# The Timing of New Technology Adoption: The Case of MRI *

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**Abstract**

This paper studies the adoption of nuclear magnetic resonance imaging (MRI) by US hospitals. I consider a timing game of new technology adoption. The dynamic game allows me to take both timing decisions and strategic interaction into account. The model can be solved using standard dynamic programming techniques. Using a panel data set of US hospitals, cross sectional variation in adoption times, market structure and demand is exploited to recover the profit and cost parameters of the timing game. In counterfactual experiments, I decompose the cost of competition into a business stealing and a preemption effect. I find substantial changes in adoption times and industry payoffs due to competition. These changes are mostly due to a business stealing effect. Preemption accounts for a significant but small share of this change.

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# 1 Introduction

This paper estimates the impact of competition on the timing of new technology adoption. In a strategic environment, a firm's decision when to adopt is not only driven by the cost of the new technology and the direct effect of adoption on current and future payoffs, but also by an indirect effect. By adopting, a firm affects its rivals' payoffs and thus their adoption timing decisions, which in turn affects the firm's payoffs. To correctly infer the effect of competition on the timing of adoption, the endogeneity and the dynamic character of the adoption decision has to be accounted for.

To accomplish this, I develop and estimate a dynamic game-theoretic model of technology adoption. Every period, firms decide whether or not to adopt the new technology. I consider subgame perfect equilibria and require that each firm's decision be optimal at every point in time. Two sources of inefficiency can arise in this model. First, there is business stealing: Firms gain from new technology adoption in part at expense of their rivals. Second, a preemption motive may determine the equilibrium adoption time: A firm adopts early to discourage its rivals from adopting and secures the rents from adoption. This paper builds a framework to quantify the relative importance of business stealing and preemption in a dynamic setting.

I assume that firms move sequentially in every period. The sequential structure of moves implies that there is a unique subgame perfect equilibrium. I can solve for the subgame-perfect equilibrium using a simple recursive algorithm. I construct a method of moments estimator based on the equilibrium adoption times.

The model is used to study hospital competition in the context of magnetic resonance imaging (MRI) adoption. MRI is a diagnostic tool for producing high resolution images of body tissues. It first became commercially available in the early 1980s and diffused slowly during the subsequent two decades. The cost of new medical technologies has repeatedly been blamed for the increase in health care expenditures. Competition among hospitals has been depicted as wasteful and leading to a 'medical arms race.' MRI is a typical example of an expensive new medical technology, given that a high fixed asset investment of US$ 2 million was required fo a new imager in 1985.

The adoption of MRI will affect revenues and costs of hospitals but it is a small investment decision relative to entering or exiting a market. Consequently, the number of hospitals and hospital characteristics are viewed as exogenous to the adoption decision. Using information on the timing of MRI adoption within markets as well as varying degrees of competition and demand across markets, the effects of competition, demand and costs on the timing decision are separated.

In equilibrium, hospitals' adoption times are determined either by their stand-alone incentive (the marginal benefit of adopting) or the preemption incentive (the incentive to adopt before your rival in order to delay her adoption). Thus, equilibrium adoption times are not only informative about the marginal benefit of adopting, but also about the relative benefit of being the follower versus the leader. This enables me to identify the effect of rivals' adoption on the payoffs of adopters and non-adopters separately. I find that returns to adoption decline substantially with the number of adopters. The effect of rival adoption on non-adopters' payoffs is significant but substantially smaller than the effect on adopters.

Hospitals' organizational structure and hospital size influence the adoption decision. Private nonprofit and for-profit hospitals are more likely to adopt the new technology than community hospitals. Large hospitals benefit more from MRI adoption. On the cost side, estimates indicate that the real cost of adopting MRI declines by three percent per year.

I perform two counterfactual experiments that quantify to what extent competition causes inefficiencies from the hospital industry's perspective. In the first experiment, a regulator chooses adoption times to maximize industry payoffs. Thus the regulator takes into account both sources of inefficiency, business stealing and preemption. This regime delays hospitals' adoption times by as much as four years and increases the industry payoffs. In the second experiment, I isolate the role of preemption by comparing adoption times in a pre-commitment Nash equilibrium to the subgame perfect equilibrium outcome.[1] In the Nash equilibrium, firms precommit to their adoption times as in Reinganum (1981), which removes the incentive to preempt in order to delay the rival's adoption time. I find that preemption accounts only for a small fraction of the overall loss in industry payoffs and is only marginally responsible for the acceleration of adoption arising from strategic adoption timing.

*Related Literature.* Existing empirical studies of new technology adoption consider competitive (Griliches (1957)) and monopolistic settings (Rose and Joskow (1990)), but also environments where strategic interaction might play a role (e.g. Karshenas and Stoneman (1993), Levin, Levin and Meisel (1992), Baker (2001), and Baker and Phibbs (2002)). A common approach in this literature is to include rivals' adoptions or the number of rivals as explanatory variables in the hazard function. The interpretation of the estimated coefficients on rivals' actions in light of the existing theoretical models is complicated by the potential endogeneity of rivals' adoption times: A firm's decision when to adopt depends on its belief about rivals' adoption times and their effect on its own profits. A number of recent studies examine the role of strategic behavior in technology adoption. Hamilton and McManus (2005) find that a new treatment technology diffused first to more competitive markets controlling for the endogeneity of market structure. Dafny (2005) finds evidence that firms make cost reducing investments to deter entry. Genesove (1999) and Vogt (1999) study the effect of firm heterogeneity and rival adoption on the adoption probabilities in duopoly markets and compare them to predictions from the theoretical literature. The endogeneity of the adoption decision has also been addressed in static frameworks either by using instrumental variable techniques (Gowrisankaran and Stavins (2004)), or by explicitly modelling technology adoption as a static game (see Dranove, Shanley and Simon (1992), and Chernew, Gowrisankaran and Fendrick (2002)). Lenzo (2006) studies strategic complementarities in the adoption of imaging technologies in the context of a static incomplete information game. The current paper builds on this literature by modelling technology adoption as a dynamic complete information game, taking

[1] The impact of preemption on the timing of adoption has been emphasized in the theoretical literature (e.g. Fudenberg and Tirole (1985) and Riordan (1992)).

into account both the endogeneity and the dynamic character of adoption decisions.

This paper also contributes to a recent literature that is concerned with the estimation of timing games. Einav (2003) studies the timing of product introduction in the context of movie release dates. Sweeting (2004) estimates a coordination game, in which radio stations simultaneously decide when to air radio commercials. As appropriate for the environments studied, these papers consider models where players commit to the timing of their action at the beginning of time. Players are thus unable to revise their decision upon observing their rivals' actions. As it is unlikely that hospitals are able to pre-commit to an adoption date several years in the future, the current paper studies a different model in which firms decide every period whether to adopt the new technology or not.

The remainder of the paper is structured as follows. The next section introduces a discrete time model of technology adoption and discusses the equilibrium properties. Section 3 describes the MRI technology and its significance for the US hospital industry, summarizes the construction of the data set, and presents evidence on the diffusion of MRI between 1986 and 1993. Section 4 describes the estimation approach and presents the estimates of the model presented in Section 2. In Section 5 counterfactual experiments are conducted to examine the role of strategic interaction on the timing of adoption. Section 6 concludes.

# 2 A Model of Technology Adoption

This section introduces a model of technology adoption. In this model, an originally expensive new technology becomes available to a fixed number of competing firms. The cost of adoption declines over time. Adoption of the new technology generates a new source of revenue, but adoption is rivalrous: Benefits to adoption decline in the number of adopters in the market. I will later argue that this type of model resembles the features of MRI adoption by US hospitals. Section 2.1 introduces the features of the model. Section 2.2 discusses the equilibrium properties of this model.

## 2.1 Model

The model assumptions are similar to those found in the existing theoretical literature. Since the emphasis of the current paper is on variation in market structure and strategic interaction in the timing of adoption, I consider a model that allows for firm heterogeneity and an arbitrary number of firms.[2] Time is discrete with $t = 1, 2, ..., \infty$. There are $I$ firms denoted by $i = 1, ..., I$.

Every period, firms decide whether to adopt or not. Let $a_i^t \in \{0, 1\}$ denote firm $i$'s action at time $t$ and $a^t$ be an $I$-vector denoting the action profile chosen at time $t$. Firm $i$'s history of actions, $h_t^i$, is a $t$ vector containing zeros until firm $i$ has adopted, and ones from then on. Let $H_t$ be the set of all possible action histories at time $t$. If firm $i$ has not moved at any $\tau < t$, i.e. $h_t^i = (0, 0, ....., 0)$, then its action set at time $t$ is

$$A_{h_t}^i = \{\text{do not adopt}, \text{adopt}\} = \{0, 1\}.$$

Firms hold on to the technology indefinitely once they have adopted. This implies that the action set is weakly increasing in time. I restrict the attention to pure strategies. A pure adoption strategy for firm $i$ is a function mapping the history to an element of the action set:

$$s_t^i : h_t \to A_t^i(h_t) \quad \forall h_t \in H_t$$

Let $n_t$ be the number of adopters in period $t$ :

$$n_t = \sum_{i=1}^{I} a_t^i$$

A firm receives $\pi_0^i(n_t)$ per period before adoption and $\pi_1^i(n_t)$ thereafter. Let $t^i$ be firm $i$'s adoption time. At the time of adoption it incurs a sunk cost of $C(t^i)$. Firms discount future returns with discount factor $\beta$. Hence, a firm's discounted

[2] Existing research either restricts the attention to duopoly markets (Fudenberg and Tirole (1985), Riordan (1992)), requires payoffs to be symmetric (Reinganum (1981)), or a monopolistic competition environment (Goetz (1999)).

intertemporal profits are

$$\Pi^i = \sum_{t=1}^{t^i-1} \beta^t \cdot \pi_0^i(n_t) + \sum_{t=t^i}^{\infty} \beta^t \cdot \pi_1^i(n_t) - \beta^{t^i} \cdot C(t^i)$$

Firms choose a strategy to maximize their discounted profits $\Pi^i$.

Let $\mathbf{s}_{\boldsymbol{\tau}}^{\mathbf{i}} = \{s_t^i\}_{t=\tau}^{\infty}$ be the sequence of firm $i$'s adoption strategies starting at time $\tau$. The sequence of strategies by firms other than $i$ is denoted by $\mathbf{s}_{\boldsymbol{\tau}}^{-\mathbf{i}}$. A subgame perfect equilibrium is an $I$-tuple of adoption strategies $\{\mathbf{s^1}, \mathbf{s^2}, .., \mathbf{s^i}, .., \mathbf{s^I}\}$ that constitutes a Nash equilibrium in every subgame.

I now introduce a set of assumptions regarding the payoff and cost functions.

