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

Philipp Schmidt-Dengler

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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.

*Mailing Address: Department of Economics, London School of Economics, Houghton Street, London WC2A 2AE. Email: p.schmidt-dengler@lse.ac.uk. I would like to thank Patrick Bayer, Dirk Bergemann, Steve Berry, Philip Haile, and Martin Pesendorfer for helpful comments and guidance. I have benefitted from conversations with many individuals and seminar participants at various institutions, especially Gautam Gowrisankaran, Otto Toivanen, and Matthias Schuendeln. Financial support from a Cowles Foundation and the Social Science Research Council' is gratefully acknowledged. All errors are my own.

1 Introduction

While technological progress is generally viewed as the fundamental driving force of economic performance, the existence of a new technology alone is not sufficient for economic progress. It is the diffusion of the new technology among potential users that determines how it affects the economic environment. We would like to understand what determines the timing of new technology adoption.

This paper focuses on how varying degrees of competition affect the decision to adopt a new technology and how technology adoption in turn affects payoffs. I develop and estimate an empirical model of new technology adoption by hospitals in the United States. I consider a timing game of new technology adoption. The dynamic game allows me to take both the timing decision and strategic interaction into account.

The empirical model developed here draws on a large theoretical literature that studies the strategic timing of technology adoption.[1] Every period, firms decide whether or not to adopt the new technology. I consider subgame perfect equilibria in adoption times and thus require that each firm's decision be optimal at every point in time. A firm's decision depends on the cost of the new technology, the direct effect of adoption on its current and future payoffs and the effect on rivals' adoption times. 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 technology adoption.

In such a model, multiple equilibria may arise. This poses a problem for estimation, because a cross-section of markets is needed to identify the parameters of interest and different equilibria may be played in different markets. In recent work Einav (2003a) and Sweeting (2004) develop methods to estimate the parameters of games of timing with multiple equilibria.[2] These papers consider models where play-

[1]See Hoppe (2002) for a survey of these models.

[2]Einav (2003a) studies the timing of product introduction in the context of movie release dates.

ers make their timing decision only once. In the application I am considering it is not plausible to assume that firms precommit to an adoption date several years in the future. Hence, I study a model where firms can decide every period whether to adopt the new technology. I assume that firms move sequentially in every period. With this sequential structure of moves there is a unique subgame perfect equilibrium in this game. 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.

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 (1999), and Baker and Phibbs (2000)). 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) carefully 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

Movie distributors announce the release dates in an exogenously fixed and predetermined order. Each player moves only once. The equilibrium in this sequential game is unique. Using measures of seasonal demand obtained in Einav (2003b), estimation results from the timing model suggest that release dates are too clustered. In Sweeting (2004) a coordination game is studied, in which radio stations simultaneously decide when to air their radio commercials. He shows that there are benefits to coordination. The presence of multiple equilibria in this coordiiegatermis eay

the adoption decision has also been addressed in static frameworks either by using instrumental variable techniques (Gowrisankaran and Stavins (2002)), or by explicitly modelling technology adoption as a static game (see Dranove, Shanley and Simon (1992), and Chernew, Gowrisankaran and Fendrick (2001)). Lenzo (2006) studies strategic complementarities in the adoption of imaging technologies in the context of a static incomplete information game. The drawback of these approaches is that the time dimension of the adoption decision has to be ignored.

The current paper accounts for both the endogeneity and the dynamic character of the adoption decision. I estimate the return and cost parameters of a general timing game. The model builds on the theoretical literature on technology adoption. I extend the existing models by allowing for a finite number of firms in a discrete time framework. This enables me to exploit cross-sectional variation in market structure and adoption times to recover the model's return and cost parameters. Knowledge of these parameters is necessary to perform counterfactual experiments that quantify the relative significance of strategic interaction in technology adoption.

I 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. A high fixed asset investment of about US$ 2 million is required for a new imager.

For the empirical analysis, I constructed a panel data set containing demographic and income variables, as well as the adoption times of hospitals for a large number of markets in the United States by combining information from the American Hospital Association's annual survey database and the U.S. Census. I consider markets with a small number of hospitals, where I expect it to be easier to isolate strategic interaction empirically than in larger markets.

