated from the model is a plausible estimate, the government is likely to have performed better with fewer amount of expenses, by incorporating explicit guidance about the choice of vendors. 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. Hospitals' profits[4] are very similar under both programs, although it is slightly higher in the presence of the untargeted subsidies in certain cases.

In all, the program of subsidizing any adopters seeks to capture the element of the actual incentive program where neither the standard of interoperability nor the restriction on the choice of vendors has been included as part of the requirements for reimbursements. Targeted subsidies towards the most popular technology in a given local market are likely to improve the market coordination with fewer amount of incentive payments. The impact is augmented in time but not so obvious at the early stage. During that time, government subsidies for any adoption lead to slightly better coordination when the amount of subsidies fall within a certain range. Intuitively, targeted subsidies to the most popular HIT systems force hospitals to be more careful in the choice of vendors. Under such a program, early adopters tend to think twice about their choices and as a result the local leading vendor is more likely to show

[4]The results are available upon request.

up early. 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 difference in the adoption rate between both programs is increasing in the amount of subsidies, as shown in Figure 6, with the green surface above the red one.

When the amount of subsidies is very low and during the first few years, early adopters, in the presence of targeted subsidies, make the choice almost randomly prior to the emergence of the leading 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. As the amount of subsidies increases, early adopters are more careful in choosing the "right" vendor and as a result the local leading vendor "stands out" sooner. In the meantime, later adopters will not wait for too long and hence, the market coordination under the targeted-subsidy program, catches up pretty soon and even outruns the other program quickly. When the amount of subsidies reaches a certain level, more and more hospitals are willing to adopt early if any type of adoption gets subsidized. However, the generous subsidies will instead defer the adoption decision of even more hospitals in the targeted-subsidy program. Therefore, early clustering is more likely to happen in the program offering unconditional support when the amount of subsidies is rather high. In general, however, the difference in the estimated coordination rates seems negligible at the initial stage of both programs, and turns more and more significant as time goes by.

Targeted subsidies to large hospitals vs. Targeted subsidies to small hospitals

The previous counterfactual has shown that targeted subsidies are likely to produce higher level of market integration with lower costs. I now conduct the counterfactual analysis to investigate the potential outcome if the amount of subsidies varies according to hospital size. In one policy experiment, only large hospitals receive reimbursements if they adopt the local leading technology and the other one works the same for small hospitals. A hospital is categorized as large if its number of beds exceeds the mean size. The result of this analysis may shed some light on the potential outcome when the government treats hospitals differently according to size. Note that the gain from adoption differs between large and small hospitals: large hospitals benefit more from profit complementarities and spend less in switching. Given the varying payoff for hospitals of different sizes, the comparison of such policy designs may provide some insight on how to allocate the financial resources more efficiently

in order to attain the goal.

Figure 7 compares the outcomes between the two policy programs, with the left panel presenting the difference in market coordination and the right one describing the total expense of incentive payments. The green surface describes the evolution of the outcome under the program in which only large hospitals receive financial supports if they choose the local leading technology and the red one presents that for the program subsidizing small hospitals only.[5] In the left panel, the red surface stays above the green one throughout the entire simulated period for any given amount of subsidies. Also note that for any given year, the green surface is rather flat with regards to the amount of subsidies, which may imply that subsidies towards large hospitals have limited impacts on market integration. Large hospitals stand in a relatively favorable position in the adoption of Health IT, and thus financial supports may not seem as crucial to them as to small players in making the choice of vendors. For small hospitals, instead, targeted subsidies not only incentivize the adoption but also reveal what is the more "appropriate" choice. In the program supporting small hospitals, both time and the financial assistance play important roles in achieving market integration.

Consider the right panel in Figure 7. At the end of the simulated period, the expense to support small hospitals amounts to twice of that to support large hospitals. The larger expenditure arises from the fact that the number of small hospitals is double of that of large hospitals.[6] Targeted subsidies specially towards small hospitals are more effective to reach market integration. Given a fixed amount of financial budget, providing more generous supports to small hospitals could have led to higher coordination than that in the present world where the financial assistance is increasing in a hospital's bed size.[7]

[5]This seems like an extreme case in which the government supports either large or small hospitals, but it separately identifies the effect of subsidies on large and small hospitals respectively. I also evaluate the pair of programs in either of which the amount of subsidies for one type of hospitals is 30%, or 50% higher or twice of the other. In addition, I examine the case in which the amount of subsidies varies according to individual bed size. All the experiments indicate very similar findings.

[6]I also run the same counterfactual on the sample where the number of large hospitals is the same as that of small hospitals. It shows greater market coordination in the program supporting small hospitals and the total expenditure is almost the same between two programs. I report the current result as the distribution of hospital size in the current sample is closer to the actual data where the number of small hospitals is about twice of that of large hospitals.

[7]According to the official formula in the current program, the amount of subsidies is associated with the number of discharge, which is closely related to the bed size (with the correlation coefficient 0.93).