*A1: (monotonicity)* $\pi_a^i(n-1) \geq \pi_a^i(n)$ *for* $a = \{0, 1\}$ *and* $1 \leq n, i \leq I,$

*A2: (positive returns)* $\pi_1^i(n) \geq \pi_0^i(n-1)$; $\forall\ 1 \leq i, n \leq I$

*A3: (decreasing returns:)* $\pi_1^i(n-1) - \pi_0^i(n-2) \geq \pi_1^i(n) - \pi_0^i(n-1)$; $\forall\ 1 \leq i \leq I$, $\forall\ 2 \leq n \leq I$

*A4: (profitability order)* $\pi_1^i(n) - \pi_0^i(n-1) > \pi_1^j(n) - \pi_0^j(n-1)$ *if and only if* $\pi_1^i(m) - \pi_0^i(m-1) > \pi_1^j(m) - \pi_0^j(m-1)$, $\forall 1 \leq i, j, m, n \leq I.$

The *monotonicity* assumption *(A1)* states that adoption is rivalrous and thus payoffs decline monotonically in the number of adopters. Rival adoption hurts both firms that have adopted and firms that have not adopted. This reflects the presumption that the new technology opens a new market that has to be shared among adopters, and that non-adopters lose revenues as rivals become more technologically advanced. Hence, the game payoff $\Pi^i$ is increasing in rivals' adoption times. I assume that there are always *positive returns (A2)* to adoption. Firms can always enjoy higher flow profits being an adopter than being a non-adopter, meaning that adoption always weakly increases flow profits at the margin: $\pi_1^i(n) \geq \pi_0^i(n-1)$. More amply, the *stand-alone incentive* to adopt is always positive. Assumption *(A3)* says that there are *decreasing returns* to adoption. That is, the marginal benefit to adoption declines with the rank of adoption. The more firms have already adopted, the less there is to gain from adoption. Assumption *(A4)* requires that the *profitability order* is invariant to the rank of adoption. If firm $A$ gains more from adopting than firm $B$ when one other firm has adopted, then it also gains more from adopting when two other firms have adopted, etc..

Next, I make the following assumption regarding the cost function:

*A5: (cost function decreasing, convex and bounded)*

*(i)* $C(t) > C(t+1)$.

*(ii)* $C(t) - C(t+1) > C(t+1) - C(t+2)$.

*(iii)* $\exists t < \infty$ *such that* $\pi_1^i(N) - \pi_0^i(N-1) > C(t) - \beta C(t+1)$

*(iv)* $\exists t < \infty$ *such that* $C(t) < (\pi_1^i(I) - \pi_0^i(0))/(1-\beta)\ \forall i$.

The *cost function (A5)* is assumed to be falling exogenously over time at a decreasing rate. I also assume that the cost falls eventually to a level such that the gains from adoption are higher than the cost.

Finally, I introduce an assumption regarding the timing of decisions.

*A6: (sequential moves) At each period t firms sequentially make the decision whether to adopt. The firm with the* $i-th$ *largest marginal benefit to adopt* $(\pi_1^i(n) - \pi_0^i(n-1))$ *moves* $i-th$.

The *sequential moves (A6)* assumption addresses the potential multiplicity present in a simultaneous move discrete time game.

## 2.2 Discussion

Here I discuss the properties of the model. I first argue that the assumptions ensure that the game has a finite horizon. Then the potential multiplicity in a simultaneous move game and how sequential moves achieve uniqueness are discussed. The solution algorithm is described and the model predictions are discussed.

*Finite horizon.* Assumption *(A5)* insures that all firms adopt in finite time. The intuition is that if a firm were never to adopt, then the continuation value of not adopting must always be higher than that of adopting. Assumption *5(iii)* states that the cost decline cannot continue for ever, so that eventually no firm would want to postpone adoption individually. Assumption *5(iv)* requires that costs fall to such an extent that even if all firms have adopted the technology, flow profits are higher for every firm than if no firm had adopted the technology.

Define $\bar{t}$ as the earliest time such that the least profitable firm has an incentive to adopt when all other firms have adopted. Assumption *(A5)* then implies that in any subgame starting $t \geq \bar{t}$, all firms not yet having adopted will adopt immediately. Consider a subgame starting at some $t \geq \bar{t}$ where $(I-i)$ firms have adopted. Suppose one of the remaining firms adopts at $\tilde{t} > t$. Then it can always increase its payoffs by adopting at $\tilde{t}-1$. Hence, all firms will adopt immediately at $t$. This enables me to solve the model backwards from $\bar{t}$. The endpoint $\bar{t}$ can be computed for a given payoff structure and cost process. It is the smallest $t$ where the marginal increase in period return when adopting $I-th$ is greater than the cost saving when delaying adoption to time $t+1$. For a formal argument see the proof of Proposition 1 in the appendix.

*Simultaneous versus sequential moves.* With firms moving simultaneously the solution concept of subgame perfect equilibrium does not always generate a unique prediction regarding adoption times and the identities of adopters. In this model of technology adoption two forms of multiplicity are present. First, situations similar to a static entry model (Bresnahan and Reiss (1991), Berry (1992)) can arise, where the number of adopters can be predicted, but not their identity. In a given period $t$ firm $A$ might be willing to adopt as long as firm $B$ does not adopt and vice versa. A second source of multiplicity stems from the dynamic nature of the game. The identity of the first adopter may be known, but it cannot be predicted in which period the first adoption will occur. A firm might delay adoption if it is the adopter in the ensuing subgame, or it may adopt immediately, because the ensuing subgame involves its rival adopting. Whether the first adoption occurs in a given period or a later period thus depends on the equilibrium strategies being played in the ensuing subgames. Multiplicity poses a problem in estimating the model because there is no unique mapping from observables to the data. I address this issue by assuming that firms move *sequentially (A6)*. Since all firms adopt in finite time, the game is equivalent to a finite horizon game of perfect information. Generically, firms will never be indifferent between two actions. Consequently, there is a unique subgame perfect equilibrium. The *sequential moves (A6)* assumption can be justified, because it produces the same order of adoptions as if time periods between moves were sufficiently small in a two player game. The intuition is that if firm $A$ receives a larger increase in period payoffs from adoption than firm $B$, and both firms face the same cost schedule, then at every point in time the benefit from adopting first today is larger for firm $A$ than for firm $B$. If time periods are short enough, there will exist a period where firm $A$ prefers to adopt first and firm $B$ does not. For the case $I = 2$ this idea is formalized in Schmidt-Dengler (2005).[3] The robustness of the *sequential moves* assumption will be discussed in Section 4.

*Solution algorithm.* Given the structure of the game, the unique equilibrium can be computed using a simple recursive algorithm. I order the firms according to their profitability.[4] Thus $i$ represents the $i-$th most profitable firm. Consider the least profitable firm $I$ and let $\bar{t}$ be the time by which all firms adopt. At $\bar{t}-1$, firm $I$ knows that all players will adopt next period, regardless of the history of play. If firm $I$ has not adopted, it adopts whenever the increase in period payoffs when adopting today outweighs the cost saving when adopting next period. This way, I can compute the value for each history before firm $I$ makes its decision. Thus, firm $I-1$ knows the continuation value of adopting versus not adopting and chooses its action accordingly. Going backwards, I compute the continuation value for all other players and every history in period $\bar{t}-2$. I repeat this until period $t = 1$. This yields the history of equilibrium play.

Figure 1 illustrates the dynamics of profits in this model for the simple case of two symmetric firms. Here, firm $A$ adopts first at time $t^A$ and firm $B$ adopts subsequently at time $t^B$. Prior to $t^A$, both firms receive flow profits of $\pi_0(0)$. At the time of adoption,

[3] A similar argument may hold for $I > 2$, but a simple inductive argument cannot be applied. This can be illustrated for the case $I = 3$. In a subgame with the two less profitable firms not having adopted, the second adoption may occur sooner than in a subgame where one of the remaining firms is the most profitable, because a more profitable firm faces a weaker preemption constraint as shown in Riordan (1992). By adopting first at time $t$, the most profitable firm may induce an earlier second adoption and enjoying monopoly payoffs for a shorter period than a less profitable firm might. Thus it is not straightforward to show that the continuation value when adopting is always highest for the most profitable firm.

[4] The specification chosen in Section 4 will ensure that firms differ in profitability with probability one.

firm $A$'s profits increase to $\pi_1(1)$, but in part at the expense of its rival $B$, whose profits drop to $\pi_0(1)$. When firm $B$ adopts at time $t^B$, its profits increase, but at the expense of firm $A$. Now both firms are in the same position and earn $\pi_1(2)$. Note that flow profits at a given point in time are only affected to the extent *whether* a firm has adopted or not, but not *when* it has adopted. Intertemporal profits though depend on when a firm has adopted.

*Stand alone incentive.* A firm has an incentive to delay adoption, because the new technology becomes cheaper over time: $C(t) > \beta C(t+1)$. On the other hand it wants to adopt sooner because adoption generates an increase in period returns, $\pi_1^i(n_t) - \pi_0^i(n_t - 1)$. A monopolist weighs the benefit of higher period payoffs when adopting today against the cost-saving when delaying adoption. The same holds for a firm whose rivals have all adopted. If $\pi_1^i(n_t) - \pi_0^i(n_t - 1) > C(t) - \beta C(t+1)$, we say that firm $i$ has a *stand-alone* incentive to adopt.

*Preemption incentive.* Further, a firm may have an incentive to adopt, because it changes its rivals incentive to adopt due to the *decreasing returns* assumption. Conversely, there is a cost of waiting, because a rival may adopt which has a negative impact on the firm's own payoffs and will delay its own adoption time. To illustrate this, consider a duopoly market with two identical firms $i = A, B$ as in Figure 2. If firm $A$ adopts at $T^A$, it will enjoy the monopoly profits from adoption until costs have fallen enough such that the stand-alone incentive justifies the second adoption by firm $B$ at $T^A$. Define the second adoption time determined by the stand-alone incentive as $T^B$. Taking this as given, the best response by the firm $A$ would be an adoption time $T^A \leq T^B$ where the stand-alone incentive justifies the first adoption. Firm $A$ would enjoy higher profits than $B$ because $\Pi^A(T^A, T^B) \geq \Pi^B(T^A, T^B)$.[5] However firm B would in fact prefer to *preempt* firm $A$ if $\Pi^B(T^B, T^P) > \Pi^B(T^A, T^B)$. Hence, the equilibrium first adoption time $T^P$ must satisfy $\Pi^B(T^B, T^P - 1) \leq \Pi^B(T^P, T^B)$. The

[5] The following argument is adopted from Fudenberg and Tirole (1985). Note that $\Pi^A(T^A, T^B) \geq \Pi^A(T^B, T^B)$, because $T^A$ is a best response. Note that $\Pi^A(T^B, T^B) = \Pi^B(T^B, T^B)$ because firms are identical and finally $\Pi^B(T^B, T^B) \geq \Pi^B(T^A, T^B)$, because payoffs are declining in rivals' adoption times.

first adoption time $T^B$ is then determined by the advantage of being the leader over being the follower, $\pi_1(1) - \pi_0(1)$ : By preempting, firm $A$ before time $T^A$, firm $B$ could gain the entired shaded area and delay firm $A's$ adoption time to $T^B$. This is the *preemption* incentive.

As the number of firms increases, the preemption incentive for an early adopter can be mitigated, because subsequent adopters will adopt soon due to the preemption motive. Consider the case of three firms. The first firm knows that the second adoption date will be 'pushed back' due to the preemptive nature of the game played by the remaining two firms, and thus monopoly profits can only be enjoyed for a short period of time. Goetz (1999) discusses the case of a continuum of firms where the preemption motive is absent.

# 3 The Diffusion of MRI

In this section I describe magnetic resonance imaging, the construction of the data set, and present the key features of the data.