The adoption of MRI will affect revenues and cost 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.[3] Using information on the timing of MRI adoption within markets as well as varying degrees of competition and demand across markets, I can separate effects of competition, demand and costs on the timing decision.

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.

The model allows for heterogeneity in hospital payoffs. I find that organizational structure and hospital size influence the adoption decision. Nonprofit and for-profit hospitals are more likely to adopt the new technology than community hospitals. Large hospitals benefit more from MRI adoption. Cost function 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 profits. 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 profits. In the second experiment, I isolate the role of preemption by comparing the adoption times in a pre-commitment Nash equilibrium to the subgame perfect equilibrium outcome.[4] In the Nash equilibrium firms precom-

[3] The potential endogeneity of market structure is addressed in Hamilton and McManus (2005).

[4] 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)). For an analysis of the welfare consequences of product innovations and product improvements over time, see Trajtenberg (1989).

mit to their adoption times as in Reinganum (1981b), 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 profits and is only marginally responsible for the acceleration of adoption arising from strategic adoption timing.

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 new 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 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. Here, I first introduce a model of new technology adoption timing. I then discuss the equilibrium properties of this model.

2.1 Model

The aim is to build a model that is capable of reproducing the patterns of MRI diffusion in small hospital markets. The model assumptions are similar to those found in the existing theoretical literature. Existing research either restricts the attention to duopoly markets (Fudenberg and Tirole (1985), Reinganum (1981a), Riordan (1992)), requires payoffs to be symmetric (Reinganum (1981b)), or a monopolistic competition

environment (Goetz (1999)). The emphasis of the current paper is on variation in market structure and strategic interaction in the timing of adoption. Thus I build a model that allows for firm heterogeneity *and* an arbitrary number of firms. Because the definition of strategies and histories involves various technical difficulties in continuous time[5] and my data are discrete, I introduce a game in discrete time which is more suitable for empirical analysis. There are I firms denoted by $i = 1, ..., I$. Firms can choose to adopt at time $t = 1, 2, ..., \infty$.

I define firm i's *history of actions,* h_t^i, to be 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

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

For now, I assume that firms choose simultaneously whether to adopt or not. Firms hold on to the technology indefinitely once they have adopted. This implies that the action set is weakly increasing in time. Let a_t^i denotes firm i's action at time t and $\mathbf{a}_t$ is the vector of actions at time t. Let n_t be the number of adopters in period t :

$$n_t = n(\mathbf{a}_t) = \sum_{i=1}^{I} \mathbf{1}_{\{a_t^i = 1\}}$$

A firm receives $\pi_0^i(n(\mathbf{a}_t))$ per period before adoption and $\pi_1^i(n(\mathbf{a}_t))$ 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 β. Hence, a firm's discounted intertemporal profits are

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

Firms choose a strategy to maximize their discounted profits Π^i.

An adoption strategy for firm i is a function mapping the history to an element of the action set:

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

[5] See for example Simon and Stinchcombe (1989).

Let $\mathbf{s_u^i} = \{s_t^i\}_{t=u}^{\infty}$ be the sequence of adoption strategies starting at time $\mathbf{u}$. The sequence of strategies by players other than i is denoted by $\mathbf{s_u^{-i}}$. 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 Π^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..

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, 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.

Finally, 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.

2.2 Discussion

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. Proposition 1 in the appendix shows that this is ruled out by assumptions *5(iii)* and *(iv)*. 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 $t' > t$. Then it can always increase its payoffs

by adopting at $t' - 1$. 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.

With firms moving simultaneously the solution concept of subgame perfect equilibrium does not always generate a unique prediction regarding the adoption times and the identities of adopters. In this model of technology adoption two forms of multiplicity are present. First, situations similar to an 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. To address this issue, 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 in the simultaneous move discrete time game. The *sequential moves* 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).[6] The robustness of the *sequential moves* assumption will be discussed in Section 4.

The *sequential moves* assumption yields a unique equilibrium of the discrete time game. Since all firms adopt in finite time, the game is equivalent to a finite horizon game of perfect information and the equilibrium can be computed using a simple recursive algorithm. This is also computationally less burdensome than solving the continuous time game.