9.3 Subsidy in mature markets

This subsection evaluates the outcome from different types of subsidies in mature markets. Special attention is placed to markets with high adoption rates but almost none coordination. I design in the first experiment an unconditional subsidy towards all switching. Any hospital that switches gets a payment equal to the mean switching cost. The counterpart experiment imposes an additional requirement that hospitals will not get reimbursed unless they switch to the market-leading vendor. 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 over time.

The left panel in Figure 8 plots the evolution of the market outcome for the cases without subsidies, with untargeted subsidies and with subsidies towards the leading technology. All of them start with zero market coordination. At the end of the simulated period, the rate of market coordination increases to 21.6% in the markets without any financial assistance while both subsidy programs push up this number to more than 37%. During the first four years, both subsidy programs perform very similar, but the targeted subsidies outrun the other program from then on and improve the market coordination by four more percents in the end. The right panel compares the total expenditure on subsidies in both programs over the years. In the program of untargeted subsidies, the government always has to pay more in total but achieve less satisfactory outcome, which is consistent with the findings in new markets. Moreover in mature markets, the government may have to offer per hospital higher incentive payments, as the mean switching cost is more than 40% of the median sunk cost. In other words, targeted subsidies before Health IT adoption becomes prevalent could have been more effective than in the present world where the application of EMR has already occurred but been fragmented at large.

10 Conclusion

This paper tries to understand the dynamics behind hospitals' adoption decision in the choice of EMR vendors. In particular, I evaluate the adoption decision of standalone hospitals: whether to choose the local market-leading vendor. On 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 becomes

easier to switch between health care providers. One 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.

In the reduced-form analysis, I find benefits exceed the potential concerns from choosing the local leading vendor. I develop a dynamic oligopoly model of technology adoption to characterize hospitals' adoption choice. Whether a particular vendor is market-leading becomes a product characteristic entering 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). Consistent with the evidence from the reduced-form estimation, I 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 any other technology. However, the impact becomes moderate when it is compared with the amount of sunk cost in implementation. Hospitals also have to bear a considerable amount of switching costs, which is about 43% of the average sunk cost. Small hospitals suffer even more due to incapability of establishing an in-house IT department.

Given the substantial amount of upfront cost, it is important for the government to provide financial supports to assist the new purchase. I run several counterfactual experiments with the structural estimates. The diffusion of HIT will be more effective if the government stresses the requirement of interoperability before the prevalence of the technology. One of the many measures is to incentivize the adoption of the local market-leading technology. By recognizing the value of such a technology, the policy makers will be better positioned in helping hospitals make sound choices to improve market coordination. Considering that payoff differs between large and small hospitals, I further explore the potential to maximize the effect of subsidies by comparing the outcomes between two programs: targeted subsidies to large and small hospitals respectively. I find that, by offering more generous supports towards small hospitals, the incentive program is likely to have performed better than in the current situation where the amount of subsidies is increasing in a hospital's size.

This paper particularly responses to the question on how much hospital profits can be increased if hospitals coordinate on the local market-leading vendor. It is important to note that I model hospital profits directly derived from adopting EMR without

too much consideration of the supply side due to data limitation. The analysis holds the supply side fixed and abstracts away from the interaction with vendors. My understanding from talking with industry participants is that the major technology innovation about EMR occurred before the period I looked at and the market structure in the industry was relatively stable during that time. While I do not model price explicitly, it is captured as part of the sunk cost of implementation. Hospitals are assumed to take as given the products and prices, but I believe that the results are still reasonable since anecdotal evidence suggests that most hospitals behave relatively passively in the interaction with vendors owing to information asymmetry. My estimates, thus, will be a useful, yet not complete, piece of information on how stand-alone hospitals evaluate choosing the local market-leading vendor. The takeaway from my research is that stand-alone hospitals benefit from choosing the leading vendor and establishing (at least) a regional standard by promoting such a technology is helpful in improving the coordination of adopting EMR. I also hope that this paper has provided a building block which could be used in future research to provide a more complete picture of how the market of EMR is configured and how the regulation affects the market structure and ultimately welfare. A more extensive analysis would require further data collection and theory development.

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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***	0.0761
(0.1256)	(0.230)

	Cerner	CPSI	Healthland	Eclipsys	EPIC	GE
Bed size	0.0049	-0.0166**	-0.0190**	0.0120	0.0053	0.0113
	(0.0076)	(0.0077)	(0.0081)	(0.0075)	(0.0078)	(0.0079)
Not-for-profit	1.1884	0.6452	0.5785	2.1430*	1.9251*	2.3711*
	(0.8864)	(0.8258)	(0.8371)	(1.2343)	(1.0416)	(1.2731)
Teaching	15.1531***	-0.2143	-0.1803	-1.7297	16.1781***	13.7384***
	(1.6325)	(1.4762)	(1.5045)	(1.8380)	(1.5973)	(2.1080)
Constant	-0.1101	3.5495***	3.1470***	-3.0334***	-1.6027 **	-3.8790***
	(0.6959)	(0.6157)	(0.6293)	(1.1744)	(0.8097)	(1.0267)
	HMS	McKessons	Siemens	Meditec	Others	
Bed size	-0.0109	0.0065	0.0074	0.0003	0.0012	
	(0.0081)	(0.0075)	(0.0075)	(0.0074)	(0.0075)	
Not-for-profit	0.2397	0.9105	1.8690**	1.1484	1.1492	
	(0.8715)	(0.8379)	(0.8848)	(0.8149)	(0.8318)	
Teaching	0.0367	12.6544***	13.4320***	12.3908***	14.6913***	
	(1.5123)	(1.8003)	(1.6478)	(1.7802)	(1.5387)	
Constant	2.1529***	0.8840	-0.4512	2.3388***	1.5688 **	
	(0.6425)	(0.6347)	(0.7322)	(0.6182)	(0.6393)	
N=9768						