## 3.1 Magnetic Resonance Imaging

Magnetic resonance imaging (MRI) is a diagnostic tool for producing high resolution images of body tissues. MRI is superior to other imaging techniques such as the computer tomography scanner (CT scanner) in soft tissue contrast resolution. It is thus particularly useful in identifying diseases in organs such as brain, heart, liver, kidneys, spleen, pancreas, breast, and other organs. In the late 1970s, the leading companies producing in the CT market recognized the potential of MRI for medical imaging. MRI scanners became commercially available in the early 1980s. By 1983 eight companies had already completed prototypes (Roessner et al. (1997)). The supply of MRI scanners has been very competitive early on. Lunzer (1988) reports that more than 25 manufacturers were supplying scanners, although General Electric enjoyed a 32 percent market share at that time. The adoption of MRI by US hospitals was slow relative to the CT scanner. One reason was the originally very high capital cost, about 10 times that of a CT scanner, with cost of the equipment ranging from \$2 million to \$2.6 million, and installation cost ranging from \$0.6 million to \$1.3 million in 1985 (Steinberg and Evens (1988)). The cost of equipment declined over time at a rate of 4.5% in real terms (Bell (1996)). A crucial reason for adopting MRI was the Health Care Finance Administration's 1985 approval of coverage for scans performed on Medicare patients,[6] because Medicare patients are typically responsible for 40% of a hospital's revenue. Hospital managers may also have been aware of the prestige effect of an imager. Muroff (1992) states for example that there is "economic impact of having a 'state-of-the art,' multipurpose MRI unit that might be necessary to win referrals in a highly competitive environment. [...] Quantifying these benefits is difficult." This prestige effect may not only directly attract patients, but may also enable a hospital to attract high quality physicians. A survey of hospital executives carried out by the American Hospital Association in 1987 shows that competition was the second most important reason for purchasing MRI, the number one reason being 'improving patient care.'

## 3.2 Data Description

I use two sources of data for the empirical analysis, adoption data derived from the American Hospital Association's (AHA) annual survey database as well as demographic data derived from the U.S. Census.

The AHA surveys all hospitals operating in the United States every year. The AHA survey has been used previously to analyze the diffusion of MRI. Baker (2001) studies the impact of HMO market share on MRI diffusion in a hazard framework. There, the emphasis is on individual hospitals in larger markets, whereas I focus on strategic interaction among hospitals in small markets. I have however adopted Bakers's definition of adoption: I record a hospital as having adopted MRI in a given year if it responds in the survey that it has a hospital based nuclear magnetic resonance imaging facility. I have constructed a dataset of non-federal general medical

[6] The coverage was limited to scans performed with imagers that had won the Food and Drug Administration's pre-market approval. In 1985, five firms supplied models with pre-market approval.

and surgical hospitals.[7] The survey also includes hospital specific information such as a control code (like non-profit versus for profit status), the number of beds, whether it belongs to the Council of Teaching Hospitals, or has a residency program. This information is available for eight years from 1986 to 1993.

Following the health economics literature (Baker (2001), Baker and Phibbs (2002)), I define a market as a so-called Health Care Service Area (HCSA). HCSA's are groups of counties constructed to approximate markets for health care services based on Medicare patient flow data (Makuc et al. (1991)). There are 802 HCSA's in the entire United States.

The Area Resource Files (ARF) provide county-level information on demographic and economic variables derived from the U.S. Census. I aggregate population and per capita income to the HCSA level, and merge the information with the hospital data derived from the American Hospital Association's annual survey.

I select 780 hospitals operating in HCSA's with a constant number of four hospitals or less operating over time. While strategic interaction may also be present in markets with more hospitals, this interaction may be restricted to a subset of hospitals within those markets. The restriction to four hospitals or less leaves 306 HCSA's, 38% of all markets. It is important to recognize the specificities of this sample of small markets relative to all US hospital markets. The key characteristics are documented in Table 1. While the sample contains more than one third of all markets as defined above, it only represents about 15% of all US hospitals. The average hospital in the sample has about the half the bed capacity (99 beds) of the average US hospital. The markets in the sample have an average population of 72,737, about 15% of the average US market. The average per capita income in the sample markets is about 1,400 dollars below the overall average. In the sample, 322 hospitals are nonfederal government hospitals, 407 are private nonprofit hospitals and 51 are for-profit hospitals. It contains proportionately less private nonprofit and for-profit hospitals, as these

[7] That means I exclude rehabilitation hospitals, childrens' hospitals and psychiatric clinics. I also exclude federal hospitals such as Army or Veterans Administration hospitals, because they only compete for a small subset of the patient population.

organizational types are more prevalent in large urban areas. The most significant difference lies in the fraction of hospitals that are approved for residency training: Less than two and a half percent of the sample hospitals are teaching hospitals compared to nineteen percent in the sample. Teaching hospitals tend to locate in urban areas. Similarly, the fraction of hospitals in the sample belonging to a multihospital system is about half of those in the US. More importantly, in only 16 markets of my sample (less than five percent), hospitals belong to the same system. Adoption decisions by hospitals are thus assumed to be made independently, regardless of system membership. Finally, the average adoption rate at 23% in the sample lies ten percent below the overall adoption rate. This may be due to different demand conditions in larger markets and -more importantly when interpreting the results of this paper- due to different competitive conditions.

## 3.3 Stylized Facts

I now focus on the main features of the data under consideration. The average adoption rate at the end of my sample is less than 25 percent. Figure 4 plots the fraction of markets with at least one MRI over time. Separate lines are drawn for markets with one, two, three and four hospitals. The fraction is almost always larger for a market with more hospitals than a market with fewer hospitals, suggesting that incentives to adopt first are larger in markets with more hospitals. Diffusion is slow, suggesting that the new technology is not immediately profitable for most hospitals.

Table 2 provides summary statistics of the covariates against the number of hospitals within a market. The average adoption rate in 1993 is not monotonic in the number of hospitals. The average adoption rate is smaller in duopoly markets than in monopoly markets, which suggests that the incentive to adopt second in a duopoly market is smaller than to adopt first in a monopoly market. The interpretation for the remaining markets however is less clear. Higher adoption rates may be due to preemption motives that are still present in 1993. Estimation of the structural model will allow me to disentangle preemption and competitive effects.

To examine the relationship between the number of hospitals in market and adoption decisions in more detail, the next four rows in Table 2 cross tabulate the fraction of markets with a given number of MRI adoptions by 1993 with the number of hospitals in a HCSA. I observe only a small number of markets with more than one hospital having adopted. The probability of having at least one MRI is increasing in the number of firms. The probability of a second adoption to occur is considerably smaller. In particular in duopoly markets, the conditional probability of a second adoption is lower than the probability of adoption by a monopolist, however the probability of seeing a second adoption in a tripoly market is considerably larger. At the same time, there are no third adoptions in the tripoly markets. This suggests that there is preliminary evidence that there is an advantage to adopting first in an oligopoly market, but that marginal benefits to adopt decline once a competing hospital has adopted.

The features of MRI can be summarized as follows. MRI was an originally expensive new technology with costs falling over time. It slowly diffused over the past two decades. The adoption generates a new source of revenue, and there is a strategic component to adopting the new technology. The next section describes an estimation technique that enables me to quantify competition and preemption effects in the adoption of MRI by US hospitals.

# 4 Estimation

This section specifies the functional form of profit and cost functions, discusses the estimation technique and presents the parameter estimates.

## 4.1 Specification

I observe $L$ independent markets, with $I^l$ firms operating in market $l$. Each firm $i'$s adoption year $t^{il}$ and a set of market and firm characteristics $X = [\mathbf{W}^i, \mathbf{Z}]$ are observed, where $\mathbf{W}^i$ is a vector of firm specific variables and $\mathbf{Z}$ a vector of market level demand shifters. I allow for an additive random component in the payoff function $\varepsilon^i$, which is a profitability shock. The random component is observed by all firms in the market, but not by the econometrician. It is drawn independently across markets from a strictly monotonic and continuous distribution function $F$. Thus, there is a strict ranking of profitability with probability one. The unobserved term can be correlated across firms within a market. This correlation is captured by a parameter $\rho$.

I make the following parametric assumptions on the payoffs when not having adopted, when having adopted, and on the cost function:[8]

$$\begin{aligned} \pi_0^i(n,\theta) &= \alpha_0 + \mathbf{Z}\boldsymbol{\gamma}_{\mathbf{0}} + \mathbf{W}^i\boldsymbol{\mu}_0 + \delta_0 \cdot \log(n+1) \\ \pi_1^i(n,\theta) &= \alpha_1 + \mathbf{Z}\boldsymbol{\gamma}_1 + \mathbf{W}^i\boldsymbol{\mu}_{\mathbf{1}} + \delta_1 \cdot \log(n) + \varepsilon^i \\ C(t^i) &= c \cdot \lambda^{t^i} \end{aligned} \tag{1}$$

Here $n$ is the number of firms that have adopted. The vector of model parameters is:

$$\theta = (\alpha_0, \alpha_1, \delta_0, \delta_1, \boldsymbol{\mu}_0, \boldsymbol{\mu}_1, \boldsymbol{\gamma}_0, \boldsymbol{\gamma}_1, c, \beta, \lambda, \rho)$$

I rescale $\mathbf{W}^i$ and $\mathbf{Z}$ such that they only take on positive values.

The assumptions regarding *monotonicity* and *decreasing returns* hold whenever $\delta_1, \delta_0 \leq 0$, and $(\delta_1 - \delta_0) \leq 0$. The inequalities say that the benefit of adoption declines with increasing competition. The number of adopters has a stronger negative effect on adopters than on non-adopters. Observe that specification (1) requires that the competitive effects, $\delta_0$ and $\delta_1$, are symmetric.[9]

A sufficient condition for the *positive returns* assumption to hold, is that $(\boldsymbol{\mu}_1 - \boldsymbol{\mu}_0)$, $(\boldsymbol{\gamma}_1 - \boldsymbol{\gamma}_0) > 0$, $(\alpha_1 - \alpha_0) + (\delta_1 - \delta_0) \cdot \log(I) > 0$, and the support of $F$ is the positive real

[8] Flow profits that satisfy asssumptions 1-4 can arise from alternative specifications. One example is a linear Cournot model in the stage game, where adoption of the new technology reduces marginal cost (Quirmbach (1986)). Another example, probably more appropriate for the hospital industry, would be a constant price cost margin toghether with logit demand system, in which the new technology increases the mean utility of choosing the hospital.

[9] The model and the estimation technique can be extended to a more flexible functional form. However, as I observe only few follow-on adoptions, there are limitations to which effects can be identified. For example, I cannot sharply estimate whether it matters that a rival adopter is a nonprofit or for-profit hospital.

line. I assume that $F$ is known. The *cost function* converges to zero at a decreasing rate when $\lambda \in (0,1)$, satisfying assumptions *A5(i-ii)*.

Assumption *A5(iv)* implies the restriction

$$\alpha_1 - a_0 + \delta_1 \cdot \log(I) + \mathbf{W}^i(\boldsymbol{\mu}_1 - \boldsymbol{\mu}_0) + \mathbf{Z}(\boldsymbol{\gamma}_\mathbf{1} - \boldsymbol{\gamma}_\mathbf{0}) > 0.$$

The restriction emerges when the cost goes to zero and imposes a lower bound on $\delta_1$ relative to $\alpha_1 - a_0$. Assumption *A5(iii)* will also be satisfied.