To illustrate the algorithm, order the firms according to their profitability.[7] Thus i represents the $i-$th most profitable firm. Consider the least profitable firm I. At $\bar{t}-1$, firm I knows that all players will adopt next period, regardless of the history of play. If $h_{\bar{t}}^{I} = (0, 0, ...0)$, i.e. firm I has not adopted, it adopts if the increase in profits minus costs when adopting today versus profits from not adopting outweighs discounted costs from 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 for every history in period $\bar{t} - 2$. I repeat this until period $t = 1$. This yields the history of equilibrium play.

The incentives for a hospital in this model can be summarized as follows. A hospital 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

[6] 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 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 monpoly profits 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.

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

because adoption generates an increase in period returns, $\pi_1^i(n_t) - \pi_0^i(n_t - 1)$. A monopoly hospital weighs the benefit of higher period payoffs when adopting today against the cost-saving when delaying adoption. The same holds for a hospital in a market where all its rivals have already adopted. If $\pi_1^i(n_t) - \pi_0^i(n_t - 1) > C(t) - \beta C(t+1)$, we say that hospital i has a *stand-alone* incentive to adopt.

Further, a hospital may have an incentive to adopt, because it may change 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 hospital'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 $\Pi^A(T^A, T^B) \geq \Pi^B(T^A, T^B)$.[8] 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 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.*

Now consider the case where firm A is more profitable than firm B: $\pi_1^A(n) > \pi_1^B(n)$.[9] Then firm A's *stand-alone* incentive is greater than firm $B's$ and $T_2^A \leq T_2^B$. This implies that it becomes less attractive for firm B to preempt firm A, because firm B would enjoy monopoly profits for a shorter period of time. This relaxes the

[8] 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.

[9] For a detailed discussion of the asymmetric duopoly case see Riordan (1992).

constraint $\Pi^2(\bar{T}_1^A - 1, T_2^A) \leq \Pi^2(\bar{T}_1^A, T_2^B)$ and firm A will adopt weakly later. When $\pi_1^A(n)$ is large enough relative to $\pi_1^B(n)$, then the stand-alone incentive for firm A will justify adoption at such an early time, such that the preemption constraint will not bind anymore: If the heterogeneity in flow payoffs is large enough, the first adoption time is determined by firm A's *stand-alone* incentive to adopt first: $\pi_1^A(1) - \pi_0^A(0)$.

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 Di¤usion 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,[10] 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. First, I use adoption data derived from the American Hospital Association's (AHA) annual survey database. 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 and surgical hospitals. That

[10]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.

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. 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 (2000)), 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. Bell (2001) shows that MRI usage by Medicare patients relative to other patient groups is surprisingly small compared to other medical technologies. This leads me to assume that this market definition is exogenous to the presence of MRI.

The second data source I use are the Area Resource Files (ARF), which provide county-level information on demographic and economic variables derived from the US 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.

The emphasis of this paper is on strategic interaction in technology adoption. Thus I restrict the analysis to 'small' markets with a constant number of four hospitals or less over time. While strategic interaction may also be present in markets with more hospitals, this interaction may be restricted to a small set of hospitals within those markets. The restriction to four hospitals or less leaves 306 HCSA's. 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 2. While the sample contains more than one third of all markets as defined above, it only represents about 15% of all US hospitals. In total, the sample contains 780 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 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 (less than five percent) of the markets in my sample, 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 sample under consideration. Recall that the sample contains 306 markets with a total of 780 hospitals. In Figure 4, I plot the fraction of markets with a given number of hospitals with at least one MRI over time. Starting in 1988 this fraction is always larger the larger the number of hospitals in a market. Ignoring market characteristics, this suggests that incentives to adopt first are larger in markets with more hospitals. Only a slow increase in the number of markets having adopted at least one MRI can be observed over time. The average adoption rate at the end of my sample is less than 25 percent. Diffusion is slow, suggesting that the new technology is not immediately profitable for most hospitals.

Table 1 cross tabulates the covariates against the number of hospitals within a market. The average hospital bed capacity is increasing in the number of hospitals in a

market. The average population is almost proportionally increasing in the number of hospitals. Interestingly, per capita income is smaller in markets with more hospitals. 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 other characteristics and adoption decisions in more detail, the next four rows in Table 1 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. In the next section I describe an estimation technique that enables me to quantify competition and preemption effects in the adoption of MRI by US hospitals.

4 Estimation

In this section I specify the profit and cost functions. I propose an estimation technique and present the parameter estimates.

