# Technology Upgrading in Imperfectly Competitive Markets

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## Abstract

**RYAN C. BURK: Technology Upgrading in Imperfectly Competitive Markets**
**(Under the direction of Dr. Brian McManus)**

Technological advancement is an inherently dynamic process. Yet, existing technology adoption models in both the theoretical and empirical economics literatures focus on firms' reaction to a single new technology. This research aims to extend both strands of the literature by examining how the prospect of future technological advancement alters firms' incentives to adopt new technologies in the presence of spillover effects. First, in joint work with Dr. Tim Moore, we extend the theoretical literature by introducing a second cost-reducing technology to the seminal duopoly technology adoption timing game. Through a variety of simulations we examine how the rate of technological diffusion and total market welfare are affected by the second advancement. We show that the presence of an additional advancement generally seems to decrease the overall inefficiency in a duopoly market. Second, I solve and estimate an innovative model where competing firms make repeated decisions regarding whether or not to upgrade their technology. Each firm's choice directly affects the incentives of its competitors as the technological frontier progresses. Firms face uncertainty regarding the release of future advancements and optimize accordingly. Not surprisingly, adding technological advancements to the standard model changes firms' equilibrium adoption dates of the first technology. Conditional on the parameterization of the model there exists a unique equilibrium outcome of the dynamic upgrading game. However, different parameterizations can generate a variety of firm behaviors. Using a novel dataset I estimate the model in the context of hospitals' replacement of MRI equipment. Results suggest that there are a complicated collection of effects that influence a hospital's decision to upgrade its MRI technology.

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# Chapter 1

# Introduction

Technologies are constantly evolving in every sector of the economy. As new advancements are released firms are forced to make repeated decisions regarding whether or not to upgrade their existing technology. In imperfectly competitive markets this decision process is complicated by the fact that each firm's choice has spillover effects on its competitors. However, there is currently a void in both the theoretical and empirical economics literatures merging the analysis of these two ideas. My research attempts to fill this gap by examining strategic interactions between firms while striving to better capture the dynamics inherent in technological innovation. In general I find that adding multiple waves of technological advancements to the standard one-technology models can cause firms' adoption incentives to vary significantly. In fact, equilibrium adoption dates in one-technology models are typically suboptimal in a multiple-technology context. As a result, any policy prescription derived from a single-technology model is likely flawed if firms are making dynamic technology upgrading decisions.

In the second chapter of this dissertation my co-author, Tim Moore, and I extend the seminal duopoly technology adoption model in the theoretical literature to include a second technology. Despite this seemingly straightforward extension we find that the equilibrium analysis quickly becomes complicated. We circumvent this issue by running a variety of simulations and comparative statics exercises aimed at examining the equilibrium properties of the model. We find that overall market inefficiency seems to decrease with the addition of a second technological advancement despite the additional adoption costs. Further, we find that firms may delay adoption of the first technology as the rate of technological diffusion increases.

The third chapter of this dissertation examines a more general technology adoption game that allows for more than two firms and technologies. The key difference between the two models is that here I assume firms make technology adoption decisions sequentially in order to make the solution tractable. Despite this difference the theoretical results from the two models are qualitatively very similar. In addition to the theoretical results I also estimate the model using a novel dataset that tracks hospitals' purchases of magnetic resonance imaging (MRI) equipment over a 28-year period. I find that adoption decisions are a complicated function of both hospital- and market-level variables. Extending the empirical framework to include multiple technologies poses significant data, computing, and modeling issues. However, the model's potential to address interesting and pertinent dynamic policy issues is promising.

# Chapter 2

# To Adopt or Not? A Duopoly Model of Technology Upgrading

## 2.1 Introduction

Dating back to the seminal works by Reinganum (1981b) and Fudenberg and Tirole (1985), a significant strand of the theoretical literature has focused on technology adoption timing games. In both models a dynamic game begins when a technological innovation is released to a duopoly market. Each firm's strategy involves choosing a single point in time to adopt the new technology. As time passes the cost of adopting the technology decreases, generating a tradeoff between adopting sooner at a higher cost (and potentially inducing one's competitor to delay adoption) versus waiting to adopt at a lower cost. Reinganum (1981b) shows that even though firms are ex ante identical, in any precommitment (Nash) equilibrium, the two firms adopt at different points in time, leading to a "diffusion" of the technology. Fudenberg and Tirole (1985) show that in the Reinganum (1981b) precommitment equilibrium the firm that commits to adopting first earns higher profits at its competitor's expense. Further, they examine subgame perfect Nash equilibria which enables each firm to preempt its competitor. They show that this preemption incentive drives the "follower" in the Reinganum (1981b) equilibrium to preempt the "leader." Each firm continues to preempt its competitor until it is no longer profitable and both firms' payoffs are equalized.[1] Fudenberg and Tirole (1985) also demonstrate that for certain parameterizations of the model late "joint" adoption equilibria

[1] The follower's adoption date is the same in both the Nash and subgame perfect Nash equilibria because conditional on acting as follower its best response is unchanged. However, the leader's adoption date is strictly earlier in the subgame perfect Nash equilibria due to the preemption incentive.

may exist in addition to the diffusion equilibrium.

A variety of papers have extended these seminal models in several directions. For example, in a model with asymmetric firms Riordan (1992) examines how price and entry regulations can affect technological diffusion. He finds that regulations can limit each firm's incentive to preempt its competitor and slow the diffusion of the new technology. There is no uncertainty regarding a technology's value and that value is realized immediately upon adoption. Other models, such as Hoppe (2000) and related papers, incorporate a learning process regarding the new technology's profitability. Stenbacka and Tombak (1994) examine uncertainty regarding the amount of time needed to successfully implement a new technology. There are also a number of duopoly models focused on situations where waiting to adopt rather than preempting can be advantageous. Three such examples are Katz and Shapiro (1987), Dutta, Lach, and Rustichini (1995), and Hoppe and Lehmann-Grube (2005).[2]

All of the aforementioned models involve a *single* new technology. However, we argue that most technological innovations are subsequently updated and improved. Newer advancements allow firms to operate more efficiently by improving productivity, decreasing costs, enhancing communication and connectivity, and providing firms with more detailed information about consumers' preferences. As a result, while a firm decides whether or not to adopt a new technology today, the technological frontier is advancing. Thus, a firm's purchasing decision implicitly incorporates expectations about the likelihood and potential benefit of future advancements. As time passes and newer technologies are released, firms must make repeated decisions regarding when/whether to *upgrade* their current technology. Yet, the current literature largely abstracts from these dynamic considerations. Two notable exceptions are Horner (2004) and Harrington, Iskhakov, Rust, and Schjerning (2010).[3] Horner (2004) models R&D competition between two firms as an endless race. In each period the two firms choose a costly

[2]For a somewhat recent review of the literature see Hoppe (2002).

[3]While Huisman and Kort (1999) and Huisman and Kort (2000) also analyze multi-technology duopoly adoption games, in both models firms are still restricted to choosing a *single* technology. In other words, a firm cannot replace or upgrade its original technology. Kamien and Schwartz (1972) analyze a monopoly adoption model with two technologies. However, they consider a stationary environment where the cost of adopting each technology is constant so that the timing decision is trivial–the monopolist either adopts immediately or never.

effort level that affects the probability of generating a successful innovation. He finds that investment efforts increase when the firms' technologies are further apart which contradicts the typical intuition in the R&D literature. In a working paper, Harrington, Iskhakov, Rust, and Schjerning (2010) also develop a dynamic duopoly model where firms can make investments in order to decrease their marginal cost of production. In each period the duopolists simultaneously decide whether or not to adopt a new technology that evolves according to a first-order Markov process. Once the technology choices are made profits are determined through a static Bertrand pricing game. While simultaneous adoption cannot be an equilibrium in a static version of the game, the authors show that investment does occur in the dynamic game.[4] Further, the authors show that a wide range of equilibria exist *for a given parameterization of the model*. Some equilibria exhibit "leap-frogging" where one firm invests in a new technology and undercuts its rival's price. The firm at a cost disadvantage may then subsequently undercut its rival when an improved technology is released. Other equilibria involve "sniping" where one firm builds a large cost advantage over time until the competitor invests and undercuts its rival. Additionally, equilibria exist where only one of the two firms ever adopts new technologies. However, certain aspects of the model are somewhat unclear. For one, the authors state that most of the "interesting" equilibria occur when firms are "asymmetric" in the sense that the firm indices matter but do not clarify the source of this asymmetry.[5] Second, the authors state that they use an equilibrium selection rule that in essence forces firms to engage in leap-frogging behavior but then illustrate "non-leap-frogging" equilibria in their simulation results. Despite these ambiguities it is clear that a simple extension to the static Bertrand

[4]Consider the standard static Bertrand pricing game except that each firm has the ability to invest in a marginal cost-reducing technology. It is unprofitable if both firms adopt the technology because equilibrium profits are driven to zero (and the firms pay a fixed cost associated with the investment). The authors define this situation as the "Bertrand Investment Paradox" and show that it does not hold in a dynamic setting.

[5]In the paper the authors essentially discuss two different models. In a complete information setting the firms play the standard Bertrand pricing game in each period. However, they also consider a situation where in each period each firm receives an IID "adoption cost shock" that is private information. Even accounting for this private information the reader is led to believe that the firms are asymmetric along some additional dimension. Further, it is not made clear whether the complete or incomplete information framework is utilized in the simulations. In a more recent version of the working paper (Iskhakov, Rust, and Schjerning (2013)) these ambiguities are still not fully resolved.

pricing game can generate a wide range of equilibrium investment and price paths. The model we propose is qualitatively similar to the Harrington, Iskhakov, Rust, and Schjerning (2010) model except for a key difference. In their model the cost of adopting each new technology is time-invariant. In other words, the cost of adopting the best technology today is the same as it would be tomorrow so long as an even newer technology is not released.[6] Given that costs are constant and the probability that a new technology is released follows a first-order Markov process, there is no incentive for a follower to wait to adopt the best technology available. Thus, technological diffusion is "degenerate" in the sense that a given technology does not diffuse gradually through time.[7]

We take a different approach and extend the model of Fudenberg and Tirole (1985) by introducing a second technology. There is objective uncertainty regarding the release of the second advancement but not its affect on each firm's profitability. We assume that the firms are Cournot competitors and choose quantities myopically in each period.[8] The cost of adopt-

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[6]Giovannetti (2001) develops a similar model where the evolution of the best technology is exogenous. Specifically, an improved technology (i.e. a lower marginal cost of production) only becomes available if a firm adopts the existing technology. Again, the cost of adopting a given technology is constant over time.

[7]It is somewhat unclear if it can ever be an equilibrium for both firms to adopt a new technology immediately when it is released if firms employ pure strategies. Joint adoption in a static version of the game cannot be an equilibrium because each firm has an incentive to deviate. However, in a dynamic setting it is hypothetically possible for both firms to adopt simultaneously in an attempt to transition to a better future state. In all of the simulated equilibria developed in the paper this outcome never occurs.

[8]Two papers use Cournot demand to examine how market concentration affects adoption dates in the one-technology model of Reinganum (1981b). Reinganum (1981a) extends Reinganum (1981b) to an n-firm model and solves for the Nash equilibrium adoption dates. She also uses a Cournot demand specification for the single-technology game to show that an increase in the number of firms results in early adopters adopting later, intermediate adopters (potentially) adopting earlier, and late adopting firms being unaffected. Quirmbach (1986) solves for the Nash equilibrium adoption dates in the Reinganum (1981b) model for the monopoly, duopoly, and socially optimal outcomes but holds the number of firms fixed. In other words, the "monopoly" is a joint-venture between two firms who attempt to maximize joint profits and the socially optimum adoption dates are chosen such that the sum of joint profits and consumer surplus is maximized. Not surprisingly he finds that the noncooperative duopoly and socially optimal adoption dates are earlier than the respective dates under the joint-venture. Unlike in the noncooperative duopoly, each firm in the joint-venture internalizes the effect of its adoption decision on its "competitor," thereby delaying adoption. We argue that in the absence of capacity constraints, it is socially optimal for a planner to shut down one of the two firms in order to limit unnecessary adoption costs. We show that in a single-technology game the planner adopts weakly earlier than a single monopolist, who adopts weakly earlier than the last adopter in a duopoly.

ing each technology declines as time passes since its release. Our goal is to examine how the rate of technological diffusion is altered when firms are faced with the prospect of a future advancement. We find that the addition of a second technology greatly complicates the equilibrium analysis. In general, very little can be said about the equilibrium properties of the entire dynamic game. This issue arises primarily from the fact that it is difficult to rank the firms' continuation values before the second technology is released. Since we cannot derive many results in general, we instead run a number of simulations aimed at illustrating the equilibrium properties of the model. Further, we solve for the monopoly and socially optimal outcomes of the game and use them as a benchmark against the duopoly game. Finally, we show that if firms instead compete in prices and time periods are "short enough," at most one of the two firms will ever adopt the new technologies. This result seems to contradict the leap-frogging behavior discussed in Harrington, Iskhakov, Rust, and Schjerning (2010).

The remainder of the paper is organized as follows. Section 2 develops the model and the solutions for the socially optimal, monopoly, and duopoly cases. Section 3 discusses the simulation results and Section 4 concludes. Appendix A.1 contains all of the figures and tables. Appendix A.2 solves for the equilibrium assuming that a Bertrand rather than Cournot stage game is played in each period. Finally, Appendix A.3 elaborates on several issues caused by the use of discrete time.

## 2.2 Model

Consider a dynamic technology adoption game between two ex-ante identical firms. Time is discrete and indexed by $t = 0, 1, 2, \ldots, \infty$. Each period unfolds in two stages. In the first stage the two firms (indexed by $i = 1, 2$) simultaneously decide whether or not to adopt the most efficient technology available. Technologies are indexed by $j = 0, 1, 2$. It is assumed that both firms enter period $t = 0$ operating with technology $j = 0$ (the "original" or "status quo" technology). A technological advancement, $j = 1$, is released at the beginning of $t = 0$.

Typically the first duopoly adopter chooses to adopt at some date between the socially optimal and monopoly dates. However, the use of discrete time causes this result to not hold in general.

Technology $j = 1$ is the most efficient technology available until $j = 2$ is released at the beginning of an unknown date in the future, $T$, where we assume $0 < T < \infty$. In each period $0 < t < T$, both firms believe that a new technology will be released at the beginning of the next period with probability $\rho$.[9] For simplicity, we assume that once $j = 2$ is released, $j = 1$ can no longer be purchased by a firm operating with technology $j = 0$.