*Identification.* The parameter vector of interest $\theta$ is point identified if two parametric specifications are not observationally equivalent. The identification of cost and payoff parameters relies on functional form. However it is useful to discuss the implications from the model that allow us to learn about the payoff function. Let

$$\Delta\pi^i(n,\theta) = \pi_1^i(n,\theta) - \pi_0^i(n-1,\theta) \tag{2}$$

be firm $i'$s marginal gain from adopting $n-th$. If firm $i$ adopts last at $t^i$, it must hold that

$$\begin{aligned} \Delta\pi^i(I,\theta) - c\cdot\lambda^{t^i}(1-\beta\lambda) &\geq 0 & (3)\\ \Delta\pi^i(I,\theta) - c\cdot\lambda^{t^i-1}(1-\beta\lambda) &< 0 & (4) \end{aligned}$$

Only *relative* profits $\Delta\pi^i(I,\theta)$ enter this condition. Thus one can only learn about $(\alpha_1 - \alpha_0, \delta_1 - \delta_0, \boldsymbol{\mu}_1 - \boldsymbol{\mu}_0, \boldsymbol{\gamma}_\mathbf{1} - \boldsymbol{\gamma}_\mathbf{0})$, the differences of the flow profit parameters. This is not surprising as it is known from discrete choice models that only relative payoffs are identified.

However, the subgame perfect solution concept imposes another restriction that can be used to separately identify the parameters $\delta_0$ and $\delta_1$, which is illustrated in Figure 3. One can learn about the stand alone incentive for the monopolist from the monopoly markets, $\Delta\pi^1(1,\theta) = \pi_1^1(1,\theta) - \pi_0^1(0,\theta)$, and thus the parameters $(\alpha_1 - \alpha_0, \boldsymbol{\mu}_1 - \boldsymbol{\mu}_0, \boldsymbol{\gamma}_\mathbf{1} - \boldsymbol{\gamma}_\mathbf{0})$. If in addition the adoption times of the second adopters in duopoly markets are observed, we can learn about those stand alone incentives: $\Delta\pi^2(2,\theta) = \pi_1^2(2,\theta) - \pi_0^2(1,\theta)$ and thus the competitive effect $(\delta_1 - \delta_0)$. As discussed in the previous section, in duopoly markets where the two hospitals are sufficiently similar in terms of their profitability, the first adoption time will be determined by the preemption incentive $\pi_1^2(1,\theta) - \pi_0^2(1,\theta)$, and thus by the parameters $(\alpha_1 - \alpha_0 - \delta_0, \boldsymbol{\mu}_1 - \boldsymbol{\mu}_0, \boldsymbol{\gamma_1} - \boldsymbol{\gamma_0})$. The hospital gains enough from adoption such that it adopts at a sufficiently early point in time where its rival prefers to be the follower and adopt later on.

The key argument is that with a cross-section of at least monopoly and duopoly markets, the coefficients $\alpha_1 - \alpha_0, \delta_0, \delta_1$ can be estimated separately. The intuition can be summarized as follows. Adding a constant to $\delta_1$ and $\delta_0$, leaves $\delta_1 - \delta_0$ unchanged, and the marginal benefit of adopting last, $\pi_1(2) - \pi_0(1)$ is unaffected. However, the relative benefit of being the leader versus being the follower in a given period, $\pi_1(1) - \pi_0(1)$, changes. The level of $\delta_0$ and $\delta_1$ influences preemption incentive and thus adoption time of the first adopter in a duopoly market, whereas it has no effect on the second adoption time. The appendix shows in more detail how the cost function along with the competitive effects can be identified separately, given the chosen functional form.

The variation of observables $[\mathbf{W}, \mathbf{Z}]$ and adoption times across markets determines the parameters $\boldsymbol{\mu}_1 - \boldsymbol{\mu}_0, \boldsymbol{\gamma_1} - \boldsymbol{\gamma_0}$. A continuum of combinations of $c$ and the discount factor $\beta$ yield the same optimality conditions in (3) and (4). I thus have to fix the discount factor. The hospital industry literature (e.g. Steinberg and Evens (1988)) uses an interest rate from $10-12$ percent for cost calculations. Accounting for inflation this corresponds to a discount factor of .94.

I assume that the distribution $F$ of the unobservable profitability shock $\varepsilon^i$ is lognormal. Note that the mean and variance of the unobservable are not identified separately from the parameters $\alpha_1 - \alpha_0$ and $c$ respectively. I fix these parameters such that the logarithm of the distribution has mean zero and variance one. Having fixed the variance and the discount factor, the cost parameter $c$ can be estimated as well.

I now illustrate the role of the unobservable $\varepsilon^i$. First, it accounts for unobserved payoff differences across firms. In absence of such an error we would be able to predict behavior perfectly. The idea is similar to Rust (1994), in that the optimal adoption time for each firm is deterministic for the participants in the market but random from the standpoint of the econometrician. Note that due to the discrete time nature of the model and data, equations (3) and (4) along with the preemption conditions yield a set of inequalities, and thus only bounds on the parameters. Making a distributional assumption about $F$, one can obtain point estimates of the parameters. Finally it enables me to integrate over adoption times of hospitals that have not adopted at the end of my sample.

To allow for unobserved market characteristics that affect the profitability of MRI for all hospitals, I allow for within market correlation of $\varepsilon^i$. Following Berry (1992), I choose a specific form for this correlation:

$$\varepsilon^i = \exp(\sqrt{(1-\rho^2)}\nu^i + \rho\nu^l)$$

Here $\nu^i$ is the firm specific component and $\nu^l$ the market specific component of the profitability shock. I assume that both are distributed i.i.d standard normal. I restrict $\rho$ to lie on the interval $[0, 1]$.[10]

There are two possible explanations for diffusion when costs fall over time. When there is no firm heterogeneity ($\rho = 1, \boldsymbol{\mu}_1 - \boldsymbol{\mu}_0 = 0$), a competitive effect will cause diffusion, because the marginal incentive to adopt changes with the rank of adoption. In absence of a competitive effect (e.g. $\delta_1 - \delta_0 = 0$), firm heterogeneity in payoffs will lead to different adoption times, because different firms have different *stand-alone* incentives. These two explanations can be distinguished as they have different cross sectional implications for adoption times. Consider first the case of no heterogeneity ($\rho = 1, \boldsymbol{\mu}_1 - \boldsymbol{\mu}_0 = 0$). The adoption times in the two markets $(T_1, T_2)$ and $(T_1', T_2')$ must satisfy $T_1 \geq T_1'$ if and only if $T_2 \geq T_2'$; both firms within a market gain the same from adoption. If the first firm gains less from adoption than the first firm in the other market, the second firm in one market must also gain less than the

[10] I chose this specification, because mean and variance of $\varepsilon^i$ are independent of $\rho$. The levels of of the other coefficients are not affected by the choice of $\rho$. The within market correlation of $\varepsilon^i$ for a given $\rho$ is:

$$corr(\varepsilon^i, \varepsilon^j) = \frac{e^{\rho^2} - 1}{e^2 - 1}$$

second firm in the other market. This implies that the second adoption time is a monotonically increasing function of the first adoption time everywhere. On the other hand, if there were no competitive effect and everything was driven by heterogeneity, the probability of an adoption occurring would be independent of the number of adoptions that have already occurred. The small sample does not allow me to directly test these nonparametric implications, but the argument shows that the identification of the competitive effect along with the within market correlation is not solely due to functional form.

## 4.2 A Method of Moments Estimator

I now introduce a method to estimate the technology adoption model. The model does not yield a closed firm solution for the expectation of the vector of adoption times conditional on the market and firm specific observables and the model parameters. I propose a Method of Simulated Moments (MSM) Estimator (McFadden (1989), Pakes and Pollard (1989)) that does not require an analytical solution for the equilibrium adoption times.

Let $\theta = (\alpha_1 - \alpha_0, \delta_0, \delta_1, \boldsymbol{\mu}_1 - \boldsymbol{\mu}_0, \boldsymbol{\gamma_1} - \boldsymbol{\gamma_0}, c, \lambda, \rho)$ be the vector of parameters to be estimated. Let $X_l = [\mathbf{W}, \mathbf{Z}]$ be exogenous market and firm specific variables and $\mathbf{T}$ the vector of adoption years. Let $\psi(\mathbf{T})$ be a $J$-dimensional function of the adoption years. The estimation method is conducted as follows:

Step 1: Compute a $J$-dimensional vector $\hat{\psi}(\mathbf{T})$ of empirical moments.

Step 2: For every market $l$, obtain $S$ draws of an $I_l$-dimensional vector $[v^1, .., v^{I_l}]$ of individual profitability shocks and a draw $\nu^l$ of the common profitability shock. Here $I_l$ is the number of hospitals in market $l$.

Step 3: For a given parameter-vector $\theta$, every draw $s$ and every market $l$, compute the period payoffs and the cost function. Determine the order of moves.

Step 4: Compute the last adoption time $\bar{t}$, and solve the model recursively from $\bar{t}$.

Step 5: Compute the equilibrium history of play. This yields $S \cdot L$ histories of play. From these simulated histories compute the vector of simulated adoption times $\mathbf{T}_s(X_l, \theta)$. The simulation draws are held fixed for different parameter vectors. For

every market $l$,compute the average simulated moments $\tilde{\psi}_{S,l} = \frac{1}{S}\sum_{s=1}^{S}\psi(\mathbf{T}_s(X_l,\theta))$.
Step 6: Let $g(\theta) = \frac{1}{L}\sum_{l=1}^{L}(\hat{\psi} - \tilde{\psi}_{S,l}) \otimes f(X_l)$ be the vector of moment conditions, where $f(X_l)$ is a $K-$dimensional vector function of the market and firm specific exogenous variables. Compute the value of the criterion function, the weighted distance between observed and simulated moments:

$$J(\theta) = g(\theta)'\Omega g(\theta)$$

Here $\Omega$ is a $J \times K$-dimensional symmetric positive definite weight matrix.

The $MSM$-estimator $\hat{\theta}$ is defined as the minimizer of the criterion function. Thus, Steps 3 to 6 are repeated until convergence, i.e. until a vector $\theta$ is found that minimizes the objective function $J(\theta)$. The estimator $\hat{\theta}$ is consistent and $\sqrt{L}(\hat{\theta} - \theta_0)$ is asymptotically normally distributed with zero mean and covariance matrix

$$(1 + \frac{1}{S})(E\frac{\partial}{\partial\theta}g'\Omega E\frac{\partial}{\partial\theta}g)^{-1}E\frac{\partial}{\partial\theta}g'\Omega Egg'\Omega E\frac{\partial}{\partial\theta}g(E\frac{\partial}{\partial\theta}g'\Omega E\frac{\partial}{\partial\theta}g)^{-1}.$$

The efficiency of the estimator can be improved by employing an optimal weight matrix $\Omega = (Egg')^{-1}$. The asymptotic distribution of $\sqrt{L}(\hat{\theta} - \theta_0)$ then becomes $(1 + \frac{1}{S})(E\frac{\partial}{\partial\theta}g'\Omega E\frac{\partial}{\partial\theta}g)^{-1}$. The optimal weight matrix is computed using a consistent estimate of $\theta$. Estimates of the standard errors are obtained by replacing the terms in the expression for the covariance matrix with consistent estimates.