4.1 Speci…cation

I observe L independent markets, with I^l firms operating in market l. Each firm i'

The assumptions regarding *monotonicity* and *decreasing returns* hold whenever $\delta_1, \delta_0 \leq 0$, and $(\delta_1 - \delta_0) \leq 0$. Thus the benefit of adoption declines with increasing competition. The number of adopters has a stronger negative effect on adopters than on non-adopters. The specification in (1) requires that the competitive effects, δ_0 and δ_1, are symmetric. In general the model and the estimation technique described can be applied to fully flexible competitive effects. For instance it would be interesting to what extent it matters whether a rival adopter is a nonprofit or for-profit hospital. Because I observe only few follow-on adoptions, identification of additional interactions is not feasible.

Sufficient conditions for the assumption *positive returns* to hold, are 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 that the support of F is restricted to the positive real 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)*.

With the cost function converging to zero, assumption *A5(iii)* implies the following restriction, which imposes a lower bound on δ_1 relative to $\alpha_1 - a_0$:

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

The parameter vector of interest θ 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 δ_0 and δ_1, which is illustrated in figure 3. I 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 $(\alpha_1 - \alpha_0, \boldsymbol{\mu}_1 - \boldsymbol{\mu}_0, \boldsymbol{\gamma_1} - \boldsymbol{\gamma_0})$. 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 δ_1 and δ_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 δ_0 and δ_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 β 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 ε^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 ε^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 allows me 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 ε^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 ν^i is the firm specific component and ν^l the market specific component of the profitability shock. I assume that both are distributed i.i.d standard normal. I restrict ρ to lie on the interval $[0, 1]$. I chose this specification, because mean and variance of ε^i are independent of ρ. The levels of of the other coefficients are not affected by the choice of ρ. The within market correlation of ε^i for a given ρ is:

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

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 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. I will not 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. 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 ν^l of the common profitability shock. Here

I_l is the number of hospitals in market l.

Step 3: For a given parameter-vector θ and for 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 $g = \frac{1}{L} \sum_{l=1}^{L} (\hat{\psi} - \tilde{\psi}_{S,l}) \otimes f(X_l)$ 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:

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

Here Ω 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 θ 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 θ. 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. After preliminary reduced form analysis, I chose a specification that 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

Tables 3 to 5 shows the parameter estimates for three specifications. The first specification (Table 3) includes no firm characteristics, such that firms are identical up to the realization of the profitability shock ε^i. The proxies for demand are the logarithms of population and per capita income. Specification 2 (Table 4) includes firm characteristics such as hospital size (the log of the number of beds), and organiza-

tional form, a dummy for nonprofit and for-profit. The reference case is a community hospital. In the third specification (Table 5)I allow for within market correlation ρ of the unobservable profitability shock ε^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.[12]

As we move to richer specifications some interesting changes in the estimated coefficients occur can be observed. Allowing for firm specific variables (moving from Table 3 to 4), 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 in the unobservable ε (Table 5). The estimated coefficient ρ corresponds to a within market correlation of the unobservable ε^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 usually yields 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 δ_0 becomes more negative, making preemption relatively more attractive. Allowing for within market

[12] 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.

correlation improves the overall fit of the model, especially the moments regarding the firm specific and market level variables. Hence, I focus on the third specification in the following discussion.

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)).

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 δ_0 and δ_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.[13] 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

To assess the fit of the model, I draw from the asymptotic distribution of parameters, simulate the model and average the 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. The model may tend to fit markets with more firms better because more adoptions are observed in these markets and hence most of the identification is obtained from these markets.

[13] The fact that hospitals have identical characteristics overstates the preemption effect.

Two questions arise with respect to the robustness of the parameter 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 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.[14] The results for the linear competitive effects are presented in Table 6. 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 in Table 7. 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 the effects

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

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 provided 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 profits from adoption. The experiments are performed under the two assumptions. First, policy changes do not trigger entry (or exit) into any of the hospital markets studied. Second, policy changes do not affect the cost of adoption and period payoffs conditional on adoption decisions. I perform two counterfactual experiments in which I decompose the effect of competition into a business stealing and a preemption effect. I first examine adoption decisions under a regime that maximizes industry payoffs. Under this regime all inefficiencies arising from strategic behavior 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.