Given the technological choices from the first stage of each period, the firms subsequently engage in a static Cournot game to determine output and flow profit levels. The game involves perfect monitoring so that once the technology choices are made they are common knowledge.[10] Let $a_i^t \in A_i^t$ denote firm $i$'s action in the first stage of period $t$, chosen from the set of feasible actions available to the firm in that period, where

$$A_i^t = \begin{cases} \{0,1\} & \text{if } t = 0 \\ \{0,1\} & \text{if } a_i^{t-1} = 0 \text{ and } 0 < t < T \\ \{1\} & \text{if } a_i^{t-1} = 1 \text{ and } 0 < t < T \\ \{0,2\} & \text{if } a_i^{t-1} = 0 \text{ and } t \geq T \\ \{1,2\} & \text{if } a_i^{t-1} = 1 \text{ and } t \geq T \\ \{2\} & \text{if } a_i^{t-1} = 2 \text{ and } t \geq T \end{cases}.$$

Thus, we prohibit the firms from downgrading their technology.[11] In each period the firms face the following market demand function:

$$D(Q) = 1 - Q,$$

where $Q = q_1 + q_2$ denotes market output. Adopting a new technology affords a firm with a decreased marginal cost. Conditional on a firm's technology, marginal cost is assumed to be constant. We assume that the firm's marginal cost associated with technology $j$, $c_j$, satisfies

[9] For now firms do not update their beliefs regarding the release of the second technology.

[10] Strictly speaking, the game is one of perfect monitoring both *within* and *between* periods.

[11] Neither firm would ever find it optimal to downgrade its technology because the fixed cost of adopting is sunk and the firm's marginal cost is decreasing in its technology.

the following:

$$\frac{1}{2} > c_0 > c_1 > c_2 = 0.$$

The upper bound of $1/2$ is imposed to prevent a firm from finding it optimal to produce zero in any period. Suppressing the time superscript, let $\pi(a_i, a_{-i})$ denote firm $i$'s flow profit in a period where it chooses technology $a_i$ and its competitor chooses technology $a_{-i}$. Given the assumption of Cournot competition, $q_i$ and $\pi(a_i, a_{-i})$ satisfy the following:

$$q_i = \frac{1 - 2c_{a_i} + c_{a_{-i}}}{3}$$

$$\pi(a_i, a_{-i}) = q_i^2,$$

where flow profits are assumed to be time-invariant and the scrap value of a firm's old technology is taken to be negligible.[12]

The cost of adopting the most recent technology $n$ periods after its release is denoted by $C(n)$. We assume that cost function is strictly positive, strictly decreasing, and strictly convex. Although we assume that both technologies follow the same cost schedule it is straightforward to allow the function to vary by technology (as long as it satisfies the aforementioned properties and all functional forms are common knowledge at the beginning of the game).

Let a state $s \in S$ be a quadruple $(t, n, a_i^{t-1}, a_{-i}^{t-1})$, where $t$ denotes the current time period, $n$ denotes the number of time periods since the release of the most recent technology, $a_i^{t-1}$ denotes firm $i$'s technology choice in the previous period, and $a_{-i}^{t-1}$ denotes firm $i$'s competitor's technology choice in the previous period. Note that if $t > n$ it must be that $t \geq T$ and the second technology, $j = 2$, has been released. Given the definition of a state, firm $i$'s Bellman

[12]Imposing a specific functional form on $\pi(\cdot)$ represents a departure from the setup in Fudenberg and Tirole (1985). The introduction of the second technology greatly complicates the equilibrium analysis of this dynamic game. Without assumptions on not only the ranking of the $\pi(\cdot)$'s but also the ranking of the *differences* in the $\pi(\cdot)$'s, little can be said about the equilibria of the game (i.e. there are a large number of very specific "cases"). Rather than imposing a laundry list of assumptions on $\pi(\cdot)$, we choose to employ a widely-used and well-known demand specification.

equation can be written as

$$
\begin{aligned}
V_i(t, n, a_i^{t-1}, a_{-i}^{t-1}) = \max_{a_i^t \in A_i^t} \quad & \pi(a_i^t, a_{-i}^t) - \mathbb{1}_{\left[a_i^t \neq a_i^{t-1}\right]} C(n) + \\
& \beta \left[\rho V(t+1, 0, a_i^t, a_{-i}^t) + (1-\rho) V(t+1, n+1, a_i^t, a_{-i}^t)\right], \qquad (2.1)
\end{aligned}
$$

where $\rho = 0$ for all $t \geq T$.

Since there are a finite number of technologies, the equilibrium analysis employs backwards induction. First, the continuation game beginning in period $T$ is analyzed. The equilibrium outcome(s) from this game form the continuation values for all periods $t < T$ when the uncertainty has yet to be resolved. Given these values each firm's optimal strategy is characterized for all states where $t < T$. At this point it is instructive to informally discuss firms' strategies and the equilibrium concept that we employ.[13] First, for simplicity we focus exclusively on pure-strategy equilibria even though mixed-strategy equilibria also exist. Additionally, we focus on a very specific type of Markov perfect equilibrium where the firms' output choices in each period are static. As a result, we abstract from situations where firms could use punishment strategies to enforce a (potentially) Pareto-improving equilibrium. Thus, conditional on the vector of technology choices in the period, firms' outputs and profits are trivial. While we solve for the Markov perfect equilibria of the game, it is somewhat unconventional for a Markov state to be a function of the time period. Here, the Markov state is dependent on the number of periods that have elapsed since the release of the best technology available. Since $C(n)$ is strictly decreasing in $n$ and flow profits are not linear in technologies, no two states in the game are the same.[14] Therefore, we cannot group states into equivalence classes and solve for the firms' optimal strategies in each set of states. We use the term "Markov" because the actual *dates* of earlier adoptions are irrelevant to the firm's optimization problem in the

[13] We choose to avoid developing unnecessary notation because we do not subsequently use it at any other point in the paper.

[14] The only exceptions are states $(t, t, 1, 1)$ and $(t, n, 2, 2)$. In $(t, t, 1, 1)$, where $t < T$, both firms have adopted $j = 1$ and $j = 2$ has yet to be released. As a result, neither firm is capable of taking any action until the release of $j = 2$. In state $(t, n, 2, 2)$, where $t > n$, both firms have adopted $j = 2$ and the game has reached completion.

current period. Put differently, it only matters *whether or not* a firm has adopted a technology, not *when* the adoption occurred. Before analyzing the duopoly game, we characterize both the Pareto optimal and monopoly outcomes. Both situations are used as benchmarks for comparison against the duopoly outcome. It is difficult (especially in the duopoly case) to prove results in general. Therefore, we often refer to specific examples in order to illustrate tradeoffs and equilibrium properties of the model. Unless otherwise noted, the reader should assume that we employ the following parameterization: $\beta = 0.9$, $\rho = 0.1$, $T = 10$, and $C(n) = 1/(1+n)$.

### 2.2.1 Pareto Efficiency

As a benchmark, consider the Pareto optimal outcome of the dynamic game. In order to maximize total surplus it is optimal for the social planner to shutdown one of the two firms and set the market price equal to the marginal cost of the remaining firm. Removing the second firm eliminates all redundant adoptions of the new technologies, thereby limiting overall adoption costs in the market.[15] We assume that the planner raises revenue to pay for a new technology through a one-time, lump-sum tax. All of the notation from the previous section holds except that a state is now only a function of the single operating firm's technology. Therefore, let a state $s \in S$ be a triple $(t, n, a^{t-1})$, where $t$ and $n$ are unchanged and $a^{t-1}$ is the operating firm's action in the previous period. Let $\sigma(a)$ denote the total flow surplus in the market when the planner chooses technology $a$. Conditional on the technology choice, total surplus in the market is given by

$$\sigma(a) = \frac{1}{2}(1 - c_a)^2.$$

In all states where $n < t$ (i.e. states where the second technology has been released) the planner faces a simple optimal stopping problem. The optimal strategy entails delaying the adoption of technology $j = 2$ until the first period where the value of adopting in the current period exceeds the value of postponing adoption until the subsequent period. In any period

[15]Here we are implicitly assuming that there are no capacity constraints so that a single firm can produce sufficient output for the entire market.

$t \geq T$, where $n = t - T$, the value of adopting $j = 2$ in the current period is given by

$$\sigma(2) - C(n) + \frac{\beta}{1-\beta}\sigma(2), \tag{2.2}$$

and the value of delaying adoption until the subsequent period is

$$\sigma(a^{t-1}) + \beta\left[\sigma(2) - C(n+1) + \frac{\beta}{1-\beta}\sigma(2)\right]. \tag{2.3}$$

Due to the strict convexity of $C(n)$, the first period where (2.2) exceeds (2.3) is the first period $t$ where the following inequality holds:

$$\sigma(2) - \sigma(a^{t-1}) > C(n) - \beta C(n+1). \tag{2.4}$$

The LHS of (2.4) is the marginal increase in surplus from adopting technology $j = 2$ while the RHS denotes the discounted cost savings from delaying adoption by a period. As a result, (2.4) states that the planner's optimal policy rule is to adopt $j = 2$ in the first period where the benefit from adopting today (an immediate increase in surplus) exceeds the benefit from delaying adoption until tomorrow (a decrease in the cost of $j = 2$). Note that since $\sigma(a)$ is increasing in $a$, the planner adopts $j = 2$ weakly earlier when she enters period $T$ with technology $j = 0$ than when she enters with technology $j = 1$.[16]

In all periods $t < T$, the planner's Bellman equation can be written as follows:

$$V(t, n, 0) = \max_{a^t \in \{0,1\}} \quad \sigma(a^t) - \mathbb{1}_{[a^t=1]}C(n) + \beta[\rho V(T, 0, a^t) + (1-\rho)V(t+1, n+1, a^t)], \tag{2.5}$$

where the value of having already adopted $j = 1$ is

$$V(t, n, 1) = \sigma(1) + \beta[\rho V(T, 0, 1) + (1-\rho)V(t+1, n+1, 1)]. \tag{2.6}$$

[16] At first glance it might appear that we should claim the planner adopts "strictly earlier" rather than "weakly earlier." In continuous time this logic is correct. However, in discrete time if $c_0$ and $c_1$ are relatively close, (2.4) could be satisfied in the same period for both costs. Some additional issues associated with the use of discrete time are discussed in the appendix.

The planner's optimal strategy is to delay adoption of $j = 1$ until the first period where the value of adopting in the current period,

$$\sigma(1) - C(n) + \beta \left[\rho V(T, 0, 1) + (1-\rho) V(t+1, n+1, 1)\right],$$

exceeds the value of delaying adoption until the subsequent period,

$$\sigma(0) + \beta\{\rho V(T, 0, 0) + (1-\rho)\left[\sigma(1) - C(n+1) + \beta\big(\rho V(T, 0, 1) + (1-\rho) V(t+2, n+2, 1)\big)\right]\}.$$

Noting that $V(t+1, n+1, 1) = V(t+2, n+2, 1)$ because $\rho$ is stationary, after simplification the planner adopts $j = 1$ in the first period $n$ (where here $n$ and $t$ are equivalent because $t < T$) when the following condition holds:

$$\sigma(1) - \sigma(0) + \beta\rho \left[V(T, 0, 1) - V(T, 0, 0)\right] > C(n) - \beta(1-\rho) C(n+1). \tag{2.7}$$

Again, the LHS of (2.7) is the marginal benefit of adopting in the current period. By adopting today the planner not only increases flow surplus, but also with probability $\rho$ she assures herself of transitioning to a more valuable state tomorrow.[17] The RHS of (2.7) is the *expected* cost savings from delaying adoption until the subsequent period. So, once again, the planner delays adoption of $j = 1$ until the first period when the marginal benefit from adopting exceeds the marginal benefit from further delay. Comparing (2.7) with the corresponding condition in a one-technology model:

$$\sigma(1) - \sigma(0) > C(n) - \beta C(n+1), \tag{2.8}$$

it is clear that the RHS of (2.7) is weakly greater than the RHS of (2.8). In waiting to adopt

[17] The proof that $V(T, 0, 1) > V(T, 0, 0)$ is forthcoming. A sketch of the proof is as follows: $(2c - c^2)/2$ is increasing in c for all $0 \leq c < 0.5$. So, the planner entering period $T$ with technology 0 adopts technology 2 weakly earlier than she would if she entered period $T$ with technology 1. Abusing notation, let $T_0$ denote the period when a planner entering period $T$ with $j = 0$ optimally chooses to adopt $j = 2$ and define $T_1$ similarly for the $j = 1$ case. We know that $T_0 \leq T_1$. However, the $j = 1$ planner could just as easily choose $T_1 = T_0$. Thus, the decreased cost of adoption must outweigh the lower flow surplus level ($\sigma(1)$ vs. $\sigma(2)$) in all periods $T_0 \leq t < T_1$. This, coupled with the fact that the $j = 1$ planner is attaining a strictly higher flow surplus than the $j = 0$ planner in all periods $T \leq t < T_0$ ensures that $V(T, 0, 1) > V(T, 0, 0)$.

$j = 1$ the planner faces a risk in the two-technology game that does not exist in the single-technology game–with probability $(1 - \rho)$ an even better technology is released and the option of adopting $j = 1$ no longer exists. Fixing the LHS of both (2.7) and (2.8), in any $t$ the cost savings threshold that must be eclipsed to induce adoption in the two-technology game is larger (relative to the one-technology game) to compensate for this risk. As $\rho$ approaches zero the planner's perceived risk falls and her optimal stopping criterions in the one- and two-technology games converge. If $\rho$ approaches one the planner believes that there is no cost benefit from waiting (because in all $t < T$ she believes $j = 2$ will be released in the subsequent period with probability one). As a result, in this case the RHS of (2.7) is simply the current cost of adoption. While the RHS of (2.7) is larger than the RHS of (2.8), the LHS is larger as well. As a result, the net effect of the presence of $j = 2$ on the adoption date of $j = 1$ is ambiguous (relative to the situation where there is only one technology). Figure A.1 illustrates the effect of a second technology on the planner's adoption date of $j = 1$ for different values of $\rho$ and $c_1$. When $\rho = 0$ the planner's decision problem is equivalent in the one- and two-technology games. Therefore, when $c_1 = 0.1$, $0.2$, and $0.3$, in a one-technology model the planner adopts $j = 1$ in $t = 1$, 2, and 4, respectively. When $c_1 = 0.1$ the increase in flow surplus from adopting $j = 1$ is relatively large. Thus, the planner adopts $j = 1$ quickly (in period $t = 1$) and this decision is unaffected by $j = 2$, *regardless of the value of* $\rho$. However, consider the case where $c_1 = 0.3$, so the marginal increase in flow surplus is relatively small. In a one-technology game the planner would adopt $j = 1$ in $t = 4$. The addition of a second technology delays the planner's adoption of $j = 1$ and this delay is increasing in $\rho$. Here $V(T, 0, 1) - V(T, 0, 0) = 0.065$, which is less than it is in the $c_1 = 0.1$ case (0.33), so the added benefit of potentially transitioning to a preferred state is mitigated in the current adoption decision.[18] Since the benefit of adopting $j = 1$ is minimal once $j = 2$ is released, the sunk cost of adoption must be recouped prior to period $T$. As $\rho$ increases the planner believes that the window of time when she can benefit from $j = 1$ shrinks and therefore she is only willing to adopt it relatively later at a lower cost.