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

market-leading	market-leading×big
0.0846	2.6721***
(0.5007)	(0.8264)

	Cerner	CPSI	Healthland	Eclipsys	EPIC	GE
Constant	1.1231***	2.5824***	2.0422***	0.41	0.5092	-0.281
	(0.4058)	(0.3669)	(0.3753)	(0.4566)	(0.4492)	(0.5394)
	HMS	McKessons	Siemens	Meditec	Others	
Constant	1.4356***	1.8076***	1.3749***	2.5006***	2.0302***	
	(0.3933)	(0.3811)	(0.3939)	(0.379)	(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***	0.0044	0.4071**
(0.2453)	(0.1947)	(0.1904)

	SD	Cerner	CPSI	Healthland	Eclipsys	EPIC
Bed size	0.0029	0.0039***	-0.0081***	-0.0097***	0.0092***	0.0030
	(0.0043)	(0.0015)	(0.0017)	(0.0024)	(0.0010)	(0.0022)
Not-for-profit	-0.3980	0.6693*	0.3075*	0.2335	1.6830**	1.3250*
	(0.8363)	(0.4063)	(0.1748)	(0.2215)	(0.8505)	(0.7686)
Teaching	-13.8569***	0.9334	-13.3599***	-13.3339***	-14.5723***	2.1994**
	(1.6132)	(0.9720)	(0.3572)	(0.4449)	(0.7770)	(0.9278)
Constant	-5.6129***	-5.1636***	-2.3821***	-2.8037***	-7.6426***	-6.4284***
	(0.4253)	(0.3077)	(0.1196)	(0.1586)	(0.8595)	(0.4848)
	GE	HMS	McKessons	Siemens	Meditec	Others
Bed size	0.0086***	-0.0039	0.0059***	0.0062***	0.0018**	0.0023**
	(0.0021)	(0.0025)	(0.0008)	(0.0010)	(0.0007)	(0.0010)
Not-for-profit	1.6069	-0.1314	0.4959**	1.4263***	0.7558***	0.7334***
	(0.9951)	(0.3494)	(0.2528)	(0.3613)	(0.1527)	(0.2237)
Teaching	-0.6056	-13.3982***	-2.0211**	-1.3320	-2.0329*	0.0326
	(1.3673)	(0.5704)	(1.0385)	(0.8674)	(1.0846)	(0.7409)
Constant	-8.2930***	-3.6769***	-4.2640***	-5.4798***	-3.1045***	-3.8352***
	(0.6505)	(0.1962)	(0.1874)	(0.3508)	(0.1244)	(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	0.0802	0.019	5.8852***	-0.4140*
(0.3872)	(0.2388)	(0.2773)	(0.182)	(0.2235)