5.1 Maximizing Industry Profits

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 profits. 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 δ_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

profits:

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

where $T^0 = 0$ and $T^{I+1} = \infty$. I define the gains from adoption $\Delta\Pi(\mathbf{T})$ as the difference between industry profits under adoption times $\mathbf{T}$ and profits when firms do not adopt at all (which is normalized to zero). The measure of profit loss ΔV is then defined as the percentage increase in the gains from adoption when moving 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 assess the profit loss, I compute the implied adoption times under the competitive and the regulatory regime, as well as the corresponding ΔV as defined above for each market.

I compute the average of these figures within a group of markets, where a group is defined as the number of hospitals in a market. Table 8 describes the effect of the regulatory solution compared to the competitive solution. Obviously, nothing changes in the monopoly markets, so I report results for duopoly, three-firm and four-firm markets only. 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. The percentage numbers in the last row of Table 8 presents estimates of the profit loss. The increase in net discounted industry-profits under the regulatory regime would be 1.86% (2 firms), 3.86% (3 firms), and 5.56% (4 firms). An increase in the demand variables lowers the effect of a regulatory solution. The profit loss

is mitigated by the higher mean demand levels in counties 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 profits is negative. The cost savings due to delayed adoption outweighs the foregone profits by delayed adoption.

I have also computed the figures reported in Table 8 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

I now examine the effect of optimal timing on hospital payoffs. 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. The effect of preemption on adoption times and profits has received wide attention in the theoretical literature (Fudenberg and Tirole 1985, Riordan, 1992). 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, 1981b), 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 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 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 $T^{NE,}$.

Table 9 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 the first adoption being delayed by less than one year. The gain in profits is only about one sixth of the profit 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 profit 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 profits. 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 profits. 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 framework provided here can also be applied to other technologies. At the

same time, the analysis carried out in this paper can be extended along various dimensions. For a complete welfare analysis, the demand side should analyzed. 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. Flow profits are constant over time and there is no uncertainty about future payoffs and costs. 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(4) 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:

$$\pi_1^I(I) - \pi_0^I(I-1) > C(t) - \beta C(t+1) \tag{5}$$

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:

$$\frac{\pi_1^i(I)}{1-\beta} - C(t) < \frac{\pi_0^i(I-2)}{1-\beta} \tag{6}$$

or

$$\frac{\pi_1^i(I) - \pi_0^i(I-2)}{1-\beta} < C(t) \tag{7}$$

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(iii)* ensures that this inequality holds and hence, all firms will adopt in finite time. ■

7.2 Identi…cation

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:

$$\begin{aligned}
\pi_0^i(n,\theta) &= \alpha_0 + \delta_0 \cdot \log(n+1) \\
\pi_1^i(n,\theta) &= \alpha_1 + \delta_1 \cdot \log(n) + \varepsilon^i \\
C(T^i) &= c \cdot \lambda^{T^i}
\end{aligned} \tag{8}$$

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 λ. 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 β and λ 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 ε^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 show that δ_0 can be identified separately. In a duopoly market, the first adopter's hypothetical optimal second adoption time is:

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

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 ε^1 that satisfies the above equation with equality. This is the largest possible value of ε^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 ε^2 that satisfies the above equation with equality. This is the lowest possible value of ε^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

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

for (T_1, T_2) to be consistent with subgame perfect equilibrium play the above equation has to be satisfied. Note that the only unknown parameter is δ_0. Call the second term

on the left $B(\varepsilon^1)$. The estimated probability of observing adoption vector (T_1, T_2), equals

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

Here $\hat{P}(T_1, T_2)$ can be estimated from the data. Hence δ_0 is the only unknown in this equation entering through $B(\varepsilon^1)$.