[18] In this specific parameterization the planner would adopt $j = 2$ in the same period $(T+1)$ regardless of whether she entered period $T$ with $c = 0.4$ or $c = 0.3$. So, when $c_1 = 0.3$, $V(T, 0, 1)$ only exceeds $V(T, 0, 0)$ by a one-period difference of $\sigma(1) - \sigma(0)$ (i.e. the difference in flow surplus in period $T$). If the planner enters period $T$ with $c = 0.1$ then she delays adoption of $j = 2$ until period $T + 3$.

### 2.2.2 Monopoly

For the sake of comparison next assume that instead of two firms, a single monopolist operates in the market. All of the notation holds from the Pareto efficiency analysis except that the monopolist maximizes intertemporal profit rather than surplus. Let $\pi(a)$ denote the monopolist's flow profit when choosing technology $a$. Conditional on his technology choice, the monopolist maximizes per-period flow profit by setting

$$Q = \frac{1 - c_a}{2} \text{ and } p = \frac{1 + c_a}{2},$$

so that $\pi(a) = Q^2$. Employing similar logic to that used in the Pareto optimal case, once $j = 2$ is released the monopolist's optimal strategy is to adopt $j = 2$ if

$$\pi(2) - \pi(a^{t-1}) > C(n) - \beta C(n+1) \tag{2.9}$$

and choose $a^t = a^{t-1}$ otherwise. Substituting and comparing the LHS of (2.4) with the LHS of (2.9) yields the following inequality for all $0 < c < 1/2$:

$$\sigma(2) - \sigma(a^{t-1}) = \frac{2c - c^2}{2} > \frac{2c - c^2}{4} = \pi(2) - \pi(a^{t-1}).$$

As a result, conditional on entering period $T$ with the same technology, the planner chooses to adopt $j = 2$ weakly earlier than the monopolist. This result is straightforward–since the monopolist sets $p > c$, the increase in his profits is less than the increase in total surplus when $p = c$. Thus, the planner has a greater incentive to adopt $j = 2$. Further, the difference between the LHS of (2.4) and the LHS of (2.9) is increasing in $c$. At first glance this relationship seems to indicate that the difference between the two adoption dates is increasing in $c$. However, this is not necessarily the case because as $c$ increases, both the planner and the monopolist want to adopt earlier, so (2.4) and (2.9) are both initially satisfied at lower values of $n$. If $C(n)$ decreases quickly at lower values of $n$ then (2.4) and (2.9) will each be satisfied by a wider range of marginal costs. Figure A.2 plots the adoption times of $j = 2$ for both the social planner and the monopolist versus marginal cost entering period $T$. It is assumed that both the planner and the monopolist enter period $T$ with the same technology. Note that the difference in adoption times in general decreases with $c$. The total intertemporal inefficiency (including adoption costs) associated with the monopolist is also plotted on the same graph and is greatest at the "extreme" values of $c$. In other words, the inefficiency is greatest when $j = 2$ provides either a significant or very negligible cost savings over the current technology being utilized. In the former case (when $c$ is close to 0.5), the result appears counterintuitive because if both the planner and the monopolist are using the same technology, per-period deadweight loss is smaller as $c$ increases. However, the fact that the planner adopts $j = 2$ a period before the monopolist causes the monopoly inefficiency to increase as $c$ increases.[19] In the latter case (when $c$ is approaching zero), there is a greater lag in the monopolist's adoption time relative to the efficient adoption date, again causing the inefficiency to increase.

The analysis of the monopolist's problem in all periods $t < T$ is identical to that for the social planner, substituting $\pi(\cdot)$ for $\sigma(\cdot)$. Thus, the monopolist's optimal strategy involves adopting $j = 1$ in the first period where

$$\pi(1) - \pi(0) + \beta\rho\left[V(T,0,1) - V(T,0,0)\right] > C(n) - \beta(1-\rho)C(n+1). \tag{2.10}$$

This inequality is analogous to (2.7) in the social planner's problem. Again, the mere presence of a second technology which is released at an uncertain date in the future increases the marginal benefit of adopting in the current period but requires a greater cost savings for adoption to be optimal.[20] Figure A.3 is a contour plot of the monopolist's hypothetical adoption

[19] This explanation is admittedly somewhat muddled. Consider the range of marginal costs $0.49 > c > 0.26$. In this range both the monopolist's and the planner's optimal adoption dates (and therefore the costs of adoption) are fixed. As $c$ falls the monopolist's profit, the planner's total surplus, and per-period deadweight loss all increase, *if the monopolist and the planner are operating with the same marginal cost.* So, if both the monopolist and the planner adopted in the same period, the black line in Figure A.2 would be increasing in this range of marginal costs. However, in period $T + 1$ the planner adopts $j = 2$ while the monopolist continues operating with $c$. Since a lower value of $c$ generates higher total surplus in the monopoly market, the total inefficiency in period $T + 1$ is smaller for smaller $c$'s. This effect dominates so the one-period difference in adoption dates causes the total inefficiency to fall in this range.

[20] The proof that $V(T,0,1) > V(T,0,0)$ for the monopolist is identical to that for the social planner,

date of $j = 1$ over the entire $c_0$-$c_1$ grid.[21] Not surprisingly, the figure suggests that there is a negative relationship between the adoption date and the difference between $c_0$ and $c_1$ (which is illustrated in Figure A.4). As $c_0 - c_1$ increases, the monopolist has a greater incentive to adopt $j = 1$ to increase flow profits before the release of $j = 2$. In other words, fixing $\rho$, a greater value of $c_0 - c_1$ makes adoption profitable at a higher cost which in turn allows the monopolist to adopt earlier. Additionally, since we have shown that $V(T, 0, 1) - V(T, 0, 0) > 0$, waiting to adopt in the current period leads to possibility of transitioning to a less-desirable state in the subsequent period. Fixing the *difference* between $c_0$ and $c_1$, Figure A.3 also shows that the monopolist's equilibrium adoption date increases as both costs increase.[22]

### 2.2.3 Cournot Competition

Now consider the original specification where two firms play a static Cournot equilibrium in the second stage of each period. Recall that in the duopoly model a state $s \in S$ is a quadruple $(t, n, a_i^{t-1}, a_{-i}^{t-1})$, where $t$ denotes the current time period, $n$ denotes the number of time periods since the release of the most recent technology, $a_i^{t-1}$ denotes firm $i$'s technology choice in the previous period, and $a_{-i}^{t-1}$ denotes firm $i$'s competitor's technology choice in the previous period. As a result, the two firms can enter period $T$ in one of four states: $s \in \{(T, 0, 0, 0), (T, 0, 1, 1), (T, 0, 1, 0), (T, 0, 0, 1)\}$. In the first two states, the continuation game beginning in period $T$ is a discrete-time version of that found in Fudenberg and Tirole (1985). As noted in Fudenberg and Tirole (1985), the use of discrete rather than continuous time generates slightly different equilibrium outcomes.[23] In the latter two states, one firm

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substituting $\pi(\cdot)$ for $\sigma(\cdot)$.

[21] If $T$ is less than the optimal adoption date, the monopolist simply would not adopt $j = 1$ in equilibrium.

[22] We think that this is being driven in part by the fact that difference between $V(T, 0, 1)$ and $V(T, 0, 0)$ decreases as $c_1$ and $c_0$ increase (holding $c_0 - c_1$ constant). For example, if the monopolist enters period $T$ with any $0.25 < c < 0.35$ then he will adopt $j = 2$ in period $T + 2$. However, the adoption dates are more dispersed at lower values of $c$ ($T + 8$ if $c = 0.05$ versus $T + 4$ if $c = 0.15$).

[23] Specifically, as noted in Fudenberg and Tirole (1985), modeling in discrete time eliminates the majority of their late "joint adoption" equilibria. Oddly enough, in some instances discrete time also causes what would be a "diffusion" equilibrium in continuous time to appear to be a joint adoption equilibrium. This issue is discussed further in the appendix. However, it is important to note that the

enters period $T$ having adopted the first advancement while the competing firm is still operating with the original technology.

### Equilibrium Strategies in (T,0,0,0) and (T,0,1,1)

To simplify the exposition we focus on state $(T, 0, 0, 0)$. The analysis in state $(T, 0, 1, 1)$ is analogous. In this state, neither firm enters period $T$ with a technological advantage so the firms' value functions are identical. Using backwards induction, first consider the situation where one of the firms (w.l.o.g. firm 1) has already adopted the second technology $j = 2$. In this case firm 2's Bellman equation is

$$V_2(t, n, 0, 2) = \max_{a_2^t \in \{0,2\}} \quad \pi(a_2^t, 2) - \mathbb{1}_{[a_2^t \neq a_2^{t-1}]} C(n) + \beta[V(t + 1, n + 1, a_2^t, 2)].$$

Note that since the competing firm's technology is fixed, firm 2 is faced with a simple optimal stopping problem similar to that discussed for both the planner and the monopolist. Since $C(n)$ is strictly decreasing, the firm maximizes its value by choosing $j = 0$ until the first point where adopting in the current period generates a greater value than delaying adoption until the subsequent period, or the first period $n$ when the following holds

$$\pi(2, 2) - C(n) + \beta[V(t+1, n+1, 2, 2)] > \pi(0, 2) + \beta[\pi(2, 2) - C(n+1) + \beta(V(t+2, n+2, 2, 2))]. \tag{2.11}$$

Noting that $V(t + 1, n + 1, 2, 2) = V(t + 2, n + 2, 2, 2) = 1/(9 * (1 - \beta))$, this condition can be simplified as follows:

$$\frac{4}{9}(c_0 - c_0^2) > C(n) - \beta C(n + 1). \tag{2.12}$$

Let $T_{2F}$ denote the first period where the above inequality holds (where "2" signifies $j = 2$ and "F" stands for "Follower"). So, for all states $(t, n, 0, 2)$ where $t > n$, firm 2's best response involves not adopting $j = 2$ in periods $t < T_{2F}$ and adopting in periods $t \geq T_{2F}$. Defining $T_{2P}$ and $T_{2M}$ similarly for the social planner and the monopolist and comparing the LHS of (2.12)

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comparison between discrete and continuous time outcomes is not the focus of this paper.

with the LHS of (2.4) and (2.9), we can deduce the following:

$$T_{2P} \leq T_{2M} \leq T_{2F},$$

so that when acting as follower, firm 2 adopts $j = 2$ weakly later than both the planner and the monopolist.

Further, as noted in Fudenberg and Tirole (1985), it is straightforward to show that it is a strictly dominant strategy for *each* firm to adopt $j = 2$ in all periods $t \geq T_{2F}$. In other words, when time is discrete, the late "joint-adoption" equilibria analyzed in Fudenberg and Tirole (1985) (where time is continuous) do not exist. To show this let $T_{2J}$ (where the "J" stands for "Joint") be defined as the first period where the following inequality holds:

$$\pi(2,2) - \pi(0,0) > C(n) - \beta C(n+1).$$

This inequality is derived from the same setup as (2.11), substituting $\pi(0,0)$ for $\pi(0,2)$. Thus, $T_{2J}$ is first time period where the continuation value of *both* firms adopting $j = 2$ in the current period (conditional on neither firm adopting $j = 2$ before that date) exceeds the value of both firms delaying adoption until the subsequent period. Put differently, $T_{2J}$ is the period where each firm's value is maximized under a joint-adoption equilibrium. Since $\pi(0,0) > \pi(0,2)$ it must be that $T_{2F} \leq T_{2J}$. Suppose that $T_{2F} < T_{2J}$. It is a strictly dominant strategy for both firms to adopt $j = 2$ in all $t \geq T_{2J}$ because in this range the value of joint adoption is decreasing in the joint adoption date (and the value of acting as follower is decreasing in the follower's adoption date). Thus, regardless of the state entering the period, each firm will find it optimal to adopt $j = 2$. Next, consider period $T_{2J} - 1$. In this period each firm recognizes that regardless of its action today, both firms will adopt $j = 2$ in the subsequent period. Each firm's continuation value from adopting $j = 2$ in $T_{2J} - 1$ is

$$\pi(2, a_{-i}^{T_{2F}-1}) - C(n) + \frac{\beta\pi(2,2)}{1-\beta},$$

and its continuation value of delaying adoption until $T_{2J}$ is

$$\pi(0, a_{-i}^{T_{2F}-1}) + \beta \left[ \frac{\pi(2,2)}{1-\beta} - C(n+1) \right].$$

After simplification, the value of adopting $j = 2$ in $T_{2J} - 1$ is greater than the value of adopting in $T_{2J}$ if the following inequality holds:

$$\pi(2, a_{-i}^{T_{2F}-1}) - \pi(0, a_{-i}^{T_{2F}-1}) > C(n) - \beta C(n+1).$$

Since $T_{2J} - 1 \geq T_{2F}$ this inequality must hold for each firm, regardless of the competing firm's action.[24] As a result, each firm has a strictly dominant strategy to adopt $j = 2$ in period $T_{2J} - 1$. Using backwards induction it is a strictly dominant strategy for each firm to adopt $j = 2$ in all periods $t \geq T_{2F}$. Therefore, in equilibrium no date $t > T_{2F}$ can be reached without both firms having already adopted $j = 2$, eliminating the possibility of a "late" joint-adoption equilibrium.