Note that when generating simulated data, I assume that the game begins at time $t = 1983$, which is the year in which MRI scanners became commercially available, and solve for the entire history of equilibrium play. The simulation procedure thus integrates out over unobserved adoptions occurring in years before 1986 and after 1993.

The moment selection is guided by the need to capture the dynamics of adoption and the fact that I only observe the time window from 1986 to 1993. I also require that the same set of moments is employed for every market, regardless of the number of hospitals or the number of adoptions actually observed. Thus, the moment selection is similar to Berry (1992), who deals with varying numbers of potential entrants across markets. The richest specification, guided by preliminary reduced form analysis, includes the firm specific variables hospital size (measured by the logarithm of the number of beds), a dummy for nonprofit hospitals and a dummy for for-profit hospitals (nonfederal government hospitals or 'community hospitals' being the reference category), and market variables population and per capita income. This implies that a total of 11 parameters is estimated and at least as many moment conditions are required. Recall that I observe the years 1986 to 1993. I first select the following eight moments: The number of adoptions by the end of 1986, the number of adoptions by the end of year 1987, etc. until the number of adoptions by the end of 1993. In order to capture the effect of market specific variables, I interact the number of adopters by 1993 with the market specific observables, population and per capita income. To capture the effect of hospital size, I add a moment defined as whether the largest hospital has adopted by 1993. Finally, to capture the effect of organizational type I add one moment defined as the number of nonprofit hospitals that have adopted by 1993, and one moment defined as the number of for profit hospitals that have adopted by 1993. This results in a total of 13 moments. With the selected specification, this yields at least two overidentifying restrictions. Higher order moments could also be employed.

## 4.3 Parameter Estimates

Table 3 shows the parameter estimates for five specifications. The first specification includes no firm characteristics, such that firms are identical up to the realization of the profitability shock $\varepsilon^i$. The proxies for demand are the logarithms of population and per capita income. Specification 2 includes firm characteristics such as hospital size (the log of the number of beds), and organizational form (a dummy for nonprofit status and a dummy for for-profit status). The reference case is a community hospital. In the third specification I allow for within market correlation $\rho$ of the unobservable profitability shock $\varepsilon^i$, to control for potential unobserved market characteristics that affect the profitability of adoption of all hospitals within a market. Standard errors are reported in parentheses beneath the estimates. The number of simulation draws

$S$ per market is 20.[11] Specifications 4 and 5 examine the robustness of estimates with respect to functional form and order of moves and will be discussed in the next subsection.

As we move to richer specifications some interesting changes in the estimated coefficients occur can be observed. Allowing for firm specific variables (moving from Specfication 1 to Specification 2) has a minor impact on the payoff coefficients and the competitive effects, but increases the initial cost $c$. This is offset by the positive coefficients on firm characteristics such as hospital size and for-profit and private nonprofit status. There is a somewhat surprising effect when I allow for within market correlation of the unobservable $\varepsilon$ in Specification 3. The estimated coefficient $\rho$ corresponds to a within market correlation of the unobservable $\varepsilon^i$ of 0.2286, which is significantly different from zero (the standard error is 0.0729). A low draw of the common component means all hospitals in a market gain less from adoption, a large draw means all firms gain more from adoption. In static entry models, accounting for positive within market correlation of the unobservable term may yield stronger competitive effects. What happens here is that firm specific effects become somewhat weaker because they may have been picking market level effects up before. At the same time the coefficient on population becomes stronger (dominating the weaker income effect). In the absence of the within market correlation, the algorithm tried to fit the few follow-on adoptions with a strong competitive effect (large negative $\delta_1 - \delta_0$), which lowers the incentives for later adopters. Now, this difference is captured by a change in the cost function parameters, where a slower cost decline has a stronger negative effect on the incentives of less profitable than on more profitable firms. At the same time $\delta_0$ becomes more negative, making preemption relatively more attractive. Allowing for within market correlation improves the overall fit of the model, especially the moments regarding the firm specific and market level variables. Hence, I focus on the Specification 3 in the following discussion.

[11] For every specification I use same set of starting values. Minimization of the criterion function was performed in two steps. First, I used an accelerated random search algorithm (Appel et al., (2003)) and second, a Nelder-Mead grid search was employed.

In Specification 3, all of the parameters are estimated very precisely. Adopting increases period payoffs evaluated at the median values of population and per capita income by 25 units, about 5.5 percent of the adoption cost when adopting at time zero. The real cost declines at a rate of about 3 percent, implying that it is reduced by 25 percent after about nine and a half years and by 50 percent after about 22 and a half years. The real 'street price' of a premium high field MRI unit fell at a rate of approximately 4.5 percent over the period from 1983 to 1993 (Bell (1996)). Since the model also includes installation cost, which increased over time (mainly due to rising labor cost and real estate prices), this result also validates the model ex-post. Payoffs decline significantly with the number of adopters, with the effect on adopters about 4 times stronger than that on non-adopters. I find that nonprofit firms have a stronger incentive to adopt the new technology than for-profit hospitals. This corresponds to recent findings that nonprofit hospitals act as if they have lower marginal costs (Gaynor and Vogt (2003)). The literature on nonprofit hospital behavior suggests several explanations for this behavior. While the present methodology does not allow me to distinguish among these explanations, they offer useful insights into why we see this strong positive effect. Nonprofit hospitals may be maximizing a weighted average of profits and quality of services provided (Gowrisankaran and Town (1997)). Sometimes donors tie their contributions to the purchase of a specific technology. Nonprofit hospitals may also have an advantage in providing a service based on a new technology because of information asymmetries. Poorly informed customers may believe that nonprofit hospitals are less likely to misrepresent the benefits of the new technology due to their lack of profit motive. Further, nonprofit hospitals may be more willing to experiment with new technologies (Rose-Ackerman (1996)).

*Interpretation of parameter estimates.* The relative economic significance of the estimated coefficients can be examined by conducting simulation exercises. I fix the market characteristics at their median values, and consider the base case with all hospitals being community hospitals of median size. First, I consider a 10% percent increase in population at the median value. This accelerates adoption by 1.2 months on average. A 10% increase in per capita income however accelerates adoption insignificantly by about 3 days. To illustrate the importance of the interaction parameters $\delta_0$ and $\delta_1$, I compare the adoption times predicted by the estimated model relative to those when $\delta_0 = \delta_1 = 0$. This removes any strategic considerations by the hospitals and they act as if they were facing independent demand curves. The effect is best illustrated in the duopoly case. The first adoption would occur 1 year later on average, whereas the second adoption occurs about 2 years earlier. The first adoption occurs later, because the preemption incentive no longer forces the first firm to adopt sooner.[12] The second adoption occurs sooner, because under this scenario the marginal benefit of adopting is the same as adopting first. The difference between the first and second adoption times is purely driven by unobserved heterogeneity in payoffs.

In Section 5, I will use the estimated parameters to quantify the effect of competition on adoption times.

## 4.4 Goodness of Fit and Robustness

*Goodness of fit.* I focus on the preferred specification, Specification 3. To assess the fit of the model, I draw from the asymptotic distribution of parameters, simulate the model and average adoption rates across simulations. The results are presented in Figure 5. Figure 5 compares the simulated adoption rates to the observed adoption rates by number of firms in the market. On average, the model tends to slightly overpredict adoption at the beginning of the observed period and underpredict after 1987 in the markets with more than one firm. More specifically, the model underpredicts adoption rates in monopoly and duopoly markets. Especially in the duopoly markets the underprediction is severe. However, the model fits markets with three firms and four firms very well. This arises possibly from the fact that most adoptions are observed in these markets, and therefore most of the identification will be due to variation in these observations.

*Robustness.* Two questions arise with respect to the robustness of the parameter

[12] Asssuming that hospitals have identical observable characteristics overstates the preemption effect.

estimates. The results will depend on the choice of functional form and the imposed order of moves. Recall that the model was tractable for any choice of functional form and for any order of moves as long as it was known to the firms ex-ante. To investigate the robustness of the chosen specification, I first test the log-specification of the competitive effect, and then reverse the order of moves so that the hospital gaining least from adoption moves first.[13] Specification 4 in Table 3 presents results for the model with linear competitive effects. Here it is assumed the $n$-th adopter steals as much from rival's profits as does the $(n+1)$-th. The effect on the coefficients can be explained as follows. With linear competitive effects, the originally estimated parameters would imply a much stronger competitive effect and there would be a stronger preemption effect. First and last adoption time would thus be further apart. Consequently the estimated competitive effects are smaller in absolute value. The cost parameters are robust to this change, as are the coefficients on population and hospital size. The only remaining parameters that are affected significantly are the coefficient on per capita income which becomes insignificant (and has already been found economically insignificant before), and the coefficient on within market correlation which becomes substantially smaller. This latter effect may be due to the algorithm attempting to offset the stronger competitive effect by increased heterogeneity across hospitals.

The results for the reversed order of moves are presented by Specification 5 in Table 3. Here I assume that rather than the hospital gaining most, the hospital gaining least from adoption moves first every period. With a reversed order of moves, a more profitable firm will often adopt one period earlier than with the original order of moves to avoid being preempted by a less profitable firm that moves earlier in the next period. To reconcile the model with the data, the competitive effects thus become smaller with the reversed order of moves, weakening the preemption incentive. Overall, several parameters are estimated less precisely than in other specifications. In particular, the within market correlation coefficient becomes statistically insignificant from zero. I will revisit the question of robustness in the next section when quantifying

[13] I also tried a randomized order of moves but the algorithm failed to converge.

the effects of competition on the timing of adoption.

# 5 The Effect of Competition on MRI Adoption

The effect of new technologies and hospital competition on health care cost has received wide attention in the literature (e.g. Weisbrod (1991)). While the results obtained here do not provide direct evidence for the impact of a new technology on health care costs or overall welfare, the framework enables me to assess how competition affects the timing of adoption and industry payoffs from adoption. In particular, I want to decompose the effect of competition into a business stealing and a preemption effect. The preemption motive to adopt a new technology early has received considerable attention in theoretical literature (see Fudenberg and Tirole (1985) and Riordan (1992)). To separate the preemption effect from the business stealing effect, I proceed in two steps. I first examine adoption decisions under a regime that maximizes industry payoffs. Under this regime all inefficiencies arising from strategic behavior, due to business stealing and preemption, are removed. I then compare this to adoption times arising from a game in which hospitals are able to precommit to an adoption time. This isolates the preemption incentive. The experiments are performed under the two key assumptions. First, policy changes do not trigger entry into (or exit from) any of the hospital markets studied. Second, policy changes do not affect the cost of adoption and period payoffs conditional on adoption decisions.