Table 1: 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 2: 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 3: Parameter Estimates (Specification 1)

θ	$\hat{\theta}$	$se(\hat{\theta})$	θ	$\hat{\theta}$	$se(\hat{\theta})$
$\alpha_1 - \alpha_0$	11.34	0.3944	$(\gamma_1 - \gamma_0)_{Pop}$	0.9442	0.0232
δ_1	-4.425	0.2205	$(\gamma_1 - \gamma_0)_{PCI}$	0.0007	0.0021
δ_0	-0.8057	0.0311			
c	410.82	7.1357			
$1/\lambda - 1$	0.0344	0.0018			

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

Table 4: Parameter Estimates (Specification 2)

θ	$\hat{\theta}$	$se(\hat{\theta})$	θ	$\hat{\theta}$	$se(\hat{\theta})$
$\alpha_1 - \alpha_0$	10.663	(1.2531)	$(\gamma_1 - \gamma_0)_{Pop}$	0.6599	(0.0370)
δ_1	-4.267	(0.8443)	$(\gamma_1 - \gamma_0)_{PCI}$	0.1923	(0.0425)
δ_0	-0.7782	(0.1348)	$(\mu_1 - \mu_0)_{beds}$	0.9218	(0.0827)
c	456.96	(4.9101)	$(\mu_1 - \mu_0)_{NP}$	1.6644	(0.4895)
$1/\lambda - 1$	0.0368	(0.0016)	$(\mu_1 - \mu_0)_{FP}$	1.3652	(2.3266)

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

Table 5: Parameter Estimates (Specification 3)

θ	$\hat{\theta}$	$se(\hat{\theta})$	θ	$\hat{\theta}$	$se(\hat{\theta})$
$\alpha_1 - \alpha_0$	10.574	(0.9752)	$(\gamma_1 - \gamma_0)_{Pop}$	0.8950	(0.1706)
δ_1	-3.467	(0.8128)	$(\gamma_1 - \gamma_0)_{PCI}$	0.1034	(0.0366)
δ_0	-0.8475	(0.2093)	$(\mu_1 - \mu_0)_{beds}$	0.8369	(0.1659)
c	468.54	(6.5589)	$(\mu_1 - \mu_0)_{NP}$	1.6018	(0.3995)
$1/\lambda - 1$	0.0311	(0.0088)	$(\mu_1 - \mu_0)_{FP}$	0.8813	(0.3521)
			ρ	0.5756	(0.0781)

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

Table 6: Parameter Estimates (Linear Competitive Effects)

θ	$\hat{\theta}$	$se(\hat{\theta})$	θ	$\hat{\theta}$	$se(\hat{\theta})$
$\alpha_1 - \alpha_0$	10.6997	0.4389	$(\gamma_1 - \gamma_0)_{Pop}$	0.8994	0.0462
δ_1	-3.0698	0.2833	$(\gamma_1 - \gamma_0)_{PCI}$	0.0069	0.0124
δ_0	-0.8061	0.0602	$(\mu_1 - \mu_0)_{beds}$	0.8327	0.0547
c	467.0345	9.4283	$(\mu_1 - \mu_0)_{NP}$	1.2925	0.3239
$1/\lambda - 1$	0.0341	0.0018	$(\mu_1 - \mu_0)_{FP}$	1.2816	0.1724
			ρ	0.2381	0.0613

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

Table 7: Parameter Estimates (Reversed Order of Moves)

θ	$\hat{\theta}$	$se(\hat{\theta})$	θ	$\hat{\theta}$	$se(\hat{\theta})$
$\alpha_1 - \alpha_0$	10.8841	3.1087	$(\gamma_1 - \gamma_0)_{Pop}$	0.7299	0.1207
δ_1	-2.9559	0.4694	$(\gamma_1 - \gamma_0)_{PCI}$	0.0009	0.0067
δ_0	-0.8104	0.2211	$(\mu_1 - \mu_0)_{beds}$	0.9186	0.1491
c	439.7912	35.3069	$(\mu_1 - \mu_0)_{NP}$	1.2909	0.2374
$1/\lambda - 1$	0.0372	0.0040	$(\mu_1 - \mu_0)_{FP}$	1.2060	0.5822
			ρ	0.1946	0.1056

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

Table 8: 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)
ΔV	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

ΔV: change in industry profits when moving regulatory regime

Standard errors are in parentheses.

Table 9: 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)
ΔV	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

ΔV: change in industry profits when moving to Nash equilibrium

Standard errors are in parentheses.