Given that we know how the "following" firm acts in equilibrium, it is now possible to determine the "leading" firm's equilibrium strategy. Taking $T_{2F}$ as given, due to the convexity of $C(n)$ the leader's optimal adoption time is the period where the value of adopting today exceeds the value of delaying adoption until tomorrow. This occurs in the first period $n$ where the following inequality holds:

$$\pi(2,0) - \pi(0,0) > C(n) - \beta C(n+1). \tag{2.13}$$

Since $\pi(2,0) - \pi(0,0) > \pi(2,2) - \pi(0,2)$ it must be that $T_{2L} \leq T_{2F}$. Fudenberg and Tirole (1985) shows that the value of leading in period $T_{2L}$ exceeds the follower's value of adopting in period $T_{2F}$ so that each firm would prefer to play the role of leader. These two adoption dates $(T_{2L}, T_{2F})$ form the Reinganum (1981b) pre-commitment (i.e. Nash) equilibrium. In continuous time, the benefit from acting as leader incentivizes the follower to preempt the

[24]It is straightforward to show that $\pi(2,0) - \pi(0,0) > \pi(2,2) - \pi(0,2)$ for all $c_0$.

leader and adopt just before $T_{2L}$, thereby forcing him to take the role of follower and adopt at $T_{2F}$.[25] Each firm continues to preempt its competitor until it is no longer profitable, which occurs when the value of leading and following are equalized. While the logic is similar in discrete time, the discontinuous jumps in the values of leading and following in each period can cause the equilibrium outcome to be slightly different. Specifically, the preemption may stop at point before the firms values are equalized, so that the leader still generates some rent at the follower's expense. Additionally, for certain marginal cost vectors the discontinuous jumps in time can generate a "faulty" joint-adoption equilibrium in period $T_{2F}$. We discuss these two issues in detail in Appendix B. Nevertheless, defining $T_{2L}^{*}$ as the leader's adoption date once preemption is completed, the set of equilibria in this continuation game involve one firm adopting in period $T_{2L}^{*}$ and the remaining firm adopting in $T_{2F}$. The equilibrium is unique up to the firm index. Figure A.5 plots the duopolists' equilibrium $j = 2$ adoption dates for all potential costs entering period $T$. The use of discrete time is generating the joint-adoption equilibria which would become diffusion equilibria if time periods were sufficiently short. The overall inefficiency of the duopoly is roughly increasing in $c$. Three types of inefficiencies arise in the duopoly model relative to the socially optimal outcome: inefficiency created by "too much" adoption, adoption at suboptimal dates, and setting price above marginal cost. While $j = 2$ is always adopted twice in this continuation game, the additional adoption increases overall market output and decreases the market price. As $c$ decreases the duopolists' adoption dates tend to diverge from the planner's adoption date but adoption costs are also falling. Overall inefficiency falls because the the adoption cost for the second adopter becomes less significant.

### Equilibrium Strategies in (T,0,1,0) and (T,0,0,1)

Without loss we focus on state $(T, 0, 1, 0)$ and assume that firm 1 enters period $T$ with a technological advantage. As a result, the firms' values from acting as leader or follower in each period are different. Slightly abusing notation, let $T_{i2F}$ denote firm $i$'s optimal period to adopt

[25] It is still optimal for the former leader to adopt at $T_{2F}$ because it is a best-response *regardless of the leader's precise adoption date.*

$j = 2$, conditional on being the second firm to adopt $j = 2$. $T_{12F}$ is therefore the first period where the following inequality holds

$$\pi(2,2) - \pi(1,2) > C(n) - \beta C(n+1), \tag{2.14}$$

and $T_{22F}$ is defined analogously for firm 2:

$$\pi(2,2) - \pi(0,2) > C(n) - \beta C(n+1). \tag{2.15}$$

Comparing the LHS of these inequalities it is obvious that $T_{22F} \leq T_{12F}$. Again, due to the use of discrete time, there exists a set of cost vectors where $T_{22F} = T_{12F}$. In these situations the equilibrium analysis is equivalent to that in state $(T, 0, 0, 0)$ except that firm 1's continuation value of leading or following is strictly greater than firm 2's respective value due to the technological advantage entering period $T$. These differences in continuation values can generate multiple asymmetric diffusion equilibria.[26]

If $T_{22F} < T_{12F}$ then the equilibrium strategies become slightly more complicated. To simplify the exposition we employ an example that is summarized in Table A.1 and depicted in Figure A.6. We assume that firm 1 enters period $T$ with marginal cost $c_1 = 0.15$ while firm 2 enters having not adopted $j = 1$ ($c_0 = 0.35$). First, using (2.14) and (2.15) it is straightforward to show that $T_{22F} = T + 3$ and $T_{12F} = T + 4$. Given these values I can then calculate each firm's value (beginning in period $T$) under the three potential equilibria: joint adoption, firm 1 leads and firm 2 follows, and firm 2 leads and firm 1 follows. These values are summarized in Table A.1 and are calculated such that the first adoption of $j = 2$ occurs in period $n$ and if $n < T_{i2F}$ then firm $i$ acts optimally by following in $T_{i2F}$. For instance, suppose that the first adoption of $j = 2$ occurs in $n = 1$. If both firms adopt in $n = 1$ then firm 1's value is

[26] An example of this occurs when $c_0 = 0.42$ and $c_1 = 0.23$. Here $T_{12F} = T_{22F} = T + 3$ and $T_{12L} = T_{22L} = T + 2$. If firm 1 adopts in period $T + 2$ in hopes of acting as leader, firm 2 preempts firm 1 in period $T + 1$ because firm 2's value of leading in period $T + 1$ exceeds its value of acting as follower were firm 1 to lead in period $T + 2$. However, if firm 2 adopts in period $T + 2$, it is not optimal for firm 1 to preempt in period $T + 1$. So, in the first case the equilibrium adoption times for $j = 2$ are $(T + 3, T + 1)$ and in the second case they are $(T + 3, T + 2)$.

$M_1 = 0.673$ while firm 2's value is $M_2 = 0.573$. If firm 1 adopts in $n = 1$ and firm 2 waits to adopt until $T_{22F} = T + 3$ then firm 1's value is $L_1 = 0.829$ and firm 2's value is $F_2 = 0.667$. Similarly, if firm 2's value from leading in $n = 1$ is $L_2 = 0.66$ and firm 1's value from acting as follower is $F_1 = 0.853$. These values are plotted for each firm in Figure A.6.

Using the logic from the previous section, it is straightforward to show that $T_{22J} < \infty$ and firm 2 has a strictly dominant strategy to adopt in all periods $t \geq T_{12F}$, eliminating the possibility of a late joint-adoption equilibrium.[27] Next, consider each period $T_{22F} \leq t < T_{12F}$. By the definition of $T_{12F}$ firm 1's value from joint adoption must be strictly less than its value from delaying adoption until $T_{12F}$. Further, firm 1's value from leading in period $t$ is equal to the value under joint adoption because given firm 1's decision to adopt, firm 2 has a strictly dominant strategy to adopt as well (since $t \geq T_{22F}$). As a result, the only potential equilibrium in this range involves firm 2 adopting in period $T_{22F}$ and firm 1 delaying adoption until $T_{12F}$. Yet, given this knowledge, firm 2 has an incentive to move its adoption time even earlier to $T_{22L}$. In the example, $T_{22L} = T + 2$ with an associated value of $L_2 = .728$. Next, we check to see if firm 1 has an incentive to preempt firm 2 in $T_{22L} - 1$ which is $t = T + 1$ in the example. If firm 1 allows firm 2 to adopt in $t = T + 2$ (and subsequently optimizes by adopting in $T_{12F} = T + 4$) his continuation value is $F_1 = .914$. If firm 1 preempts firm 2 in $t = T + 1$ (forcing firm 2 to optimally adopt in $T_{22F} = T + 3$) his continuation value decreases to $L_1 = 0.829$. Thus, firm 1 has no incentive to preempt firm 2 and the unique equilibrium of this continuation game involves firm 2 adopting $j = 2$ in $t = T + 2$ and firm 1 subsequently adopting in $t = T + 4$. While simulation results suggest that this type of equilibrium is unique (where firm 2 acts as the leader and firm 1 follows) if $T_{22F} < T_{12F}$, we are struggling to prove this result in general.[28]

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[27]If $\pi(2, 2) - \pi(1, 0) < 0$ firm 1 prefers to delay a joint-adoption equilibrium indefinitely. However, the fact that $t \geq T_{12F}$ ensures that if firm 2 adopts, firm 1's best response is to adopt as well.

[28]We have attempted to prove that firm 1 has a strictly dominant strategy to choose to not adopt in period $T_{22L}$ but cannot show that it is always true. We think that there are certain cost vectors where firm 1 might be willing to preempt firm 2 but firm 2 is subsequently willing to preempt to an even earlier date. In other words, firm 2 doesn't necessarily adopt in $T_{22L}$–it might adopt at an earlier date due to the threat of preemption from firm 1. Even though it is clear that firm 2 has a greater incentive to act as leader because ($T_{22F} < T_{12F}$) and $\pi(2, 1) - \pi(0, 1) > \pi(2, 0) - \pi(1, 0)$ (which can be

### Equilibrium Play Beginning in (0,0,0,0)

Given a marginal cost vector $(c_0, c_1)$, each firm can calculate the four pertinent expected continuation values $EV(T, 0, a, b),\ \forall a, b = 0, 1$.[29] At this point it would seem logical to proceed as we did in the analysis of $(T, 0, 0, 0)$. However, the expected continuation values cannot be ranked for all values of $(c_0, c_1)$. As a result, differences in the $EV(\cdot)$'s may have different signs, leading to varying optimality conditions for the adoption of $j = 1$. Ultimately we will need to consider several different cases which are explained in detail below.

First consider the situation where one firm has adopted $j = 1$ and the competing firm is deciding whether or not to adopt. In period $t$, the follower's Bellman equation is

$$V(t, t, 0, 1) = \max_{a^t \in \{0,1\}} \quad \pi(a^t, 1) - \mathbb{1}_{[a^t \neq a^{t-1}]} C(t) + \beta[\rho EV(T, 0, a^t, 1) + (1-\rho) EV(t+1, t+1, a^t, 1)].$$

Again, the follower is faced with a simple optimal stopping problem due to the strictly decreasing and strictly convex nature of $C(t)$. So, applying the same logic used to derive (2.7) and (2.10), the follower waits to adopt $j = 1$ until the first period $t$ where the following inequality holds:

$$\pi(1, 1) - \pi(0, 1) + \beta\rho \underbrace{[EV(T, 0, 1, 1) - EV(T, 0, 0, 1)]}_{x} > C(t) - \beta(1 - \rho)C(t + 1). \qquad (2.16)$$

In the efficient and monopoly cases we proved that the difference in continuation values (term "$x$" above) was positive. Or stated differently, the continuation value was increasing in the planner's/monopolist's technology. However, in a duopoly market this is not always the case.[30]

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shown to be true for $0.5 > c_0 > c_1$), we cannot show that this outweighs the higher cost of adopting at an earlier date.

[29] While all uncertainty is technically resolved at the beginning of period $T$, there is still the potential issue of multiple equilibria. Thus, $EV(T, 0, a, b)$ is the average continuation value for a firm entering period $T$ with technology "a" (and competitor's technology "b") across all equilibrium outcomes. Any marginal cost vector generates a maximum of two pure strategy equilibria in the continuation game beginning in $T$. If multiple equilibria exist they are generated by each firm wanting to act as leader in period $T_{2F} - 1$ in states $(T, 0, 0, 0)$ and $T_{22F} - 1$ in state $(T, 0, 1, 0)$.

[30] Setting $\beta = 0.9$ and $C(t) = 1/(1 + t)$ we found that 84 of the 1176 marginal cost vectors analyzed generated $EV(T, 0, 1, 1) - EV(T, 0, 0, 1) < 0$ and 53 resulted in $EV(T, 0, 1, 1) - EV(T, 0, 0, 0) < 0$.

If $EV(T,0,1,1) - EV(T,0,0,1) < 0$, the follower's optimal adoption date for $j = 1$ is pushed far into the future and if the difference is significant, so that the entire LHS of (2.16) is negative, the follower will find it optimal to never adopt $j = 1$. Further, while we showed in the analysis of the continuation game beginning in $(T,0,0,0)$ it must be that $T_{2F} \leq T_{2J}$, that isn't necessarily true for $j = 1$. Defining $T_{1J}$ as the optimal date for the two firms to jointly adopt $j = 1$, it is straightforward to show that $T_{1J}$ is the first $t$ satisfying the following condition:

$$\pi(1,1) - \pi(0,0) + \beta\rho\left[EV(T,0,1,1) - EV(T,0,0,0)\right] > C(t) - \beta(1-p)C(t+1). \qquad (2.17)$$

While $\pi(0,0) > \pi(0,1)$, it may be that $EV(T,0,0,1) > EV(T,0,0,0)$ so that the LHS of (2.17) is greater than the LHS of (2.16) and $T_{1J} \leq T_{1F}$. While this is a departure from Fudenberg and Tirole (1985) who explicitly show that $T_{1J} \geq T_{1F}$ using a quasiconcavity argument, it is still straightforward to characterize the firms' equilibrium strategies in this case. If $T_{1J} = T_{1F}$ then both firms have a strictly dominant strategy to adopt $j = 1$ in all periods $t \geq T_{1J} = T_{1F}$. From that point backwards-induction can be used to solve for the firms' equilibrium strategies in all $t < T_{1J}$ using logic similar to that employed in $(T,0,0,0)$ continuation game. Next, consider $T_{1J} < T_{1F}$. In $T_{1F}$ the firms again have a strictly dominant strategy to adopt $j = 1$ in all potential states. In all periods $T_{1J} \leq t < T_{1F}$ a joint adoption equilibrium will occur in state $(t,t,0,0)$ but the follower will delay adoption until $T_{1F}$ if the leader has already adopted. However, state $(T_{1J}, T_{1J}, 0, 0)$ will never be reached in equilibrium if there exists a period $t < T_{1J}$ where the value of leading exceeds the value of joint adoption at $T_{1J}$. If this date $(T_{1L})$ exists then a diffusion equilibrium will ensue where the leader's actual date of adoption may occur before $T_{1L}$ due to the preemption incentive. However, the inability to rank the $EV(\cdot)$'s prevents us proving the existence of $T_{1L}$ in general.