## 5.1 Maximizing Industry Payoffs

I first examine the effect of competition by comparing the adoption times under competition to those chosen by an industry regulator, who wishes to maximize industry payoffs. To achieve this, the regulator takes into account the effect on the firms having adopted as well as the firms not having adopted, which makes knowledge of the parameter $\delta_0$ essential for this analysis. The regulator thus eliminates both, the business stealing and the preemption effect. Order the firms $i = \{1, 2......, I\}$ according to their profitability. Naturally, the optimal solution requires more profitable firms to adopt sooner than less profitable firms (as long as competitive effects are symmetric). The industry regulator chooses adoption times $\mathbf{T} = \{T^1, T^2, ...., T^I\}$ to maximize industry payoffs:

$$
\begin{aligned}
\Pi^R_{(\mathbf{T})} &= \sum_{i=1}^{I}\sum_{n=0}^{I} \mathbf{1}_{\{i>n\}} \pi_0^i(n) \cdot \frac{\beta^{T^n} - \beta^{T^{n+1}}}{1-\beta} \\
&\quad + \sum_{i=1}^{I}\sum_{n=0}^{I} \mathbf{1}_{\{i\leq n\}} \pi_1^i(n) \cdot \frac{\beta^{T^n} - \beta^{T^{n+1}}}{1-\beta} \\
&\quad - \sum_{n=1}^{I} \beta^{T^n} \cdot C(T^n)
\end{aligned}
$$

where $T^0 = 0$ and $T^{I+1} = \infty$. We can now compare the adoption times $\mathbf{T}^R$ under the regulatory regime to the equilibrium adoption times $\mathbf{T}^*$.

Table 4 describes the effect of the regulatory solution compared to the competitive solution. To assess this effect, I compute the implied adoption times under the competitive and the regulatory regime for every market. Table 4 presents the average change in adoption times within a group of markets, where a group is defined as the number of hospitals in a market. Obviously, nothing changes in the monopoly markets, so only results for duopoly, tripoly and four-hospital markets are reported. The standard deviations are reported in parentheses. The top four rows in Table 4 describe how the adoption times change on average in these markets. Because the returns to adoption decline with the rank of adoption and the negative impact on competitors' profits is larger, adoption times are delayed more the lower the adoption rank. The fifth row presents the average delay in a given market. It is immediate from the table, that competition among hospitals accelerates adoption significantly, from 2.3 years per hospital in duopoly markets up to 4 years per hospital in four-hospital markets.

The percentage numbers in the last row of Table 4 presents estimates of the payoff loss.[14] The increase in net discounted industry-payoffs under the regulatory regime would be 1.86% (2 firms), 3.86% (3 firms), and 5.56% (4 firms). An increase in

[14] I define the gains from adoption $\Delta\Pi(\mathbf{T})$ as the difference between industry payoffs under adoption times $\mathbf{T}$ and payoffs when firms do not adopt at all (which is normalized to zero). The measure of payoff loss $\Delta V$ is then defined as the percentage increase in the gains from adoption when moving

the demand variables lowers the effect of a regulatory solution. The payoff loss is mitigated by the higher mean demand levels in markets with a larger number of hospitals. The effect can be decomposed into a profit effect and a cost effect. The total effect on discounted flow payoffs is negative. The cost savings due to delayed adoption outweighs the foregone payoffs by delayed adoption.

I have also computed the figures reported in Table 4 using the alternative specifications discussed in Section 4. In the specification with linear effects, the optimal adoption times for the first adopters are close to the ones presented here, while adoption times by follow on adopters are delayed significantly more. This is due to the competitive effect not declining in the rank of adoption in a linear specification. Changing the order of moves has virtually no effect on the relative impact of competition on adoption times.

## 5.2 The Role of Preemption

Here the aim is to quantify how the advantage of being an early adopter affects the corresponding strategic behavior and profits. In particular, I want to quantify the effect of preemption. Preemption is the phenomenon that a firm adopts earlier to prevent its rival from adopting. I compare payoffs in the subgame perfect equilibrium to payoffs if firms were playing an 'open-loop' or a Nash equilibrium strategy. In a Nash equilibrium firms precommit to their adoption times (Reinganum (1981)), which removes the incentive to preempt. A vector of adoption times $T^{NE}$ constitutes a 'pre-commitment' or 'open loop' equilibrium if

$$\Pi^i(T^{NE,i}, T^{NE,-i}) \geq \Pi^i(T^i, T^{NE,-i})$$

for all $T^i$ and $i$. Again, there may be multiple pure strategy equilibria. For the analysis here, I choose the equilibrium where the most profitable firm moves first. It is easy

from the competitive regime with adoption times $\mathbf{T}^*$ to the regulatory regime with adoption times $\mathbf{T}^R$ :

$$\Delta V = \frac{\Delta\Pi(\mathbf{T}^R) - \Delta\Pi(\mathbf{T}^*)}{\Delta\Pi(\mathbf{T}^*)}$$

to verify that this equilibrium always exists and is unique. The adoption time $T^{NE,i}$ of the $i-th$ most profitable firm $i$ must satisfy

$$c \cdot \lambda^{T^{NE,i}}(1-\beta\lambda) - \Delta\pi^{i}(i,\theta) \leq 0 < c \cdot \lambda^{T^{NE,i}-1}(1-\beta\lambda) - \Delta\pi^{i}(i,\theta)$$

This allows me to compute the Nash equilibrium adoption times $T^{NE,\cdot}$.

Table 5 compares the adoption times and welfare gains of the Nash equilibrium play relative to the subgame perfect equilibrium outcome. Again, nothing changes in monopoly markets. Further, the adoption times of the last firm do not change, as it makes only a marginal decision even in the subgame perfect equilibrium. The effects here are much smaller, with adoptions being delayed by less than half a year on average. Also, the estimated payoff loss is only about one sixth of the payoff maximizing regime. In the specification with linear competitive effects the impact of preemption is again found to be stronger. However the results are robust to changes in the order of moves.

The results from these counterfactual experiments let me conclude that preemption has a significant but small effect, and most of the payoff loss due to competition is due to a regular 'business stealing' effect, caused by firms simply not taking into account the negative impact their adoption has on other firms. These results are robust with respect to sequential order of moves assumption that enables me to compute the equilibrium.

# 6 Conclusion

In this paper I studied a timing game of technology adoption by US hospitals. I develop an estimable model that allows me to recover the structural parameters of the timing game. I find that there is a strong competitive effect on hospital profits. Knowledge of the game parameters enables me to conduct counterfactual experiments to quantify the effect of competition on adoption times and hospital payoffs. Results of these experiments show that the competitive solution leads to significantly earlier adoption times than we would see under a regime that maximizes industry payoffs.

The acceleration of adoption times ranges from 2.3 years in duopoly markets to four years in markets with four hospitals. The bulk of this effect is due to regular business stealing. The 'preemption' effect, which has received considerable attention in the theoretical literature, accounts for a small share of this change.

The analysis carried out in this paper can be extended along various dimensions and applied to other technologies. Measuring the effect of technology adoption on consumer welfare requires a demand model. When patient discharge data are available, a demand system as in Chernew, Gowrisankaran and Fendrick (2002) could be estimated. In addition, one might obtain better measures of hospital payoffs, and the effect of competition on profits could be weighed against the potential benefits of earlier adoption to patients.

The model analyzed here bears some features which may not be accurate for the hospital environment. Assuming that flow profits are constant over time and that there is no uncertainty about future payoffs and costs may be restrictive. Incorporating more realistic features along these dimensions would make the solution and estimation of this model considerably more complicated. The current framework does not take into account potential complementarities between adoption decisions for multiple technologies and the possible endogeneity of market structure. These issues have recently been addressed by Hamilton and McManus (2005) and Lenzo (2006) in static frameworks. The extension to a dynamic context is left for future research.

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# 7 Appendix

## 7.1 Finiteness of the Game

Here I show that given the assumptions about the payoffs, all firms will adopt in finite time and that the order of adoption is unique as time periods become sufficiently short.

**Proposition 1** *Given assumptions (A1) to A(5) all firms will adopt in finite time.*

**Proof.** Suppose $I-1$ firms have adopted at time $t$. Let $I$ be the least profitable firm. Firm $I$ will adopt if and only if the benefits to adopting exceed the costs:

$$\pi_1^I(I) - \pi_0^I(I-1) > C(t) - \beta C(t+1)$$

By the *positive returns* and the *monotonicity* assumptions, the term on the left is always positive and given our assumptions on the cost function *A5(iii)* there exists a $\bar{t} < \infty$ such that this inequality holds. Now suppose $I-2$ firms have adopted at some time $t' > \bar{t}$. Denote the remaining two firms $i = j, k$. Then firm $j$ knows that if it adopts it triggers immediate adoption by the last remaining firm $k$ and vice versa. So either firm will always want to adopt, if the benefit from adopting is greater than the maximum benefit from not adopting. Let $V_0^i(I-2)$ be the continuation value of not adopting when $I-2$ firms have adopted and $V_1^i(I-1)$ be the continuation value when having adopted along with $I-2$ other firms. For either of the two firms never to adopt, the continuation value of not adopting must be greater than that of adopting for all $t$:

$$\pi_0^i(I-2) + \beta V_0^i(I-2) \geq \pi_1^i(I-2) - C(t) + \beta V_1^i(I-2)$$

So for firms $i = j, k$ never to adopt it must hold for all $t$:

$$\pi_1^i(I-1) + \beta\frac{\pi_1^i(I)}{1-\beta} - C(t) < \frac{\pi_0^i(I-2)}{1-\beta}$$

By *monotonicity* this implies:

$$\frac{\pi_1^i(I)}{1-\beta} - C(t) < \frac{\pi_0^i(I-2)}{1-\beta}$$

or

$$\frac{\pi_1^i(I) - \pi_0^i(I-2)}{1-\beta} < C(t)$$

The first term represents the payoff from immediate adoption. Since it triggers adoption from the remaining firm, it will earn $\pi_1^i(I)$. We need to find a $\bar{t}$ such that the inequality is reversed. Similarly, if $I-3$ firms have adopted, all firms will adopt eventually if

$$\frac{\pi_1^i(I) - \pi_0^i(I-3)}{1-\beta} > C(t)$$

for some $t < \infty$. Applying the argument above repeatedly up to a situation where no firm has yet adopted yields

$$\frac{\pi_1^i(I) - \pi_0^i(0)}{1-\beta} > C(t)$$

for all $i = 1.....I$. Assumption *A5(iv)* ensures that this inequality holds and hence, all firms will adopt in finite time. ■

## 7.2 Identification

Here I show that given that the parametric assumptions are sufficient to identify the competitive effects and cost parameters. I look at the simplified model:

$$\begin{aligned}
\pi_0^i(n,\theta) &= \alpha_0 + \delta_0 \cdot \log(n+1) \\
\pi_1^i(n,\theta) &= \alpha_1 + \delta_1 \cdot \log(n) + \varepsilon^i \\
C(T^i) &= c \cdot \lambda^{T^i}
\end{aligned}$$

I argue how $(\alpha_1 - \alpha_0, \delta_0, \delta_1, \lambda, c)$ can be identified. In a monopoly market, a firm will have adopted by year $t$ if

$$\begin{aligned}
\Delta\pi^i(1,\theta) - c \cdot \lambda^t(1-\beta\lambda) &\geq 0 \\
\alpha_1 + \varepsilon^i - \alpha_0 - c \cdot \lambda^t(1-\beta\lambda) &\geq 0
\end{aligned}$$

The probability that firm $i$ has adopted by year $t$ is thus

$$\Pr(\varepsilon^i \geq -\alpha_1 + \alpha_0 + c \cdot \lambda^t(1-\beta\lambda)$$