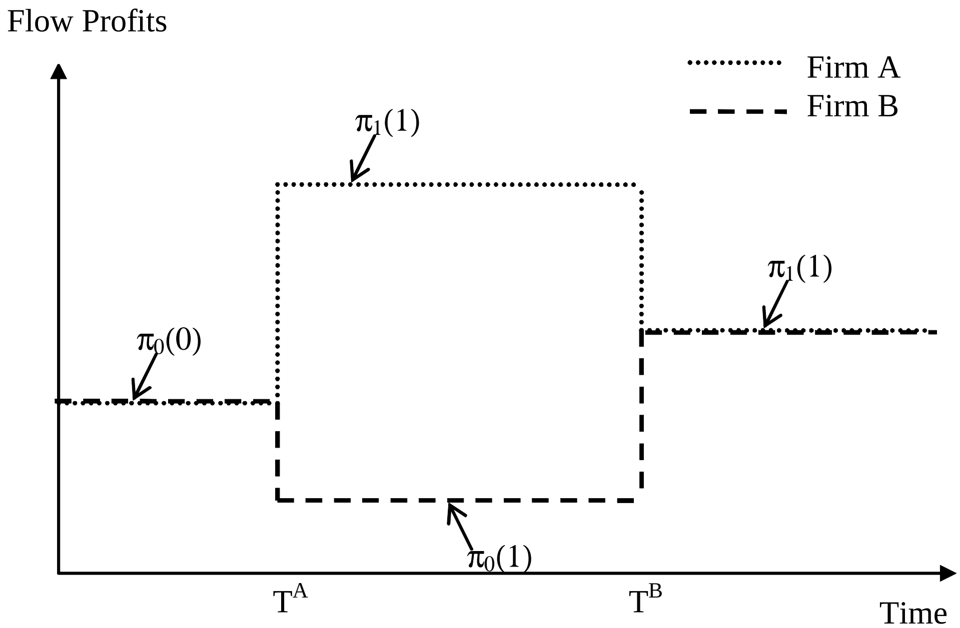

Figure 1: Flow Profits: 2 Symmetric Firms

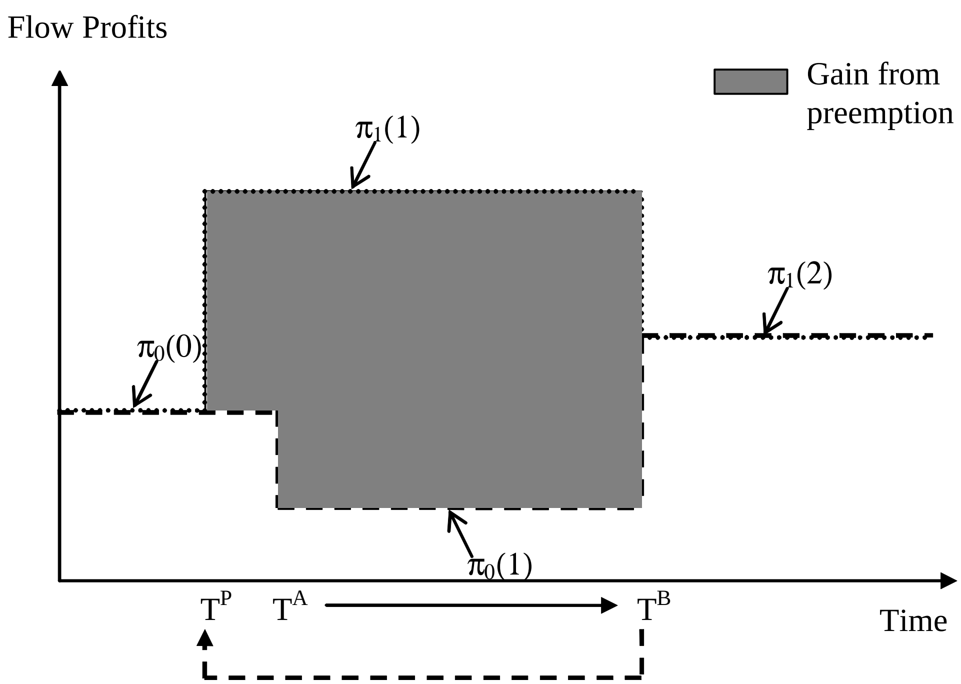

Figure 2: Gain from Preemption

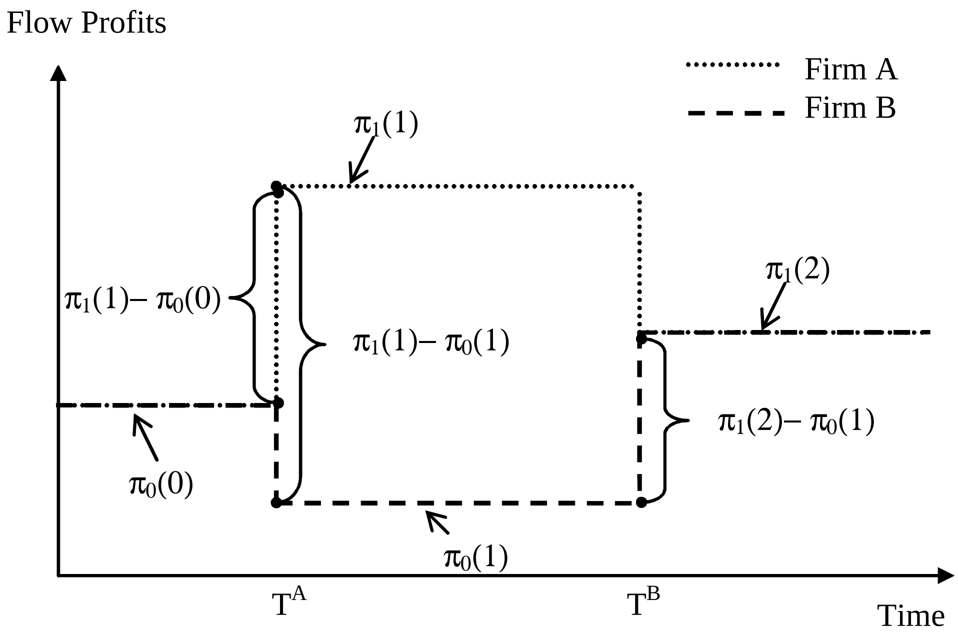