The real difficulties for this analysis arise when $T_{1F}$, $T_{1J}$, or both values equal $\infty$ (i.e. the LHS of (2.16), (2.17), or both are negative). In what follows we describe the algorithm used in each of four different cases. Recall that in period $T-1$ the firms are still unsure about whether or not $j = 2$ will be released in the subsequent period. As a result, with probability

$(1-\rho)$ the firms believe that they will transition to state $(T, T, a_i^{T-1}, a_{-i}^{T-1})$, which we have not solved for at that point in the backwards-induction process (because working backwards from the end of the game to $T$ this state does not exist). To calculate $EV(T, T, a_i^{T-1}, a_{-i}^{T-1})$ we need to determine the hypothetical date when all firms have a strictly-dominant strategy to adopt $j = 1$.[31] The fact that this hypothetical date is potentially infinite (if at least one firm has a strictly) is what generates the following cases:

**Case 1: Both $T_{1F}$ and $T_{1J}$ are finite**

- Determine which date is greater and start the backwards induction from that point
- In all potential states entering that date each firm has a strictly dominant strategy to adopt $j = 1$ (by the definition of $T_{1F}$ and $T_{1J}$)
- Using stationarity it is straightforward to solve for each firm's value in this hypothetical last period:

$$\begin{aligned} EV(\bar{t}, \bar{t}, a_i^{\bar{t}-1}, a_{-i}^{\bar{t}-1}) =& \pi(1,1) - \mathbb{1}_{\left[a_i^{\bar{t}} \neq a_i^{\bar{t}-1}\right]} C(n) + \\ & \beta \left[ \rho EV(T, 0, 1, 1) + (1-\rho) \frac{\pi(1,1) + \beta \rho EV(T, 0, 1, 1)}{1 - \beta(1-\rho)} \right], \end{aligned}$$

where $\bar{t} = max\{T_{1F}, T_{1J}\}$

**Case 2: $T_{1F}$ is finite but $T_{1J}$ is infinite**

- The analysis here is similar to that used for the continuation game beginning in state $(T, 0, 0, 0)$. From the previous analysis we know that there can be no joint adoption equilibrium after $T_{1F}$ when time is discrete.
- If one firm has adopted $j = 1$ at an earlier date then we know the remaining firm responds optimally by adopting in $T_{1F}$ and the values are the same as in Case 1

[31] For instance, suppose that $T = 10$ but $T_{1F} = 14$. Conditional on being preempted at some date $t < 10$, the follower will not be able to (optimally) adopt $j = 1$ before $j = 2$ is released. However, the fact that the follower *would have* adopted $j = 1$ in $t = 14$ means that the we would hypothetically reach a stationary state in $t = 14$ that would persist until $j = 2$ is released. This stationarity allows us to use backwards induction to calculate $V(T, T, a_i^{T-1}, a_{-i}^{T-1})$.

- If both firms enter $T_{1F}$ having not adopted $j=1$ then it must be that either both or neither of the firms want to adopt $j=1$ (because if only one firm adopts $j=1$, by the definition of $T_{1F}$ the non-adopter would want to adopt as well). If joint-adoption is optimal, values are calculated as in Case 1. If not, each firm's value is:

$$EV(T_{1F}, T_{1F}, 0, 0) = \pi(0,0) + \beta\left[\rho EV(T, 0, 0, 0) + (1-\rho)\frac{\pi(0,0) + \beta\rho EV(T, 0, 0, 0)}{1-\beta(1-\rho)}\right]$$

**Case 3: $T_{1J}$ is finite but $T_{1F}$ is infinite**

- If both firms enter period $T_{1J}$ with $j=0$ then a joint-adoption equilibrium ensues and each firm earns the value in Case 1

- If one of the two firms has adopted then the remaining firm finds it optimal to never adopt $j=1$. The continuation value for the adopting firm is:

$$EV(T_{1J}, T_{1J}, 1, 0) = \pi(1,0) + \beta\left[\rho EV(T, 0, 1, 0) + (1-\rho)\frac{\pi(1,0) + \beta\rho EV(T, 0, 1, 0)}{1-\beta(1-\rho)}\right]$$

  and the continuation value for the non-adopting firm is:

$$EV(T_{1J}, T_{1J}, 0, 1) = \pi(0,1) + \beta\left[\rho EV(T, 0, 0, 1) + (1-\rho)\frac{\pi(0,1) + \beta\rho EV(T, 0, 0, 1)}{1-\beta(1-\rho)}\right].$$

**Case 4: Both $T_{1F}$ and $T_{1J}$ are infinite**

- In this situation states $(t,t,1,0)$, $(t,t,0,1)$, and $(t,t,1,1)$ are all temporarily stationary until $j=2$ is released. The values in these states are calculated using the correct forms from Cases 1-3.

- While joint-adoption is not optimal, it may be true that a single firm would find it optimal to adopt in state $(t,t,0,0)$. So, we solve for the earliest $t$ such that a single firm would find it optimal to adopt. This occurs in the smallest $t$ such that the following inequality holds:

$$\pi(1,0) - \pi(0,0) + \beta\rho\left[EV(T,0,1,0) - EV(T,0,0,0)\right] > C(t) - \beta(1-\rho).$$

If this condition is not satisfied for a very large value of $t$[32] then we assume that neither firm will adopt $j = 1$. If the condition is satisfied then there are two equilibria in state $(T_L, T_L, 0, 0)$: one in which firm 1 adopts and firm 2 does not adopt and another where the indices are reversed. In this case we simply pick one of the two equilibria and begin working backwards from $T_{1L}$.

For each case we now have a way of "closing" the $j = 1$ and can work backwards to calculate the value of $V(T, T, a_i^{T-1}, a_{-i}^{T-1})$ for every combination of actions. With this value the backwards-induction process can be continued until we reach $t = 0$. The presence of these different cases makes it very cumbersome to discuss the equilibrium adoption dates for $j = 1$. Without imposing additional assumptions on $C(n)$ and the ranking of both the $EV(\cdot)$'s and the differences in $EV(\cdot)$'s we cannot make any general comment on the equilibrium adoption dates. However, we run a variety of simulations to illustrate the dynamics of the technology adoption game. There are at most four pure strategy Markov perfect equilibria in the dynamic game. Since firms are ex ante identical all of the equilibrium adoption dates of $j = 1$ are necessarily isomorphic in the sense that if in one equilibrium firm 1 adopts $j = 1$ in period $x$ and firm 2 adopts in period $y$ then the other equilibrium involves firm 1 adopting in $y$ and firm 2 adopting in $x$. If both firms enter period $T$ with the same technology then the equilibrium adoption dates in that subgame are also necessarily symmetric. However, as previously discussed in section 2.2.3, if one firm enters period $T$ with a technological advantage then multiple equilibria need not be symmetric.

## 2.3 Simulations

In this section we examine the equilibrium properties of the model for a variety of parameterizations. Before discussing all of the simulations in detail it is helpful to highlight some of the main results which are bulleted below:

- Leap-frogging behavior is most likely when the adoption cost function is relatively flat and the first advancement is relatively large. In this situation there is a large preemption

[32]In the simulations we choose $t = 500$.

incentive for the first technology but once preempted the remaining firm has little incentive to adopt. However, the preempted firm (if it does not adopt the first technology) has a much higher marginal benefit from adopting the second technology. If the adoption cost function declines faster there is a greater chance that both firms will find it optimal to adopt the first technology.

- As $\rho$ increases both firms tend to delay the adoption of the first technology. The effect is most evident when the first advancement is relatively small (i.e. high values of $c_0 - c_1$) and the adopt cost function is relatively flat. However, when the adoption cost function is significantly convex and the first advancement is large, changes in $\rho$ may have no effect on the equilibrium adoption dates of the first technology.

- Inefficiency in the model is caused by suboptimal adoption dates, too much adoption, and setting price above marginal cost. Only rarely does the preemption incentive drive a duopolist to adopt before the planner's adoption date. Total inefficiency is largest for high values of $(c_0 - c_1)$ where both duopolists adopt the first technology relatively early. Further, when $(c_0 - c_1)$ is high and adoption costs are relatively flat, a monopoly market is more efficient than a duopoly market. However, the relationship between total inefficiency and $(c_0 - c_1)$ is not monotonic.

- For most marginal cost vectors a steeper adoption cost function will result in lower total inefficiency. While the adoption average adoption date of the first technology decreases, adoption costs decrease at a faster rate.

- Ceteris paribus, as $\rho$ increases (i.e. the firms believe that the second advancement is more imminent) the duopoly inefficiency tends to decrease as firms delay the adoption of the first technology.

- Comparing a one-technology model with a two technology model, there is no systematic relationship between firms' adoption dates of $j = 1$. However, as $c_0 - c_1$ increases, the leader and follower's adoption dates in the two-technology model (very roughly) decrease relative to the values in the respective values in the one-technology model. This relationship becomes more pronounced as $\rho$ increases.

- For the chosen parameterization, inefficiency is higher in the one-technology model than in the two-technology. The discrepancy is largest when both $c_0$ and $c_1$ are small and smallest when both values are large.

We first vary the convexity of the cost function and calculate the duopoly equilibrium adoption dates for three different cost vectors. Table A.2 summarizes the results for different values of $x$, where we parameterize the cost function as follows:

$$C(n) = \frac{1}{(1+n)^x},$$

so that a lower value of $x$ corresponds with a relatively flatter cost function. In all three cases we set $c_0 = 0.40$, $\rho = 0.1$, $\beta = 0.9$, and $T = 10$. We arbitrarily define firm 1 as the first adopter of either technology. Recall that if neither or both of the firms adopt $j = 1$ then there are (potentially) two pure strategy Markov perfect equilibria in the continuation game beginning in $T$ (i.e. either firm can play the role of leader or follower in equilibrium). As a result, in these situations the firm index for $j = 2$ is meaningless. However, if only one of the two firms adopts $j = 1$ then the firms enter period $T$ in an asymmetric state and the indices do have meaning when considering the $j = 2$ adoption dates.[33] For $j = 1$ we list the date when each firm would *hypothetically* adopt in the event that $j = 2$ has not been released. A value of "500" indicates that the firm would not find it optimal to adopt by $t = 500$. Consider the situation where $x = 0$ so that $C(n)$ is constant. Since there is no cost savings from delaying adoption until $t = 1$, a firm must either adopt $j = 1$ immediately or never. In all three cases neither firm ever adopts $j = 1$. However, the marginal benefit from adopting $j = 2$ is large enough to make immediate adoption profitable for both firms. When $x = 0.1$, $C(n)$ is decreasing but is still relatively flat. Only when the difference in $c_0 - c_1$ is significant does one firm find it optimal to adopt $j = 1$ before $j = 2$ is released. Since the inter-period cost savings is still negligible, preemption drives

[33] As long as $c_0$ and $c_1$ are not terribly close the equilibrium in this subgame will typically be unique. However, if multiple equilibria exist we only display one of the two equilibria in an attempt to limit confusion.

the leading firm to adopt $j = 1$ immediately. However, since the difference between $c_1$ and $c_2$ is relatively small, entering period $T$ the non-adopting firm has a significantly higher incentive to adopt $j = 2$ ($\pi(2,1) - \pi(0,1) > \pi(2,0) - \pi(1,0)$). The original adopter's optimal response is pushed far into the future because $\pi(2,2) - \pi(1,2)$ is small and costs are decreasing very slowly. Similar to the result derived in Harrington, Iskhakov, Rust, and Schjerning (2010), we suspect that this type of leap-frogging behavior would persist if the model is extended to include more than two technologies but costs remain relatively flat. As $x$ increases and the cost function becomes more convex the firms adopt $j = 1$ at earlier dates. While the adoption dates of $j = 1$ are increasing in $c_1$, the optimal adoption dates of $j = 2$ are decreasing in $c_1$. Fixing $c_0$, as $c_1$ falls the first technological advancement is becoming increasingly significant while the second advancement is being marginalized. A greater advancement increases the marginal benefit of leading ($\pi(1,0) - \pi(0,0)$) which strengthens the preemption incentive and leads to earlier adoption. The reverse is true for less-significant technologies.

Table A.3 is similar to Table A.2 except that we now vary the firms' commonly-held belief that a new technology will be released ($\rho$) in all periods $t < T$. We simulate the equilibrium adoption dates for two different cost functions ($x = 0.5$ and $x = 1.0$). When $\rho = 0$ the equilibrium adoption dates of $j = 1$ coincide with the dates in a one-technology model because the firms believe that no additional advancements will be released. A change in $\rho$ will have no effect on the firms' optimal adoption dates of $j = 2$ as long as the firms' technology vector entering period $T$ is unchanged on the equilibrium path. Recall that a change in $\rho$ has two countervailing effects on a firm's decision to adopt $j = 1$. Since the difference in expected continuation values associated with adopting ($EV(T,0,1,a_{-i}) - EV(T,0,0,a_{-i})$) is typically positive, the decision to adopt allows the firm to transition to a preferred state (in expectation) when $j = 2$ is released. As $\rho$ increases the firm believes that this transition is more imminent and thus it is incentivized to adopt sooner. However, at the same time an increase in $\rho$ also decreases the amount of time that the firm believes it will be able to take advantage of the the benefits of $j = 1$ before an even better technology is released. The firm hedges against this risk by only adopting $j = 1$ at a lower cost, pushing the equilibrium adoption date later. Table A.3 suggests that the latter effect dominates the former and causes the equilibrium adoption dates to increase as $\rho$ increases. The effect of an increase in $\rho$ is greatest when $c_1$ is relatively high (so that the first technological advancement is less significant) and the cost function is flat. In this situation it takes much longer for the cost function to fall to compensate for the perceived risk associated with a greater $\rho$. As $c_1$ falls and/or the cost function decreases at a faster rate, the effect of a change in $\rho$ is lessened. In fact, when $x = 1.0$ and $c_1 = 0.1$ the $j = 1$ adoption dates are unaffected by changes in $\rho$.