The fraction of firms that have not adopted by year $t$, $S(t)$, is thus equal to

$$S\left(t\right)=F(-\alpha_1+\alpha_0+c\cdot\lambda^t(1-\beta\lambda))$$

Since we observe $S(t)$, we can form

$$F^{-1}(S(t))=-\alpha_1+\alpha_0+c\cdot\lambda^t(1-\beta\lambda)$$

There are three parameters of interest entering this equation: $(\alpha_1-\alpha_0,\lambda,c)$. Knowing $F$ suppose we observe the fraction of monopolists that have adopted in three periods $t,t+1,t+2:\hat{S}(t),\hat{S}(t+1)$ and $\hat{S}(t+2)$. Then we can form:

$$\begin{aligned}\frac{F^{-1}(\hat{S}(t))-F^{-1}(\hat{S}(t+1))}{F^{-1}(\hat{S}(t))-F^{-1}(\hat{S}(t+2))} &= \frac{c\cdot\lambda^t(1-\beta\lambda)-c\cdot\lambda^{t+1}(1-\beta\lambda)}{c\cdot\lambda^t(1-\beta\lambda)-c\cdot\lambda^{t+2}(1-\beta\lambda)}\\ &= \frac{1}{1+\lambda}\end{aligned}$$

This uniquely determines $\lambda$. Next, we use $F^{-1}(\hat{S}(t))-F^{-1}(\hat{S}(t+1))=c\cdot\lambda^t(1-\beta\lambda)-c\cdot\lambda^{t+1}(1-\beta\lambda)$. Knowing $\beta$ and $\lambda$ determines $c$. Finally,

$$F^{-1}(\hat{S}(t))=-\alpha_1+\alpha_0+c\cdot\lambda(1-\beta\lambda)$$

determines $(\alpha_1-\alpha_0)$. Next, consider identification of the composite parameter $(\delta_1-\delta_0)$. The second firm in a duopoly market will have adopted by year $t$ if

$$\begin{aligned}\Delta\pi^2(2,\theta)-c\cdot\lambda^t(1-\beta\lambda) &\geq 0\\ \alpha_1+\varepsilon^2+\delta_1\cdot\log(2)-\alpha_0-\delta_0\cdot\log(2)-c\cdot\lambda^t(1-\beta\lambda) &\geq 0\end{aligned}$$

Since the second firm is less profitable, the distribution of $\varepsilon^2$ is that of the second order statistic $F_{(2)}$. The fraction of firms that have not adopted can again be related to the parameters in the following way:

$$F_{(2)}^{-1}(\hat{S}(t))=-\alpha_1+\alpha_0-\delta_1+\delta_0+c\cdot\lambda^t(1-\beta\lambda)$$

Where $(\delta_1-\delta_0)$ is the only parameter unknown. What remains is to be shwon is that $\delta_0$ can be identified separately. In a duopoly market, the first adopter's hypothetical optimal second adoption time is:

$$T_2'(\varepsilon^1)=\left\lceil\frac{\log(\frac{\alpha_1-\alpha_0+\delta_1-\delta_0+\varepsilon^1}{c\cdot(1-\beta\lambda)})}{\log(\lambda)}\right\rceil$$

Where $\lceil x \rceil$ is the least integer greater or equal to $x$. Because the first adopter adopted no earlier than $T_1$, it must hold that

$$\varepsilon^1 < -\alpha_1 + \alpha_0 + c \cdot \lambda^{T_1 - 1}(1 - \beta\lambda),$$

because the stand alone incentive was not satisfied. Let $\bar{\varepsilon}^1$ be the value of $\varepsilon^1$ that satisfies the above equation with equality. This is the largest possible value of $\varepsilon^1$ consistent with optimal behavior of the first adopter. Similarly, the fact that the second firm adopted at $T_2$ implies that

$$\varepsilon^2 \geq -\alpha_1 + \alpha_0 - \delta_1 + \delta_0 + c \cdot \lambda^t (1 - \beta\lambda)$$

Let $\underline{\varepsilon}^2$ be the value of $\varepsilon^2$ that satisfies the above equation with equality. This is the lowest possible value of $\varepsilon^2$ consistent with optimal behavior by the second adopter. We know it was not optimal for the second firm to preempt the first firm at $T_1 - 1$, thus:

$$\begin{aligned} & (\alpha_1 + \varepsilon^2)\frac{1 - \beta^{(T_2'(\varepsilon^1) - T_1 + 1)}}{1 - \beta} + (\alpha_1 + \delta_1 \log(2) + \varepsilon^2) \cdot \frac{\beta^{T_2'(\varepsilon^1) - T_1 + 1} - \beta^{(T_2 - T_1 + 2)}}{1 - \beta} - c \cdot \lambda^{T_1 - 1} \\ \leq \;\; & \alpha_0 + (\alpha_0 + \delta_0 \log(2)) \cdot \frac{\beta - \beta^{(T_2 - T_1 + 2)}}{1 - \beta} - c \cdot \beta^{(T_2 - T_1)} \cdot \lambda^{T_2} \end{aligned}$$

Rearranging terms yields

$$\begin{aligned} & (\alpha_1 - \alpha_0 + \varepsilon^2)\frac{1 - \beta^{(T_2 - T_1 + 2)}}{1 - \beta} + (\delta_1 - \delta_0)\log(2)\frac{\beta^{T_2'(\varepsilon^1) - T_1 + 1} - \beta^{(T_2 - T_1 + 2)}}{1 - \beta} + .. \\ & .. + \delta_0 \log(2)\frac{\beta - \beta^{(T_2'(\varepsilon^1) - T_1 + 1)}}{1 - \beta} \\ \leq \;\; & c \cdot \lambda^{T_1 - 1} - c \cdot \beta^{(T_2 - T_1)} \cdot \lambda^{T_2} \end{aligned}$$

or

$$\varepsilon^2 - \frac{1 - \beta}{1 - \beta^{(T_2 - T_1 + 2)}} \cdot \left( \begin{array}{c} c \cdot \lambda^{T_1 - 1}(1 - \beta^{(T_2 - T_1)} \cdot \lambda^{T_2 - T_1 - 1}) - (\alpha_1 - \alpha_0)\frac{1 - \beta^{(T_2 - T_1 + 2)}}{1 - \beta} - .. \\ .. - (\delta_1 - \delta_0)\log(2)\frac{\beta^{T_2'(\varepsilon^1) - T_1 + 1} - \beta^{(T_2 - T_1 + 2)}}{1 - \beta} - \delta_0 \log(2)\frac{\beta - \beta^{(T_2'(\varepsilon^1) - T_1 + 1)}}{1 - \beta} \end{array} \right) \leq 0$$

For $(T_1, T_2)$ to be consistent with subgame perfect equilibrium play, the above equation has to be satisfied. Call the second term on the left $B(\varepsilon^1)$. The estimated probability of observing adoption vector $(T_1, T_2)$, equals

$$\hat{P}(T_1,T_2) = \int\limits_{\underline{\varepsilon}^2}^{\bar{\varepsilon}^1} \int\limits_{\underline{\varepsilon}^2}^{B(\varepsilon^1)} f(\varepsilon^1) f(\varepsilon^2) F(\varepsilon^2) d\varepsilon^1 d\varepsilon^2$$

Here $\hat{P}(T_1, T_2)$ can be estimated from the data. Hence $\delta_0$ is the only unknown in this equation entering through $B(\varepsilon^1)$.

Table 1: Comparison of Sample Markets to all US markets

| | **Sample** | **US** | | **Sample** | **US** |
|---|---|---|---|---|---|
| **Total # of** | | | % of Hospitals | | |
| HCSA's | 306 | 802 | w/ Residency training | 2.44% | 19.01% |
| Hospitals | 780 | 5,094 | Private nonprofit | 52.05% | 60.22% |
| **Average** | | | Government | 41.41% | 25.17% |
| Bed Capacity | 99 | 195 | For-profit | 6.54% | 14.60% |
| Population | 72,737 | 473,895 | System member | 23.97% | 39.92% |
| Per Capita Income | 16,600 | 18,083 | w/ MRI | 23.33% | 33.63% |

Table 2: Hospital & Market Characteristics by # of hospitals in a market

| | **# of Hospitals** | | | | |
|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | Total |
| **Average** | | | | | |
| Bed capacity | 80 | 95 | 102 | 108 | 99 |
| Population | 24,089 | 55,668 | 89,563 | 114,680 | 72,737 |
| Per Capita Income | 16,701 | 16,623 | 16,548 | 16,550 | 16,600 |
| Adoption rate | 22.4% | 19.2% | 21.9% | 27.5% | 23.3% |
| **% of Markets** | | | | | |
| w/ 1 MRI | 22.6% | 27.5% | 36.4% | 33.3% | 30.4% |
| w/ 2 MRI | | 5.5% | 14.8% | 20.3% | 10.5% |
| w/ 3 MRI | | | 0.0% | 10.2% | 2.3% |
| w/ 4 MRI | | | | 1.4% | 0.3% |
| # number of markets | 58 | 91 | 88 | 69 | 306 |

Table 3: Parameter Estimates

| $\theta$ | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| $\alpha_1 - \alpha_0$ | 11.3400 | 10.6630 | 10.5740 | 10.6997 | 10.8841 |
| | (0.3944) | (1.2531) | (0.9752) | (0.4389) | (3.1087) |
| $\delta_1$ | -4.425 | -4.267 | -3.467 | -3.0698 | -2.9559 |
| | (-0.2205) | (-0.8443) | (-0.8128) | (0.2833) | (0.4694) |
| $\delta_0$ | -0.8057 | -0.7782 | -0.8475 | -0.8061 | -0.8104 |
| | (0.0311) | (0.1348) | (0.2093) | (0.0602) | (0.2211) |
| | | | | | |
| $c$ | 410.82 | 456.96 | 468.54 | 467.0345 | 439.7912 |
| | (7.1357) | (4.9101) | (6.5589) | (9.4283) | (35.3069) |
| $1/\lambda - 1$ | 0.0344 | 0.0368 | 0.0311 | 0.0341 | 0.0372 |
| | (0.0018) | (0.0016) | (0.0088) | (0.0018) | (0.0040) |
| | | | | | |
| $(\gamma_1 - \gamma_0)_{Pop}$ | 0.9442 | 0.6599 | 0.895 | 0.8994 | 0.7299 |
| | (0.0232) | (0.0370) | (0.1706) | (0.0462) | (0.1207) |
| $(\gamma_1 - \gamma_0)_{PCI}$ | 0.0007 | 0.1923 | 0.1034 | 0.0069 | 0.0009 |
| | (0.0021) | (0.0425) | (0.0366) | (0.0124) | (0.0067) |
| $(\mu_1 - \mu_0)_{beds}$ | | 0.9218 | 0.8369 | 0.8327 | 0.9186 |
| | | (0.0827) | (0.1659) | (0.0547) | (0.1491) |
| $(\mu_1 - \mu_0)_{NP}$ | | 1.6644 | 1.6018 | 1.2925 | 1.2909 |
| | | (0.4895) | (0.3995) | (0.3239) | (0.2374) |
| $(\mu_1 - \mu_0)_{FP}$ | | 1.3652 | 0.8813 | 1.2816 | 1.2060 |
| | | (2.3266) | (0.3521) | (0.1724) | (0.5822) |
| | | | | | |
| $\rho$ | | | 0.5756 | 0.2381 | 0.1946 |
| | | | (0.0613) | (0.2381) | (0.1056) |

Note: Standard errors are in parentheses. Number of simulations is 20.