	Cerner	CPSI	Healthland	Eclipsys	EPIC	GE
Bed size	0.0013	-0.0129***	-0.0196***	0.001	0.0016	0.0023*
	(0.0011)	(0.0022)	(0.0031)	(0.0016)	(0.0013)	(0.0014)
For-profit	-1.3010**	0.5389	-1.5226***	-1.4885***	-2.6347***	0.1332
	(0.6575)	(0.4868)	(0.462)	(0.5538)	(0.693)	(0.8156)
Teaching	0.3018	-10.5295***	-10.6777***	1.0249	0.8907	0.8781
	(0.8891)	(0.777)	(0.7898)	(0.9378)	(0.918)	(0.87)
Constant	0.8503**	2.7640***	3.0426***	0.3158	1.0952**	-1.7326***
	(0.4173)	(0.4343)	(0.5161)	(0.5835)	(0.4712)	(0.6666)
	HMS	McKessons	Siemens	Meditec	Others	
Bed size	-0.0136***	0.0003	0.0015	-0.0009	-0.0005	
	(0.0042)	(0.0014)	(0.0012)	(0.0012)	(0.0013)	
For-profit	-1.2161*	-2.2365***	-0.6236	-2.4632***	-0.0096	
	(0.686)	(0.7165)	(0.4669)	(0.9237)	(0.4624)	
Teaching	-10.1295***	0.2218	0.1521	-1.4998*	0.734	
	(0.9406)	(0.961)	(0.8238)	(0.8419)	(1.0517)	
Constant	1.9324***	1.0681**	0.0895	2.3956***	-0.388	
	(0.4937)	(0.508)	(0.4849)	(0.4163)	(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***	0.0021***	-0.0069**	-0.0143***	0.0020*	0.0012*
	(0.0007)	(0.0006)	(0.003)	(0.0042)	(0.0012)	(0.0007)
Not-for-profit	-0.8441**	0.4582**	-0.5896*	-0.0908	1.6677**	3.2469***
	(0.3774)	(0.2226)	(0.3348)	(0.3563)	(0.7533)	(0.7101)
%Medicare	-1.2401*	-1.6060**	1.4855	0.0684	-2.1646	-1.5231*
	(0.6365)	(0.686)	(1.2944)	(1.2139)	(1.9756)	(0.8769)
Constant	-3.5953***	-3.0245***	-3.9492***	-2.9596***	-5.3726***	-5.5964***
	(0.429)	(0.4199)	(0.8509)	(0.809)	(1.2677)	(0.8697)
	GE	HMS	McKessons	Siemens	Meditec	Others
Bed size	0.0024***	-0.0026*	0.0020***	0.0004	0.0005	0.0014*
	(0.0009)	(0.0015)	(0.0005)	(0.0007)	(0.0006)	(0.0008)
Not-for-profit	2.2271***	-1.4520***	0.7611***	0.0887	1.2992***	0.7282**
	(0.7336)	(0.3466)	(0.2035)	(0.2075)	(0.1911)	(0.3312)
%Medicare	-0.8437	-2.3751***	-1.3543**	-3.9831***	-1.1476*	-1.5962
	(1.2326)	(0.5267)	(0.6567)	(0.5953)	(0.6338)	(0.9959)
Constant	-6.1285***	-1.4750***	-3.3206***	-1.5589***	-3.8481***	-3.8598***
	(1.1405)	(0.3537)	(0.3795)	(0.2993)	(0.4008)	(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***	4.8336***	-0.2557*
(0.0957)	(0.0987)	(0.1345)

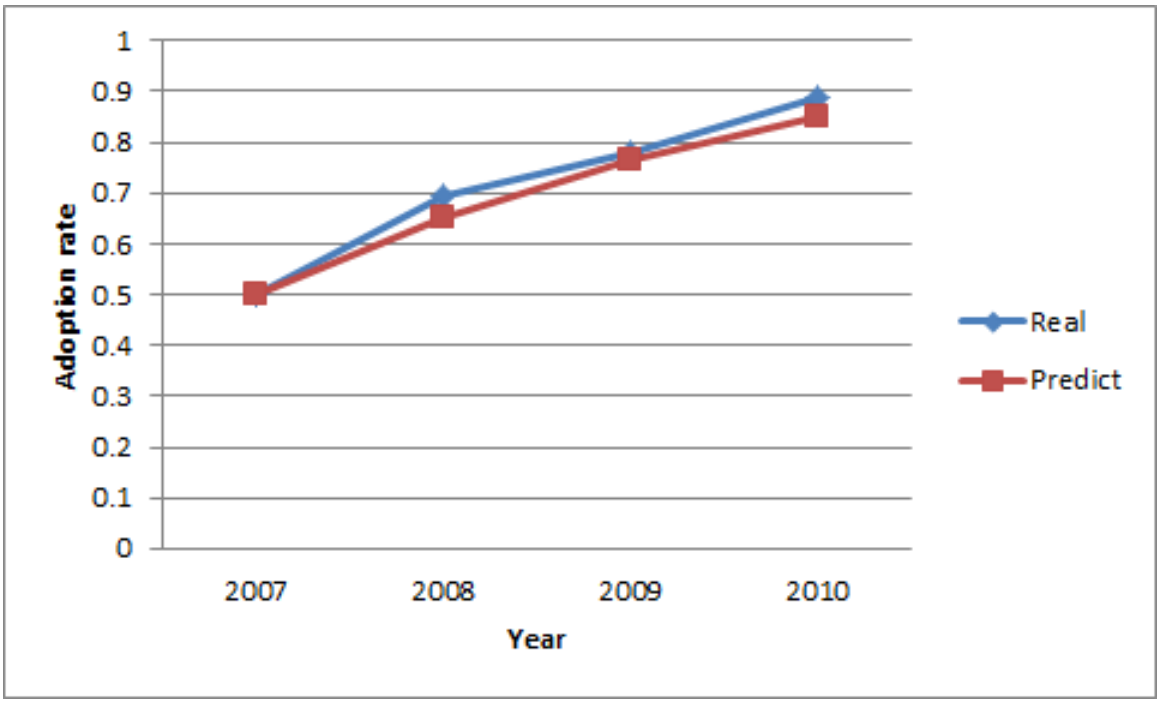
	Cerner	CPSI	Healthland	Eclipsys	EPIC	GE
Bed size	0.0019***	-0.0044***	-0.0073**	0.0028***	0.0028***	0.0017**
	(0.0007)	(0.001)	(0.003)	(0.0007)	(0.0006)	(0.0007)
%Medicare	3.7011***	4.3433***	5.4168***	3.4056**	3.1445***	2.193
	(1.0458)	(1.0596)	(1.7236)	(1.5248)	(1.0454)	(1.4086)
%Medicaid	2.5690*	3.2605**	1.9818	1.1805	-2.0057	-0.3332
	(1.5042)	(1.4944)	(3.9046)	(2.3911)	(1.8089)	(1.7571)
Constant	-2.1377***	-2.3350***	-3.4792**	-2.6049***	-1.1816*	-1.8963**
	(0.6027)	(0.6464)	(1.4056)	(0.9931)	(0.6655)	(0.8419)
	HMS	McKessons	Siemens	Meditec	Others	
Bed size	-0.0049***	0.0011	0.0002	0.0001	0.0012	
	(0.0013)	(0.0008)	(0.0007)	(0.0007)	(0.001)	
%Medicare	3.9610***	3.8027***	1.7096	3.7860***	6.1945***	
	(1.4713)	(1.3155)	(1.1398)	(1.1509)	(1.5661)	
%Medicaid	4.4903**	4.3568**	2.0883	3.1581*	5.1797***	
	(1.7558)	(1.7312)	(1.6912)	(1.738)	(1.8224)	
Constant	-2.3549**	-2.8050***	-1.9669***	-2.2121***	-4.9706***	
	(0.9196)	(0.8024)	(0.7314)	(0.6859)	(0.9676)	
N=89724						