Next we examine the relationship between the monopoly, duopoly, and welfare-maximizing adoption dates. Table A.4 summarizes the adoption dates for various marginal cost vectors and two different specifications of the cost function ($x = 0.2$ and $x = 1.0$). In the table "$P$" stands for "planner," "$M$" stands for "monopolist," and "$D_1$" and "$D_2$" signify the two duopolists. In analyzing the continuation game beginning in state $(T, 0, 0, 0)$ we showed that following condition holds:

$$T_{2P} \leq T_{2M} \leq T_{2F}.$$

While the presence of the expected continuation values prevent us from proving that this relationship holds with certainty for $j = 1$, the results in Table A.4 suggest that it may be true. In several instances the follower in the duopoly market adopts $j = 1$ in the same period as the monopolist but never adopts in an earlier period. Unless costs are too flat and/or the marginal benefit from adopting $j = 1$ is small, the leader in the duopoly market typically adopts in a period $t$ such that $T_{1P} \leq t \leq T_{1M}$. Put differently, from a welfare-maximizing perspective the preemption incentive rarely causes either duopolist to adopt "too soon" and pay an adoption cost that is "too high." In contrast, both firms adopt later than the socially optimal date which keeps the market price high and total output and consumer surplus low. When the second duopolist chooses to adopt $j = 1$ then the extra adoption cost adds to the inefficiency. The only case in the table when a duopolist adopts "too early" occurs when $x = 0.2$, $c_0 = 0.25$, and $c_1 = 0.05$. Here the cost function is relatively flat so if preempted the follower will need to delay adoption significantly in order for it to be profitable. This, coupled with the fact that the technological improvement is significant generates a high value of leading. As a result, the preemption incentive is very strong and drives the leader's adoption date before $T_{1P}$.

Figures A.8 and A.9 plot the total intertemporal inefficiency for the monopoly and duopoly markets, respectively. All adoption costs are included in the calculations. First consider Figure A.8. When the cost function decreases slowly ($x = 0.2$) there is a "wedge" of relatively low inefficiency where the value of $c_0 - c_1$ is close to the value of $c_1 - c_2$. Here the planner finds it optimal to adopt $j = 1$ just before $j = 2$ is released and the monopolist does not adopt $j = 1$. Since $\sigma(2) - \sigma(1) > \sigma(1) - \sigma(0)$ the planner still has an incentive to adopt $j = 2$ quickly (as does the monopolist). The increased inefficiency generated in the short window between when the planner adopts $j = 1$ and $j = 2$ is offset by the fact that the monopolist does not incur an adoption cost for $j = 1$. However as $x$ increases there is a greater likelihood that both the monopolist and the planner adopt $j = 1$. The window of time between the planner's adoption date and the monopolist's date is roughly the same but now the monopolist incurs an additional cost which increases the total inefficiency. It is important (although somewhat obvious) to note that the greatest per-period inefficiency is generated when the planner is operating with a technology that is sufficiently better than the monopolist's technology. In this case the discrepancy between the monopoly and efficient prices is large. Figure A.9 is analogous to Figure A.8 for the duopoly market. For $x = 1$ the inefficiency is *roughly* increasing in the difference between $c_0$ and $c_1$. When $c_0$ is high and $c_1$ is low, the planner and both of the duopolists adopt $j = 1$ quickly. As a result, two large adoption costs are incurred in the duopoly market. Further, the difference between the planner's adoption date of $j = 2$ and the duopoly adoption dates are significant because for low values of $c_1$, the difference between $\sigma(2) - \sigma(1)$ and $\pi(2, 1) - \pi(1, 1)$ increases. As the value of $c_0 - c_1$ decreases, all of the adoption dates tend to converge. In other words, the relative incentive to adopt $j = 1$ falls and the incentive to adopt $j = 2$ increases. There is a greater chance that one or both of the duopolists choose not to adopt $j = 1$, thereby limiting the adoption costs in the market. Even though the equilibrium adoption dates of $j = 2$ occur earlier, the decreased costs for $j = 1$ combined with the compression of the planner's $j = 2$ adoption date with the duopoly dates causes the total inefficiency in the market to fall. For certain "intermediate" cost vectors, as $x$ rises total inefficiency initially increases but then falls. Consider the case where $c_0 = 0.35$

and $c_1 = 0.16$. As $x$ increases the total inefficiency is initially 0.53 ($x = 0.2$), increases to 0.75 ($x = 0.6$), and then falls to 0.66 ($x = 1.0$). In the first case neither duopolist adopts $j = 1$ (the planner adopts in $t = 6$). As a result, there is a high incentive to adopt $j = 2$ in the duopoly market and preemption drives one firm to adopt immediately in $t = 10$ (the planner adopts in $t = 12$). When $x$ increases to 0.6 both duopolists adopt $j = 1$ (in periods $t = 3$ and $t = 8$) and the planner adopts earlier ($t = 3$). The increased adoption costs in the duopoly market do not compensate for the increased total surplus generated (due to higher output and lower price), so the overall inefficiency increases. However, in the $x = 1.0$ case the adoption cost falls sufficiently fast so that the same marginal increase in surplus in the duopoly market can be attained at a lower cost.

Figure A.10 plots the difference in total surplus generated in the duopoly and monopoly markets. The monopolist only generates greater surplus when the adoption cost is relatively flat and the first technological advancement is significant while the second advancement is marginal. In this situation the preemption incentive for $j = 1$ is great which leads to two high adoption costs in the duopoly market. As $x$ increases there is greater incentive to delay adoption so the additional adoption cost in the duopoly market is less severe. Relative to the duopoly, the monopoly is most inefficient when both $c_0$ and $c_1$ are both very small. In these cases neither the monopolist nor either of the duopolists have an incentive to adopt $j = 1$ and the adoption dates of $j = 2$ occur significantly after $T$ so the additional cost incurred in the duopoly is minimized.

Next, Figure A.11 illustrates how the duopoly inefficiency varies with $\rho$. Recall that as $\rho$ increases the equilibrium adoption dates of the first technology tend to increase as well. However, the positive relationship is more evident when $c_0 - c_1$ is relatively small and/or the adoption cost function is flatter. Table A.5 summarizes the changes in adoption dates and total surplus for three different marginal cost vectors in Figure A.11. We define $\sigma_P$ and $\sigma_D$ as total surplus for the planner and duopolists, respectively, and $\Delta_\sigma$ as the difference in the two values (i.e. the total intertemporal market inefficiency). When $c_1 = 0.3$ changes in $\rho$ have no effect on the equilibrium outcome or total inefficiency in the market because in all three cases neither the planner nor either duopolist adopts the first technology. Next, consider the case where

$c_1 = 0.20$. When $\rho = 0.1$ the planner and one of the two duopolists adopt $j = 1$. However, as $\rho$ increases the adoption dates of the first technology are delayed until it becomes optimal for no one to adopt $j = 1$. Interestingly, total surplus in the socially optimal outcome declines as the planner's adoption date is delayed and $\rho$ strays from the "consistent" value of 0.1.[34] However, total surplus in the duopoly actually *increases* slightly as $\rho$ increases, suggesting that the preemption incentive is driving the duopolists to adopt too soon. Put differently, the increase in consumer surplus (generated by a lower market price and higher market output) is not compensating for the higher adoption costs associated with earlier adoption. Combining the decrease in the planner's surplus with the slight increase in the duopoly surplus we find that typically market inefficiency will fall as $\rho$ increases.

Finally, in Figures A.12 and A.13 we compare the adoption times and total inefficiency in a duopoly market when there is only one versus two new technologies. We compare the adoption times and inefficiency for different values of $\rho$.[35] In Figure A.12, a positive (negative) value indicates that the firm in the two-technology case is adopting $j = 1$ after (before) the corresponding firm in the one-technology case. Comparing panel (a) with panel (b) and panel (c) with panel (d) we see that an increase in $\rho$ causes both firms in the two-technology game to delay adoption (as we discovered in Table A.3), which shrinks the area of the plot where the two-technology firms adopt before their one-technology counterparts. In the $\rho = 0.1$ case the leaders' adoption dates are typically very close except when difference between $c_0$ and $c_1$ is very small. We believe that a significant amount of the "spottiness" is being generated by the joint-adoption equilibria (which are solely a consequence of modeling in discrete time). The comparison is somewhat more clear for the followers. Drawing straight lines through the origin of the graph with different slopes, it appears as though the follower in the two-technology game is more likely to adopt before its counterpart in the one-technology game if $c_1$ is a smaller fraction of $c_0$. Fixing $\rho$ and $x$, when this fraction is high neither firm has great incentive to adopt $j = 1$. However, in the one-technology game the follower essentially has no

[34]Recall that the second technology is released in $T = 10$ so that "consistency" implies $\rho = 1/T$.

[35]In Figure A.12 it is important to note that the color scale is held constant in all four contour plots.

other option–at some point in time if costs have declined sufficiently then it will be optimal to adopt. In contrast, in the two-technology game the follower has even less incentive adopt $j = 1$ because once $j = 2$ is released it will adopt relatively fast, thus limiting the potential benefit from $j = 1$. As $c_1/c_0$ falls the relative magnitude of the first advancement rises compared to the second advancement and the follower in the two-technology game has less incentive to wait. Therefore, it must be true that $EV(T, 0, 1, 1) - EV(T, 0, 0, 1)$ increasing. Figure A.13 plots the difference in total inefficiency between the one- and two-technology models. Interestingly, with the chosen parameterization ($\beta = 0.9$, $x = 1.0$, and $T = 10$) we find that the one-technology duopoly is always more inefficient than the two-technology duopoly. The difference is low when both $c_0$ and $c_1$ are high. In the one-technology game both firms eventually adopt $j = 1$ after some delay. In the two-technology game neither firm typically adopts $j = 1$ before $j = 2$ is released but both subsequently adopt $j = 2$ quickly. Therefore, the per-firm adoption costs are much higher in the two-technology game. At the opposite end of the spectrum suppose both $c_0$ and $c_1$ are very small. Here very small differences in $c$'s generate large differences in total surplus.[36] In the one-technology model the difference between the planner's optimal adoption date and the duopolists' adoption dates is similar to the value under high marginal costs. However, the inefficiency generated in each period between when the planner adopts and the duopolists' adopt is significantly larger. In the two-technology model the adoption dates are condensed so the intermediate inefficiency is much smaller.[37] Lastly, setting both duopolists' technology equal to the planner's technology, per-period inefficiency is decreasing in $c$. When both $c_0$ and $c_1$ were high, the "ending state" of the one-technology game (when both duopolists adopted) was more efficient than ending state in the two-technology game. When both $c_0$ and $c_1$ fall toward $c_2$ this discrepancy is minimized.

[36]Suppose $c_0 = 0.49$ and $c_1 = 0.48$. In every period where the planner owns $j = 1$ but both duopolists operate with $j = 0$, the per-period inefficiency is 0.020. Next, suppose $c_0 = 0.02$ and $c_1 = 0.01$. In this case the per-period inefficiency when the planner has adopted $c_1$ but the duopolists operate with $c_0$ is 0.063. Even though the difference between the technologies is unchanged, the per-period inefficiency has more than tripled.

[37]If neither the planner nor the duopolists adopt $j = 1$ then they all adopt $j = 2$ very quickly.

## 2.4 Conclusion

Technological progress is rarely a one-shot game. Thus, firms are often forced to make repeated decisions regarding whether or not to upgrade their technology as the technological frontier progresses. This paper develops a multiple-advancement technology adoption game in an attempt to better understand the dynamic tradeoffs facing firms as technologies improve. We extend the seminal model of Fudenberg and Tirole (1985) to include a second technological advancement that is released at an uncertain date in the future. While the extension is seemingly straightforward, the resulting equilibrium analysis quickly becomes complicated due in large part to the expected continuation values associated with the release of the second technology. To remedy this issue we examine the equilibrium properties of the model by simulating results using a well-known demand specification and form of competition. This approach allows us to avoid making a large number of assumptions regarding firms' flow profit functions which may lack a reasonable economic justification. The simulated results and comparative statics exercises reveal how firms' incentives to adopt vary with changes in market structure, adoption costs, magnitudes of the technological innovations, and beliefs regarding the release of an improved technology. Further, we shed light on the inefficiencies generated by suboptimal adoption dates, "redundant" adoptions, and market power. These results are an important first step in better understanding multiple-advancement technology adoption games. Further, these results are relevant to policymakers tasked with determining how to best promote (or discourage) the uptake of a new technology in different markets/industries to maximize overall welfare. For instance, the difference in total duopoly inefficiency generated in a one-technology model versus a two-technology model could yield significantly different policy prescriptions. The anticipated presence of future advancements may limit current market inefficiencies and the need for intrusive adoption quotas. This type of long-term, dynamic consideration simply cannot be addressed in a single-technology model. Hopefully the insights provided by the model will help to guide future research in this strand of the literature.

# Chapter 3

# Technology Upgrading in Imperfectly Competitive Markets: The Case of MRI

## 3.1 Introduction

Technological innovation is an inherently dynamic process. The "most innovative" firms in the world spend billions of dollars on research and development annually in an attempt to improve the existing state-of-the-art and bring new products and services to market.[1] These technological advancements allow firms to operate more efficiently by improving productivity, decreasing costs, enhancing communication and connectivity, and providing firms with more detailed information about consumers' preferences. In many instances significant technological advancement can persist for an extended period of time.[2] As a result, while a firm decides whether or not to adopt a new technology today, the technological frontier is advancing. Thus, a firm's purchasing decision implicitly incorporates expectations about the likelihood and potential benefit of future advancements. As time passes and newer technologies are released, firms must make repeated decisions regarding when/whether to *upgrade* their current technology.

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[1] In a 2011 study, Booz & Co. surveyed over 500 "innovation leaders" in corporations around the world to select the companies they viewed as most innovative. These executives ranked, in order, Apple, Google, 3M, GE, and Microsoft as the world's most innovative firms. In 2010 these five firms combined to spend more than $19.6 billion on research and development.

[2] A well-known example of persistent technological change is embodied in Moore's Law, which states that the number of transistors placed on a microprocessor should roughly double every two years. Originally posited by Intel co-founder Gordon Moore in a 1965 paper, the trend roughly continues to hold to this day.

However, most empirical economic research fails to account for these dynamic considerations. There is a sizable literature that examines the process by which competing firms adopt a new technology, and a significant number of these analyses stem from the seminal model developed by Fudenberg and Tirole (1985). Their game begins when a new technology is released to an oligopoly market. The fixed cost of adopting the technology decreases with time and each firm's strategy entails choosing a single date to adopt the technology and incur the fixed cost. Each firm's flow profit is a function of both its own and its competitors' technology choices. Adopting the new technology increases a firm's profit at its competitors' expense. Thus, there is a tradeoff between adopting the technology sooner and immediately realizing its benefits versus waiting to purchase it at a lower cost. The game ends once all firms have adopted the technology.[3]

To better capture the dynamic nature of technological innovation, I extend this literature by developing, solving, and estimating a model where competing firms make repeated technology upgrading decisions. As in Fudenberg and Tirole (1985), the game begins with the release of a technology. However now, with some commonly-known probability, an even better technology is released in the subsequent period.[4] So, in deciding whether or not to adopt the current technology, each firm must consider the strategic implications of the decision once an improved technology is made available. For instance, the benefit from adopting the current technology may be short-lived if innovation is swift, potentially leading to a "leap-frogging" equilibrium where firms alternate between adopting and waiting. In each period I assume that firms act sequentially with asymmetric information about their competitors' idiosyncratic preferences. The sequential-move assumption generates a unique equilibrium outcome that I solve for using a backwards induction algorithm. However, by changing ex-ante market characteristics and/or the parameterization of the model, I can generate a wide range of equilibrium outcomes. In

[3]Fudenberg and Tirole (1985) make assumptions on both the marginal benefit of adoption and the convexity of the fixed cost function so that it is never optimal for a firm to delay adoption indefinitely.