Table 4: Regulatory Regime versus Subgame Perfect Equilibrium

| | # of Hospitals | | | | | |
|---|---|---|---|---|---|---|
| | 2 | | 3 | | 4 | |
| | $\mathbf{T}^R - \mathbf{T}^*$ | $se(\Delta\mathbf{T})$ | $\mathbf{T}^R - \mathbf{T}^*$ | $se(\mathbf{\Delta T})$ | $\mathbf{T}^R - \mathbf{T}^*$ | $se(\mathbf{\Delta T})$ |
| $1^{st}$ | 1.2747 | (0.0964) | 2.0341 | (0.1204) | 2.5942 | (0.1174) |
| $2^{nd}$ | 3.3956 | (0.0539) | 3.9205 | (0.0651) | 4.3043 | (0.0975) |
| $3^{rd}$ | | | 4.2159 | (0.0522) | 4.4493 | (0.0787) |
| $4^{th}$ | | | | | 4.6667 | (0.0674) |
| Mean | 2.3352 | (0.0552) | 3.3902 | (0.0483) | 4.0036 | (0.0627) |
| $\Delta V$ | 1.86% | (0.09) | 3.86% | (0.15) | 5.56% | (0.21) |

Notes: $T^*$: Adoption time in subgame perfect equilibrium

$T^R$: Adoption time maximizing industry profits

$\Delta V$: change in industry profits when moving regulatory regime

Standard errors are in parentheses.

Table 5: Nash Equilibrium versus Subgame Perfect Equilibrium

| | # of Hospitals | | | | | |
|---|---|---|---|---|---|---|
| | 2 | | 3 | | 4 | |
| | $\mathbf{T}^{NE} - \mathbf{T}^*$ | $se(\Delta\mathbf{T})$ | $\mathbf{T}^{NE} - \mathbf{T}^*$ | $se(\mathbf{\Delta T})$ | $\mathbf{T}^{NE} - \mathbf{T}^*$ | $se(\mathbf{\Delta T})$ |
| $1^{st}$ | 0.4725 | (0.0846) | 0.7613 | (0.1047) | 0.5362 | (0.0890) |
| $2^{nd}$ | | | 0.2046 | (0.0462) | 0.3768 | (0.0656) |
| $3^{rd}$ | | | | | 0.1159 | (0.0388) |
| $4^{th}$ | | | | | | |
| Mean | 0.4725 | (0.0846) | 0.4830 | (0.0557) | 0.3430 | (0.0424) |
| $\Delta V$ | 0.33% | (0.07) | 0.84% | (0.10) | 0.91% | (0.12) |

Notes: $T^*$: Adoption time in subgame perfect equilibrium

$T^{NE}$: Adoption time in Nash equilibrium

$\Delta V$: change in industry profits when moving to Nash equilibrium

Standard errors are in parentheses.

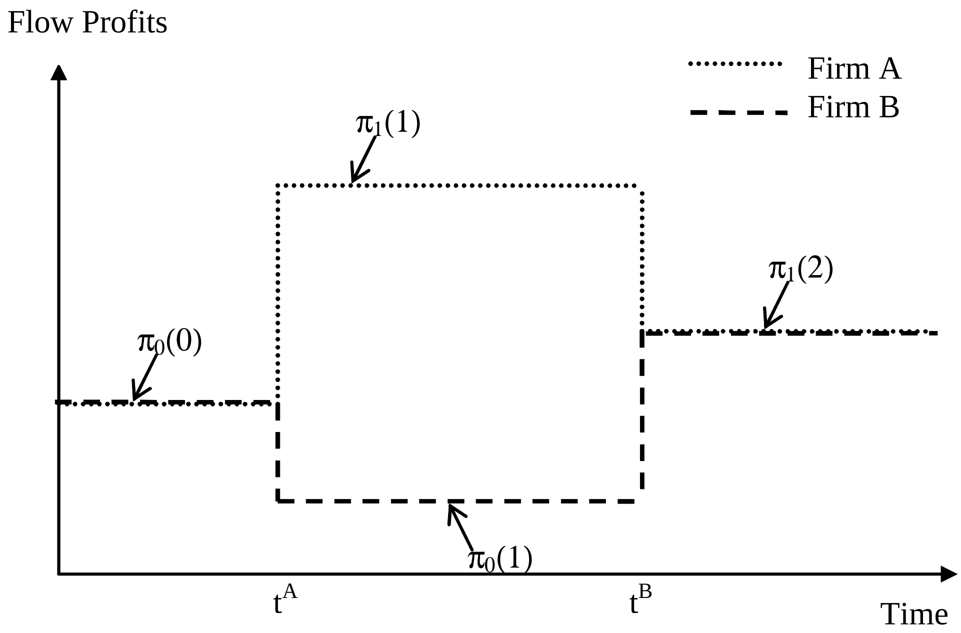


Figure 1: Flow Profits: 2 Symmetric Firms

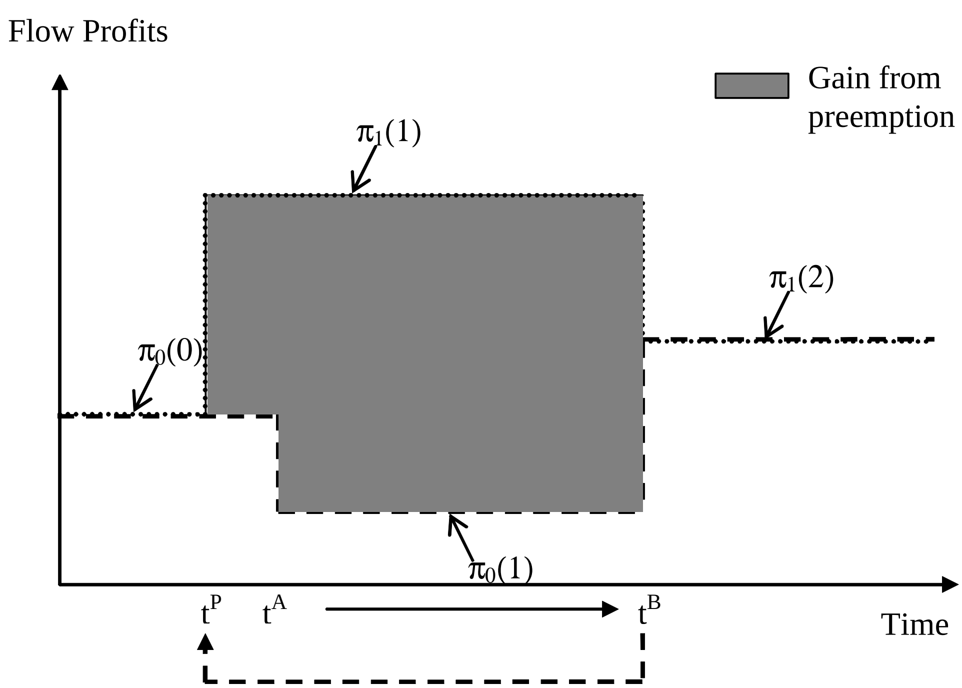


Figure 2: Gain from Preemption

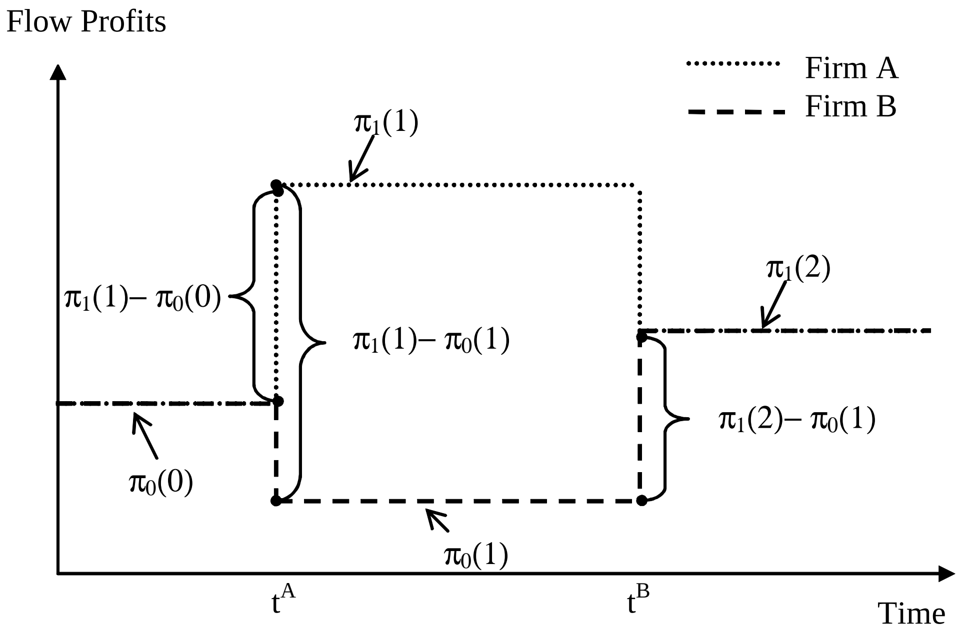


Figure 3: Profit Margins Determining Adoption Times

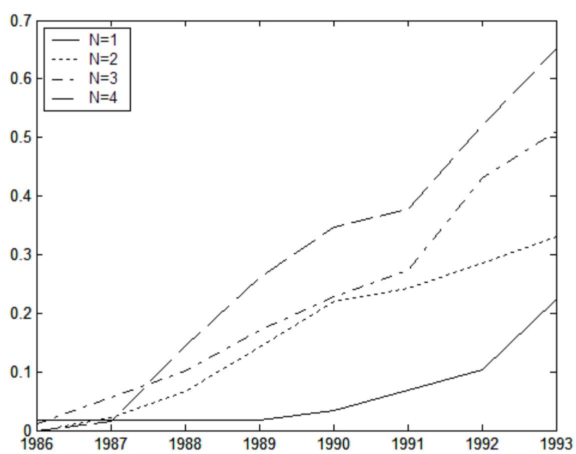


Figure 4: Fraction of Markets with at Least One MRI

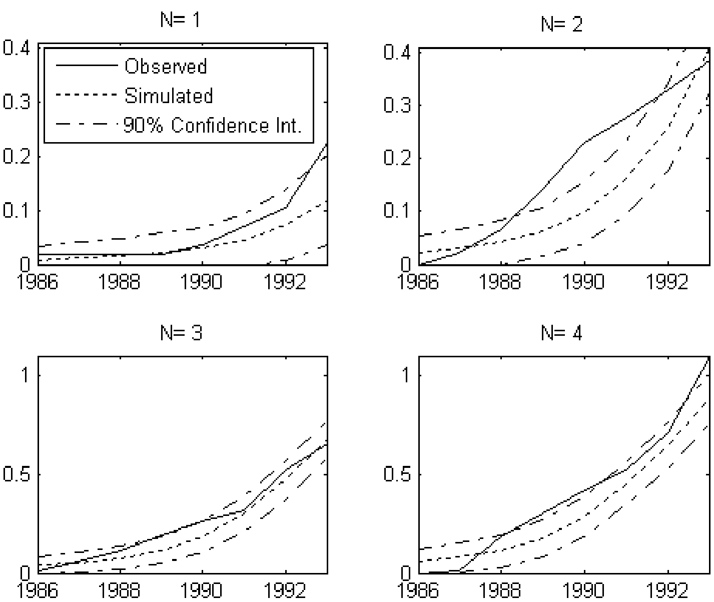


Figure 5: Number of Adoptions per Market by Number of Hospitals