Table 10: Structural estimates for the dynamic model

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

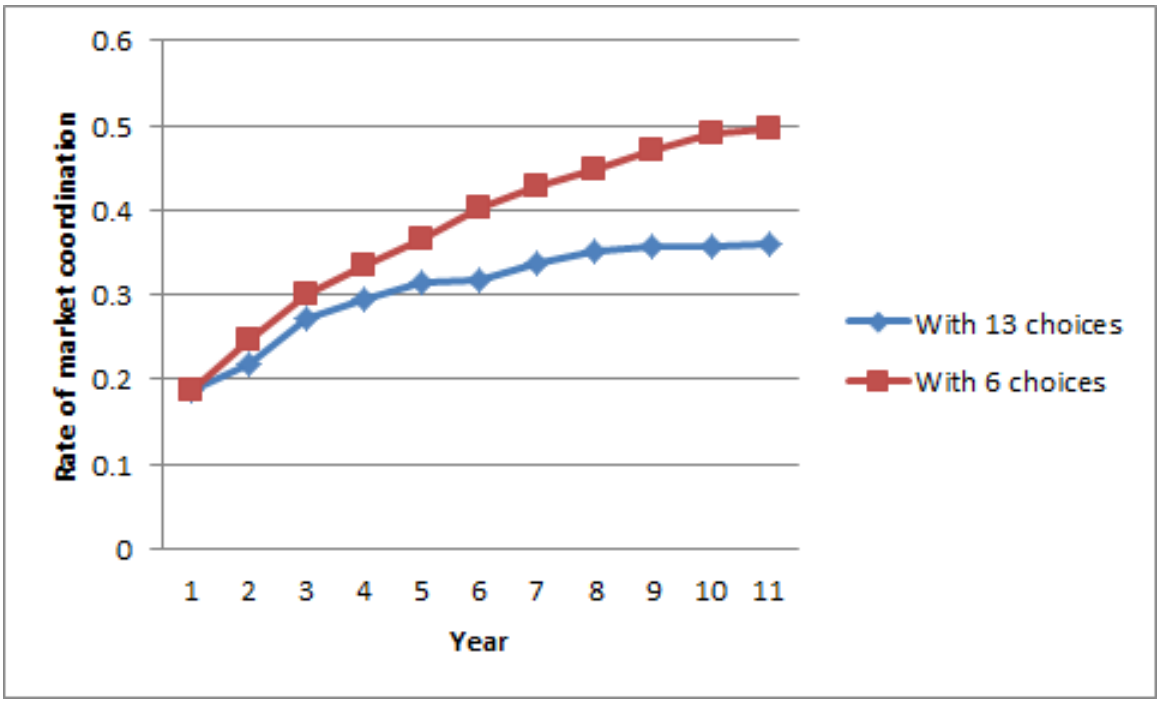
	Sunk cost	Cost saving per 100 beds
Self_developed	5.8169***	0.018***
	(0.2945)	(0.0041)
Cerner	5.2462***	0.0362***
	(0.2452)	(0.0047)
CPSI	2.7055***	-0.0158
	(0.1338)	(0.0103)
Healthland	3.0657***	-0.0303*
	(0.1724)	(0.016)
Eclipsys	5.6912***	0.0374***
	(0.3177)	(0.0042)
EPIC	5.5308***	0.0418***
	(0.2661)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