[4]There is no uncertainty regarding a technology's value and that value is realized immediately upon adoption. So, I abstract from situations where a firm learns about a technology's profitability as time passes (as analyzed in Jensen (1982), Hoppe (2000), and related papers) and instances where there is uncertainty regarding the amount of time needed to successfully implement a new technology as in Stenbacka and Tombak (1994).

general I find that equilibrium adoption dates of the first technology differ in one-technology (where the first technology is the only technology) versus multi-technology models. This result holds even in parameterizations of the model where technological progress is relatively "slow," corroborating the importance of modeling firms' replacement decisions in industries subject to recurrent innovation.

An example of an industry that is being increasingly driven by technology and innovation is the U.S. market for healthcare. Newer technologies increase a hospital's productivity and afford it enhanced diagnostic capabilities and treatment options that consumers value. However, these benefits come at a significant cost. In 2008 the Congressional Budget Office concluded "that about half of all growth in health care spending in the past several decades was associated with changes in medical care made possible by advances in technology." This estimate suggests that between 1985 and 2005, technological advancements have increased total healthcare spending by more than half of a trillion dollars.[5] Given the enormity of this figure, the prospect of continued growth in healthcare spending,[6] and the prevalence of expensive, rapidly evolving technologies in the industry, it is important to understand the process by which healthcare providers purchase and subsequently upgrade their medical technologies. As a result, I collect and compile a novel dataset that allows me to track hospitals' magnetic resonance imaging (MRI) equipment purchases over a twenty-seven-year period which I use to estimate my dynamic model. MRI technology was originally introduced to the healthcare industry in the early 1980s and has experienced marked advancement since its inception. Not surprisingly, parameter estimates from my empirical model suggest that larger hospitals are more likely to purchase and subsequently upgrade their MRI equipment. Larger hospitals typically utilize multiple scanners and have greater resources available to upgrade their equipment. Parameter estimates also suggest that there may exist a spillover effect between competing hospitals in local markets. However, in contrast to the existing empirical literature, I find

[5]Congress of the United States, Congressional Budget Office. *Technological Change and the Growth of Health Care Spending*, (January 2008).

[6]In *An Update to the Budget and Economic Outlook: Fiscal Years 2012 to 2022*, the CBO estimates that the federal government's spending on healthcare will exceed total discretionary spending by 2016 (August 2012).

that the effect is *positive*. Specifically, an improvement in a competitor's technology increases a hospital's marginal benefit from upgrading its own technology. While this type of positive spillover is often ruled out by assumption in the technology adoption literature, it is important to note that I make no such ex ante restrictions on hospitals' profit functions. Additionally, the result highlights the importance of better understanding the complicated collection of effects driving firms' technology upgrading decisions in oligopoly markets.

The remainder of the paper is organized as follows. I conclude this section with a discussion of the related literature. Section 3.2 develops the dynamic model and the solution algorithm. In Section 3.3 I discuss the market for MRI scans and the data. Section 3.4 develops the empirical model and discusses the results. Finally, Section 3.5 concludes.

### 3.1.1 Related Literature

This paper is related to several strands of both the theoretical and empirical economic literatures. As previously mentioned, there is a sizable theoretical literature examining technology adoption games. The literature dates back to Reinganum (1981b), who develops and solves a duopoly technology adoption game. Symmetric firms each choose a date to incur a sunk cost and adopt a new technology where the sunk cost decreases with time. She shows that although the firms are symmetric, in any Nash equilibrium they adopt the technology at different points in time. Thus, there is a "diffusion" of the technology through time. Fudenberg and Tirole (1985) show that the firm who adopts the technology first in the Reinganum (1981b) model earns strictly greater profits. They solve for the subgame-perfect Nash equilibria of the game and demonstrate that the "follower" in the Nash equilibrium has an incentive to preempt the "leader." This preemption incentive drives the leader's adoption date back to the point that the two firms' payoffs are equalized. Again, the technology diffuses in equilibrium, the leading firm adopts earlier than it would in a Nash equilibrium and the following firm adopts at the same time.[7] In a duopoly model similar to Fudenberg and Tirole (1985) but with asymmetric

[7]The follower adopts at the same time in both the Nash and subgame-perfect Nash equilibria because conditional on the competing firm having already adopted, the follower solves the same optimal stopping problem. Fudenberg and Tirole (1985) also show that certain parameterizations of the model

firms, Riordan (1992) examines how price and entry regulations can affect technological diffusion. He finds that such regulations can limit each firm's incentive to preempt its competitor and slow the diffusion of a new technology.[8]

Several more recent papers incorporate multiple technologies into duopoly models of competition.[9] Horner (2004) models R&D competition between two firms as an endless race. In each period the two firms choose a costly effort level that affects the probability of generating a successful innovation. He finds that investment efforts increase when the firms' technologies are further apart which contradicts typical intuition. In my model I take the innovation process as exogenous and examine how firms compete subject to this innovation. Harrington, Iskhakov, Rust, and Schjerning (2010) show that two symmetric firms engaging in static Bertrand competition in each period still make cost-reducing investments in new technologies. Many asymmetric equilibria exist where firms invest at different points in time. Some equilibria exhibit leap-frogging adoptions while others involve "sniping," where one firm builds a large technological advantage over time until the competing firm adopts and undercuts its rival's price. Additionally, in some instances only one of the two firms may ever choose to adopt a new technology. While I also assume that firms play a static Bertrand pricing game in each period, firms are asymmetric so there is no surprise that adoption decisions may differ as well. My model also allows for more than two firms to compete in a market which complicates the equilibrium analysis.

This paper also relates to the empirical technology adoption literature. Levin, Levin, and Meisel (1987) use a hazard model to examine how optical scanners diffused in the supermarket industry. They find that the scanners diffused quicker in markets with greater competition.

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can generate additional "late joint adoption" equilibria where both firms simultaneously adopt the technology at a date beyond the follower's optimal adoption date in the diffusion equilibrium. However, these equilibria only exist when time is continuous.

[8]While the aforementioned papers all incorporate a potential first-mover advantage (that can be nullified through preemption), there are also a number of duopoly models focused on situations where following is advantageous. Three such examples are Katz and Shapiro (1987), Dutta, Lach, and Rustichini (1995), and Hoppe and Lehmann-Grube (2005).

[9]In addition to the models discussed below, Huisman and Kort (1999) and Huisman and Kort (2000) also analyze multi-technology duopoly adoption games. However, in both of these papers firms are still restricted to choosing a *single* technology.

Genesove (1999) studies the adoption of offset printing presses in the newspaper industry and shows that smaller firms tend to adopt earlier than larger firms in monopoly markets because the fixed investment cost is smaller. However, in duopoly markets, larger firms tend to adopt earlier than smaller firms, suggesting the presence of a preemption incentive. Dranove, Shanley, and Simon (1992) attempt to determine the extent of the "medical arms race" between competing hospitals in California. Their technology adoption game is static and they use a reduced form estimation routine. They find that competition mildly affects the number of specialized services offered within a market but their results are sensitive to the market definition. Baker (2001) and Baker and Phibbs (2002) use standard hazard models to examine the effect of HMO market share on the diffusion of MRI and neonatal intensive care technologies, respectively. As the authors anticipate, managed care is found to slow the diffusion of both technologies. Hamilton and McManus (2005) find that a new treatment technology for in vitro fertilization diffused faster in markets with more than one clinic than it did in monopoly markets. The paper controls for the fact that the adoption of a new technology can act as an entry deterrent.[10] Goettler and Gordon (2011) examine dynamic endogenous R&D and pricing competition between innovating firms (Intel and AMD) in the microprocessor industry. Since microprocessors are durable goods the firms face competition from not only each other but also previous sales. They find that relative to the duopoly case, innovation would increase if Intel was a monopolist but the resulting increase in the price of microprocessors would cause consumer surplus to fall. However, in a duopoly setting an increase in one firm's market share can cause consumer surplus to rise as the benefits from more frequent innovation outweigh the cost of a higher market price. In this paper I take the competition between MRI manufacturers as exogenous and instead focus on the strategic interactions between the "consumers" of new technologies.[11]

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[10]In my analysis I abstract from entry/exit considerations and fix the number of firms in a market. This is obviously a gross oversimplification (especially in the healthcare market). However, as I will demonstrate in the next section, even my "simple" game suffers from an incredibly large state space.

[11]An interesting, albeit computationally intensive extension would involve endogenizing MRI manufacturers release dates of new technologies. However, it is not immediately clear how responsive release dates are to the existing state of the MRI equipment in the healthcare industry.

This paper is most closely related to the work of Schmidt-Dengler (2006), who develops a timing game of MRI technology adoption between hospitals in local markets. He assumes that hospitals are asymmetric and focuses on the initial adoption of MRI technology. Firms move sequentially in each period but there is no uncertainty about competing firms' profit functions. He finds that competition has a significant effect on the rate of technology diffusion in a market (greater competition leads to faster diffusion). Using parameters from his estimation, he runs counterfactual experiments suggesting that faster diffusion is due more to "business stealing" than preemption. He reaches this conclusion by comparing the equilibrium adoption dates in the full model with those in a pre-commitment (i.e. Reinganum (1981b)) equilibrium and an equilibrium where industry profits are maximized. He isolates the preemption effect by comparing the subgame-perfect Nash equilibrium with the pre-commitment equilibrium. The discrepancy in adoption dates between these two types of equilibria is small relative to the overall difference between the adoption dates in the subgame-perfect Nash equilibrium and the industry-profit-maximizing equilibrium. As a result, he concludes that the business stealing effect (i.e. the negative effect on competitors' profits resulting from adoption) is what largely drives adoption dates earlier. This paper is similar to Schmidt-Dengler (2006) in that both examine the relationship between competition and technology diffusion. However, in an attempt to better capture the dynamic nature of technological innovation, this paper incorporates uncertainty with respect to future advancements and repeated interactions between firms. Further, unlike Schmidt-Dengler (2006), I do not restrict the competition between firms to be consistent with the Fudenberg and Tirole (1985) diffusion equilibrium.

Finally, this paper contributes to a more general class of timing games. Sweeting (2009) develops a static, incomplete information timing game where competing radio stations (potentially) choose to coordinate the timing of commercial breaks in order to limit listener switching between stations. He shows how the presence of multiple equilibria in both the model and the data can be used to identify the stations' incentive to coordinate. In my model solving for multiple equilibria in each state in every period becomes computationally infeasible.

In addition, there is no clear evidence that multiple equilibria exist in my dataset.[12] Einav (2010) studies the timing of motion picture release dates. In each movie “season” distributors sequentially choose release dates (weeks) for their movies with asymmetric information about competing distributors’ payoff functions. Decisions made across seasons are assumed to be independent. He finds that distributors could increase revenues if they moved their release dates a few weeks away from holiday weekends (when there is greater competition). He also argues that the presence of asymmetric information lessens the importance of the order of moves in a sequential-move game because the commitment power associated with moving early is mitigated by the uncertainty about the remaining competitors’ actions.[13]

## 3.2 Model

In this section I develop a dynamic technology adoption game where competing firms make repeated adoption decisions as the technological frontier progresses. In each period firms sequentially decide whether or not to adopt the best technology available. Each firm’s decision is observable by all other firms in the market. However, overall there is asymmetric information in the model. Specifically, in each period all firms receive an iid draw from a known distribution that is assumed to be private information. Thus, a firm has incomplete information regarding competing firms’ payoffs and cannot perfectly anticipate the choices of its competitors who have yet to act in the period. For instance, consider a market with three firms. The first firm to act makes its adoption decision while forming an expectation about the second and third firms’ subsequent actions. The second firm takes the first firm’s action as given, forms an expectation about the third firm’s strategy, and chooses the optimal technology. Finally, the third firm takes the first and second firms’ actions as given and simply optimizes accordingly. In addition to the uncertainty over competitors’ flow profit levels, all firms are uncertain about

[12]Sweeting (2009) plots histograms of the number of commercials played in each minute of the hour in different markets. Upon viewing these histograms it is clear that commercials are clustered at different times across markets, suggesting that there are multiple equilibria in the data. A preliminary analysis of my dataset did not reveal any systemic relationship between adoption dates across different markets.

[13]In other words, upon viewing the actions of their competitors, the firms moving later in each period have an informational advantage over the early-moving firms.

the release date of the next "best" technology. I assume that this uncertainty is objective and takes the form of a time-invariant, commonly-held belief.[14] Once all firms make their adoption decisions in a given period, equilibrium flow profit levels are determined via a static Bertrand pricing game. In what follows I first discuss the static pricing game and then develop the properties of the dynamic technology upgrading game. I conclude this section by discussing a variety of simulation results for different parameterizations of the model.

### 3.2.1 Static Pricing Game

Time is assumed to be discrete and periods are indexed by $t = 0, 1, 2, \ldots, \infty$. There are $M$ independent markets indexed by $m = 1, 2, \ldots, M$. Each market $m$ is comprised of a continuum of consumers and $J_m$ firms, where a representative consumer is indexed by $i$ and firms are indexed by $j_m = 1, 2, \ldots, J_m$. I assume that each firm produces a single differentiated good so that the notions of "firms" and "products" are synonymous. For instance, in my empirical application purchasing product $j$ can be thought of as "choosing to have an MRI scan performed at hospital $j$." In each period consumers choose to purchase one of the $J_m$ products available or the outside option, denoted by $j = 0$.[15] In what follows I employ the differentiated product demand system developed by Berry (1994) to specify firms' per-period flow profits.

Omitting market subscripts, consumer $i$'s flow utility from purchasing product $j$ in period $t$ is given by:

$$u_{ijt} = x_{jt}\gamma + \theta_{jt}\tau - \alpha p_{jt} + \xi_j + \epsilon_{ijt}, \tag{3.1}$$

[14] For now I simply fix the value of this parameter before solving for the equilibrium of the model. Estimating this probability would be relatively straightforward as long as it is time-invariant and constant across firms. However, solving for a perfect Bayesian equilibrium of the dynamic game would be incredibly complex.