Figure 3: Profit Margins Determining Adoption Times

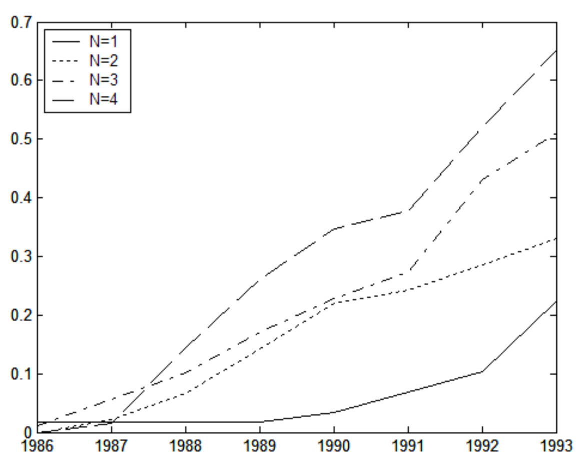

Figure 4: Fraction of Markets with at Least One MRI

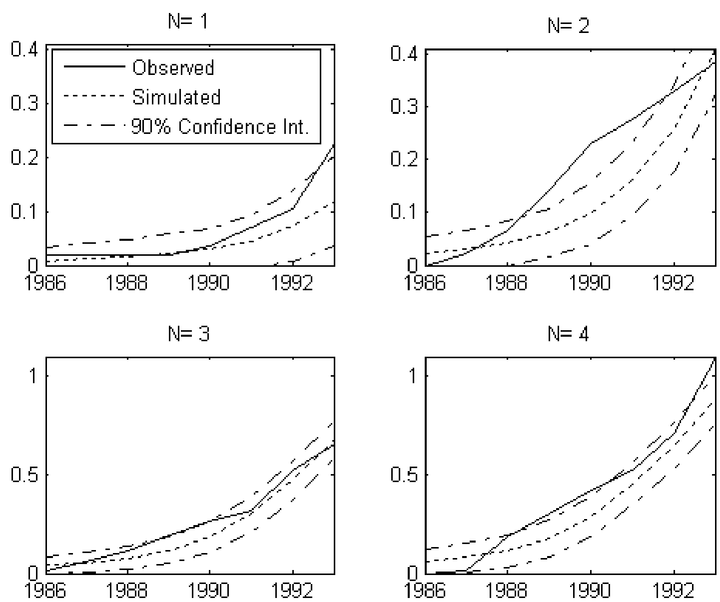

Figure 5: Number of Adoptions per Market by Number of Hospitals