Figure 1: In-sample prediction of adoption rate



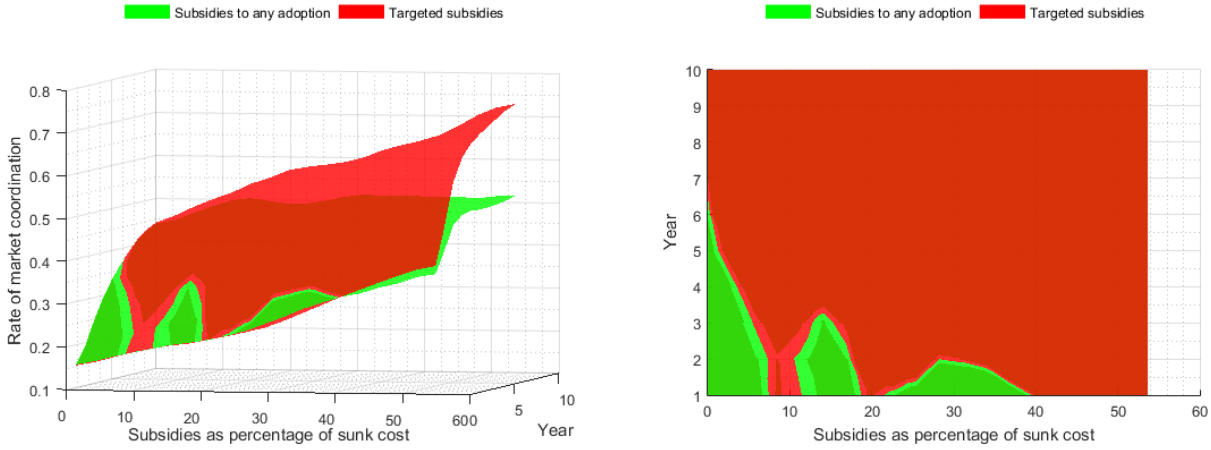
Note: Figure 1 compares the trend of the adoption rate computed from the actual data with the in-sample prediction. The blue line shows the pattern generated from the data while the red line depicts the path predicted by the estimated model primitives. The model is doing a reasonable job for the in-sample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

Figure 2: Market coordination between different choice sets



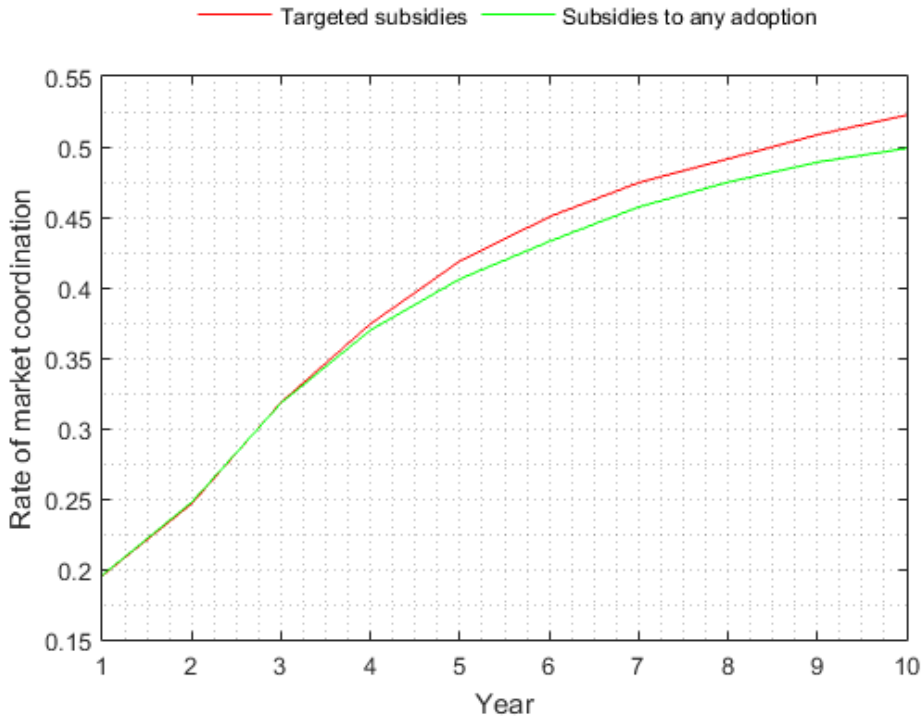
Note: Figure 2 shows how the rate of market coordination evolves over time. The blue line describes the trend for the market with the full choice set while the red line for the experiment in which only six options are available. Both cases start with 18% of market coordination. Ten years later, it increases to 49% in the case of 6 choices while the markets with the original choice set have 36% coordination. The gap between two lines expands across time, implying having fewer options is helpful to improve the market coordination.

Figure 3: Market coordination between targeted and untargeted subsidies—new markets



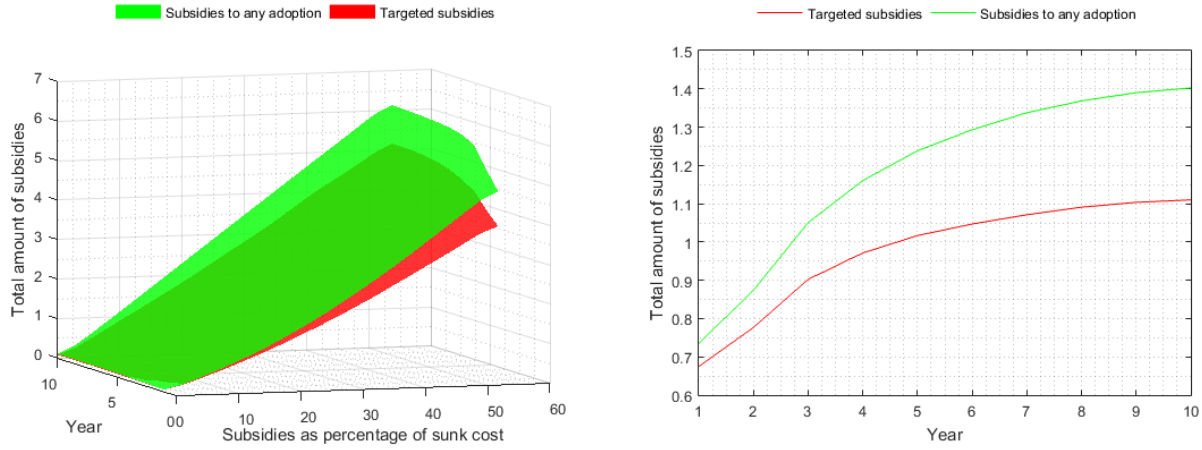
Note: Figure 3 presents the comparison of market coordination under two policy regimes. This is a 3-D graph with X axis being the amount of subsidy measured by the percentage of the median sunk cost, Y axis representing year and Z axis denoting the rate of market coordination. Both the left and right 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: Market coordination at the actual amount of subsidies



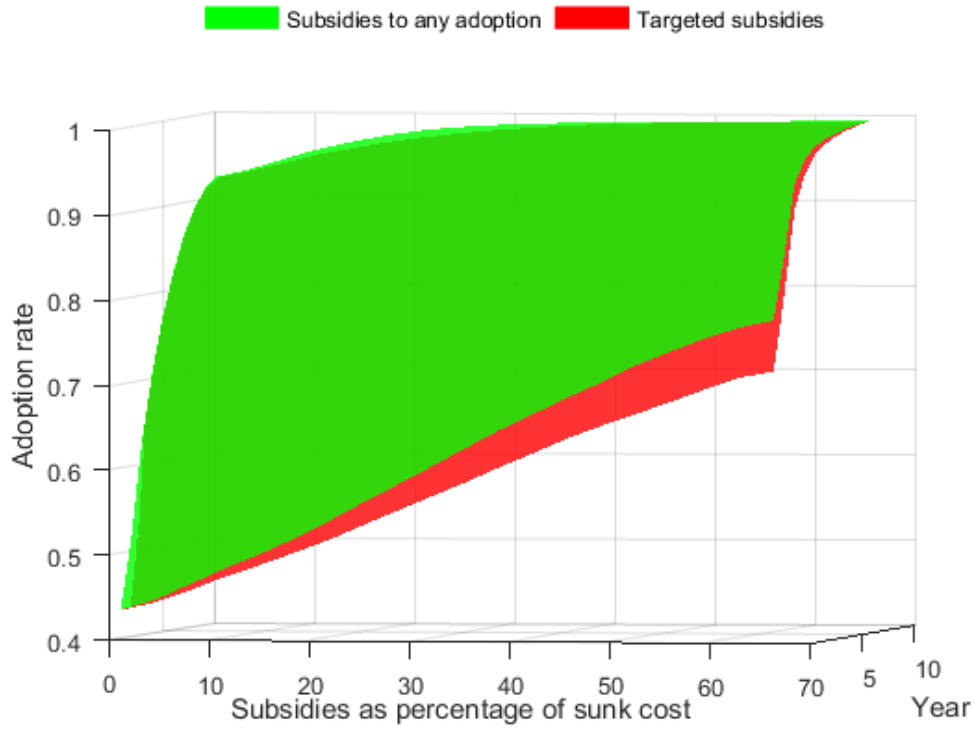
Note: Figure 4 shows the two-dimensional profile of Figure 3 at the actual amount of subsidies, with the X axis being the year and Y axis the level of market coordination. According to the back-of-the-envelope calculation, an eligible hospital with an average size (with 250 beds, 10,000 total discharge per year and 30% medicare discharge) can receive \$1.2 million, which is about 12.3% of the estimated median sunk cost. I obtain Figure 4 by slicing Figure 3 along this amount of subsidies. The red line presents the outcome under the targeted-subsidy program while the green one describes the situation when any type of adoption is subsidized.

Figure 5: Total amount of subsidies between targeted and untargeted subsidies—new markets



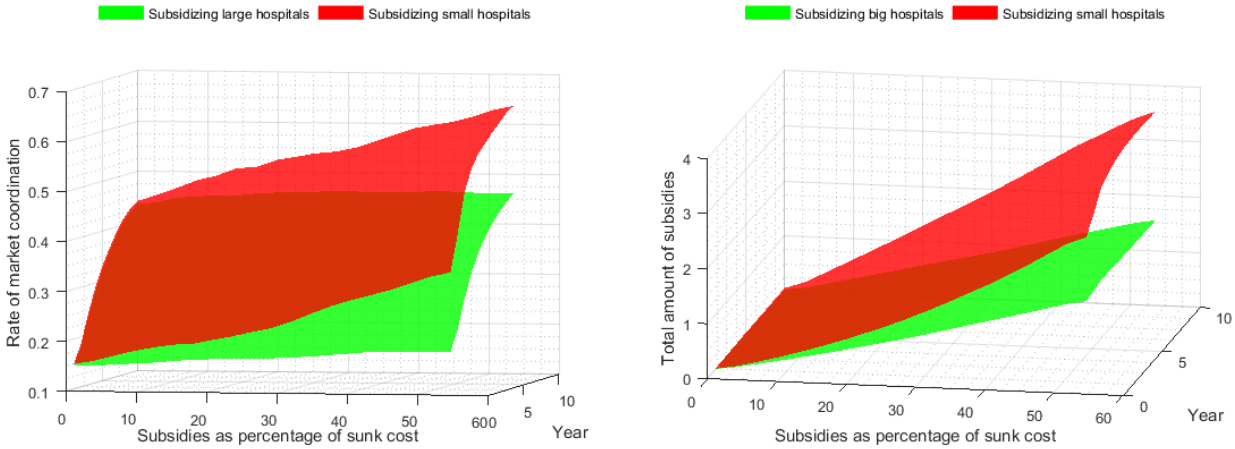
Note: Figure 5 compares the total amount of subsidies under two policy regimes. The left panel is a 3-D graph with X axis being the amount of subsidy measured by the percentage of the median sunk cost, Y axis representing year and Z axis denoting the total amount of subsidies. The right one presents a cross section of the left-hand side surfaces with the subsidies at 12.3% of the median sunk cost. The green surface describes the evolution under the untargeted-subsidy program and the red one presents that for the targeted subsidies. Whichever goes above represents greater amount of total expenditure on incentive payments.

Figure 6: Adoption rate under between targeted and untargeted subsidies—new markets



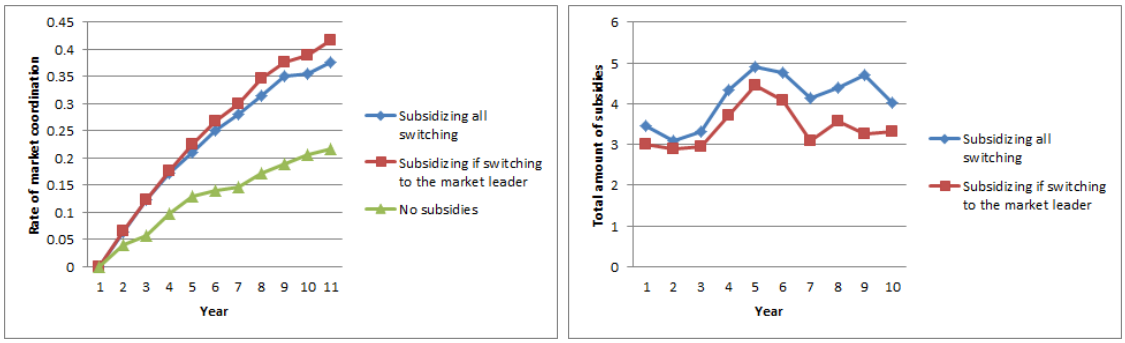
Note: Figure 6 presents the comparison of adoption rates under two policy regimes. This is a 3-D graph with X axis being the amount of subsidy measured by the percentage of the median sunk cost, Y axis representing year and Z axis denoting the adoption rate in the market. The green surface describes the evolution under the unconditional program and the red one presents that for the targeted subsidies. Whichever goes above represents higher adoption rates.

Figure 7: Market coordination and total amount of subsidies between subsidizing large and small hospitals—new markets



Note: Figure 7 presents the relation under two policy regimes: targeted subsidies towards large or small hospitals only. The left panel compares the level of market coordination in 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 level of market coordination. The right one compares the total amount of subsidies over time between these two programs for any given amount of subsidies. The green surface describes the outcome under the program in which only large hospitals receive financial supports if they choose the local leading technology and the red one presents that for the program subsidizing small hospitals only.

Figure 8: Market coordination under different subsidy regime—mature markets



Note: The left panel in Figure 8 plots the evolution of the market outcome for the cases without subsidies, with untargeted subsidies and with subsidies towards the leading technology. All of them start with zero market coordination. The rate of market coordination increases to 21.6% after 10 years in the markets without any financial assistance while both subsidy programs push up this number to more than 37%. In the first four years, both subsidy programs perform almost the same, but the one with the extra requirement outruns the other after then. The right panel compares the total amount of subsidies in both programs.