[15] For now I assume that the outside option is exogenous and time-invariant. In other words, the price of $j = 0$ is determined outside of the model prior to the start of the game. While this assumption is common, it is potentially restrictive in the context of my empirical application. In each market only hospitals are considered "players" in the dynamic game. Therefore, all independent imagining facilities are not explicitly modeled. The extent of the competition between hospitals and these imaging facilities in the market for MRI scans is somewhat unclear. I plan to further investigate this issue and potentially employ a time-varying outside option in future work.

where $x_{jt}$ is a vector of product and market-level variables, $\theta_{jt}$ is firm $j$'s technology, and $p_{jt}$ is the price of product $j$. Assuming $\tau$ is positive, on average a consumer values a firm's technology. Both $\xi_j$, a product characteristic, and $\epsilon_{ijt}$, an idiosyncratic consumer taste variable, are unobserved to the econometrician. Thus, $\xi_j$ can be interpreted as permanent unobserved heterogeneity for product $j$. Following Berry (1994), I denote the mean utility of product $j$ at time $t$ as

$$\delta_{jt} \equiv x_{jt}\gamma + \theta_{jt}\tau - \alpha p_{jt} + \xi_j \tag{3.2}$$

and normalize $\delta_{0t} = 0, \forall t$. Assuming that each $\epsilon_{ijt}$ is an IID draw from a Type 1 EV distribution, firm $j$'s market share in period $t$ is given by the standard logit equation:

$$s_{jt}(\delta) = \frac{e^{\delta_{jt}}}{\sum_{k=0}^{J} e^{\delta_{kt}}}. \tag{3.3}$$

I assume that a firm's marginal cost is constant in output and is specified as

$$c_{jt}(\theta_{jt}, \omega_{jt}, \phi) = e^{\phi_0 - \phi_1\theta_{jt} + \phi_2 w_{jt} + \omega_{jt}}, \tag{3.4}$$

where $w_{jt}$ and $\omega_{jt}$ are observable and unobservable firm-specific cost shifters, respectively. $\phi_0$, $\phi_1$, and $\phi_2$ are parameters. Adopting a new technology decreases a firm's marginal cost, where the extent of the cost reduction is governed by $\phi_1$. It is important to note that in the current specification the benefit from adopting a new technology is twofold–through an increase in consumer utility and therefore demand ($\tau$) along with a decrease in marginal cost ($\phi_1$). However, the equilibrium predictions of the model do not change qualitatively if one of the two effects is removed.[16]

I assume that conditional on the vector of chosen technologies, firms subsequently engage

[16]While I assume that both effects are beneficial to an adopting firm, this might not always be the case. For instance, a new technology might increase a firm's marginal cost if it requires more electricity or labor to operate compared with previous versions. In the case of MRI it is assumed that that any increase in variable costs required to operate a more advanced scanner are far outweighed by the decrease in time needed to perform a scan. Thus, it is assumed that a more advanced scanner causes a hospital's marginal cost per scan to decrease. In addition to a decrease in the time required for a scan, consumers are also assumed to benefit from the improved comfort and detail of images afforded by a newer scanner.

in a static Bertrand pricing game to determine prices and flow profits. Letting $I_m$ denote the size of market $m$, flow profit for firm $j$ is defined as

$$\pi_{jt} = I_m s_{jt}(p_{jt} - c_{jt}). \tag{3.5}$$

A pure strategy Bertrand equilibrium requires that each firm's price satisfies the following first-order condition:

$$p_{jt} = c_{jt} + \frac{s_{jt}}{|\partial s_{jt}/\partial p_{jt}|}. \tag{3.6}$$

Using the chain rule it is straightforward to show that

$$\frac{\partial s_{jt}}{\partial p_{jt}} = -\alpha \frac{\partial s_{jt}}{\partial \delta_{jt}} = -\alpha s_{jt}(1 - s_{jt}), \tag{3.7}$$

so that (3.6) simplifies to

$$p_{jt} = c_{jt} + \frac{1}{\alpha(1 - s_{jt})}. \tag{3.8}$$

The set of equilibrium prices (and corresponding market shares) is then defined as the solution to both (3.3) and (3.8) for all $j \in J$. To solve for the equilibrium price vector I set each firm's price above its marginal cost and gradually decrease the prices until a fixed point is reached. Equilibrium flow profits are then calculated using (3.5).[17]

### 3.2.2 Dynamic Technology Adoption Game

Given this demand specification I now develop the properties of the dynamic technology adoption game. In each period firms sequentially decide whether or not to adopt the best technology available. I assume that the order of moves is known to all firms in the market and does not

[17]Berry (1994) develops a technique to estimate the parameters of this demand system in the presence of unobserved product characteristics ($\xi$) that are correlated with prices. To cope with this endogeneity issue Berry (1994) inverts the mean utility levels ($\delta$) so that observed market shares can be regressed on the observables, treating $\xi$ as an unobserved error term. Unfortunately due to data limitations I cannot take advantage of this approach in my empirical application because I do not view firm-level shares and prices. As a result, I will not discuss the details of the mean-utility inversion approach here.

change over time.[18] To generate an ending point for the game I assume that a finite number of technologies ($N$) are released over a period of time. Each technology $\theta$ is simply an integer value from zero to $N$ ($\theta = 0, 1, \ldots, N$). I restrict each firm's choice set such that it can only choose between keeping its current technology and adopting the newest technology. Formally, let firm $j$'s action in period $t$, denoted by $a_{jt}$, be chosen from the set of feasible actions,

$$A_{jt} \equiv \begin{cases} \{a_{jt-1}, \theta_{Bt}\} & \text{if } a_{jt-1} \neq \theta_{Bt} \\ \{a_{jt-1}\} & \text{if } a_{jt-1} = \theta_{Bt} \end{cases}, \tag{3.9}$$

where for completeness I define each firm's action in period $t = -1$ to equal 0 and $\theta_{Bt}$ is defined as the best technology available at the beginning of period $t$. Thus, once a new technology is released I do not allow firms to adopt previous technological releases. Further, if a firm adopts technology $\theta_{Bt}$ in period $t$ and no new technology is released in period $t+1$ ($\theta_{Bt} = \theta_{Bt+1}$), then the firm operates with technology $\theta_{Bt}$ in period $t+1$ with probability one. In other words, firms are never allowed to downgrade their current technology.[19]

Let $T_{\theta_{Bt}}$ denote the release date of the best technology available in period $t$. All technologies follow the same cost structure, $C(\Delta_t)$, where $\Delta_t = t - T_{\theta_{Bt}}$ denotes the number of periods since the release of the current best technology. I assume that $C(\Delta_t)$ is a strictly positive, decreasing, and convex function. I also assume that $C(\Delta_t)$ is common knowledge to all firms. Both Fudenberg and Tirole (1985) and Schmidt-Dengler (2006) employ analogous assumptions on $C(\cdot)$. However, in a game with more than one technology the cost function will "reset" each time a new technology is released and then decrease deterministically until the technological frontier is advanced. As I will discuss in greater detail below, the deterministic decrease in costs each period (conditional on technology) complicates both the state space and the resulting equilibrium analysis.

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[18] Through simulations I will show that altering the order in which heterogeneous firms act does not have a significant impact on equilibrium adoption dates.

[19] Anecdotal evidence from the healthcare industry suggests that hospitals with a fixed MRI scanner rarely downgrade their MRI technology.

A game state $\psi_t \in \Psi_t$ is an ordered triple:

$$\psi_t \equiv (t, T_{\theta_{Bt}}, \Theta_{t-1}), \tag{3.10}$$

where $\Theta_{t-1}$ denotes the vector of firms' technologies at the end of the previous period. It is important to note that the state is a function of the time period $t$ and the vector of firm technologies entering period $t$ but not the complete history of actions leading to that point. In other words, only the vector $\Theta_{t-1}$ is payoff relevant entering period $t$, not the dates in which the firms adopted the technologies. However, even though firms enter period $t$ in state $\psi_t$, when called upon to act a firm may face a technology vector different from $\Theta_{t-1}$. Consider a state where all firms enter period $t$ operating with technology $\theta = 1$ and $\theta_{Bt} = 2$. If the first firm to act adopts $\theta = 2$ this alters all of the subsequent firms' incentives to adopt $\theta = 2$ relative to the case where they acted in the state where all firms owned $\theta = 1$. Therefore, the *effective* state for each firm $j$ (other than the first in the adoption order) will be a function of the choices of all firms acting earlier than firm $j$.

The timing of the game is as follows:

1. All firms enter $t = 0$ operating with the "status quo" technology, $\theta = 0$. At the beginning of $t = 0$, $\theta = 1$ is released to the market.

2. At the beginning of the period each firm receives its marginal cost draws $(w_{jt}, \omega_{jt})$ and its idiosyncratic profitability draws $(\zeta_{jt0}, \zeta_{jt1})$, which are defined below. The $\zeta$'s are private information to each firm.

3. Firms sequentially decide whether or not to adopt $\theta = 1$ in a predetermined order. Each firm's adoption decision is public information once it is made. After all firms have made their adoption decisions they engage in the static Bertrand pricing game to determine flow profits. Any firm that adopts $\theta = 1$ must incur the appropriate adoption cost, $C(\Delta_t)$.

4. The game state transitions according to the parameter $\rho$. With probability $\rho$, $\theta = 2$ is released at the beginning of $t = 2$. With probability $1 - \rho$, no new technology is released

at the beginning of period $t = 2$.

5. In period $t = 2$ firms realize their idiosyncratic draws, sequentially make adoption decisions (in the same order), determine flow profits, and the game state transitions.

6. Step 5 is repeated until all $N$ technologies are released. At that point firms continue to make sequential adoption decisions until all firms have adopted $\theta = N$.

In every period $t$, each firm $j$ receives at most two iid Type 1 EV profitability draws, $\zeta_{jt0}$ and $\zeta_{jt1}$. A firm receives both draws if it has not adopted the best technology available, where the "0" subscript corresponds with the decision to not adopt the best technology and the "1" subscript denotes the choice to adopt the technology. If a firm has already adopted the best technology available then it only receives $\zeta_{jt1}$.[20] These $\zeta$'s are private information to each firm and are meant to capture each firm's idiosyncratic preferences for adoption that are unobserved to both competing firms and the econometrician.[21]

Note that I assume $\rho$ is time-invariant and constant across technologies. To simplify the solution algorithm for the dynamic game I assume that $\rho$ is commonly known by all firms at the start of the game.[22] I also assume that $C(\cdot)$ decreases sufficiently so that all firms have an incentive to adopt $\theta = N$ in finite time.[23] Finally, I make the sequential moves assumption to

[20]Note that the "0" and "1" subscripts are simply used for clarification when I write the value functions for adopting versus not adopting later in this section. If a firm has yet to adopt the best technology available then only the difference between $\zeta_{jt1}$ and $\zeta_{jt0}$ is relevant in its decision-making process (not the actual values of the two draws). If a firm has already adopted the best technology available then it does not make any decisions until an even better technology is released (since I prevent firms from downgrading).

[21]Since the $\zeta$'s are additive it is also straightforward to interpret them as "adoption cost shocks" instead of profitability shocks (i.e. a higher value of $\zeta_{jt1} - \zeta_{jt0}$ would correspond with a lower idiosyncratic cost of adopting a new technology). In future extensions I hope to consider serial correlation in the $\zeta$'s for each individual firm and within-market correlation. The current specification is employed to simplify the solution algorithm for the dynamic game.

[22]In essence, this assumption coupled with the known functional form of $C(\Delta_t)$ imply that I am abstracting from all strategic behavior on the part of technology manufacturers. The adopting firms take the technological innovation process as exogenous and can perfectly anticipate the value of future advancements. The only uncertainty surrounds the release dates of technologies $\theta = 2, \ldots, N$. Forcing firms to develop subjective beliefs about technology release dates or values would severely complicate the equilibrium analysis.

[23] Let $\pi_{Lt}(N-1)$ denote the flow profit of the firm with the *least* incentive to adopt the last

eliminate multiplicity and simplify the algorithm necessary to solve for the full equilibrium of the dynamic game. Schmidt-Dengler (2006) makes the same assumption and shows that the order of moves in each period is largely irrelevant. I imagine (and will check) that this notion also holds in my game where firms act with asymmetric information about their competitors' adoption decisions.

Let firm $j$'s strategy in period $t$ be a mapping between states and actions. Formally:

$$\sigma_{jt} : \psi_t \rightarrow A_{jt}(\psi_t). \tag{3.11}$$

I focus exclusively on pure strategies and define firm $j$'s strategy at all points in time as $\boldsymbol{\sigma_j}$. In this context a pure strategy Markov perfect equilibrium is a set of strategies $\{\boldsymbol{\sigma_1}, \boldsymbol{\sigma_2}, \ldots, \boldsymbol{\sigma_J}\}$ that is a subgame-perfect Nash equilibrium in the continuation game beginning in every $\psi_t \in \Psi_t$. The assumption that firms act sequentially in each period coupled with the idiosyncratic $\zeta$'s (which generically ensure that no firm will ever be indifferent between adopting and not adopting in any period) generate a unique equilibrium outcome to the dynamic game. It is important to note that I am focusing on a specific type of Markov perfect equilibrium where firms set prices myopically. Given this assumption I take advantage of the "static-dynamic breakdown" in the game and calculate flow profit levels in a first step before solving for the full dynamic technology adoption equilibrium.[24]

---

technology when all other firms except $L$ have already adopted $\theta = N$. Let $\pi_{Lt}(N)$ denote the least profitable firm's profit after adopting the last technology. In other words, let firm $L$ be the one with the smallest value of $\pi_{Lt}(N) - \pi_{Lt}(N-1)$. The assumption requires that there exists a $t$ such that $\pi_{Lt}(N) - \pi_{Lt}(N-1) + (\zeta_{Lt1} - \zeta_{Lt0}) > C(\Delta_t) - \beta C(\Delta_{t+1})$. In a deterministic setting where the $\pi(\cdot)$'s are constants and the $\zeta$'s equal zero it is straightforward to solve for the first $t$ that satisfies this condition. In the current setting the presence of marginal cost shocks result in $pi(\cdot)$'s that are time-varying which can cause the identity of the least profitable firm to change each period, complicating the process of determining the last period of the game. However, as $t$ increases, the fact that $C(\cdot)$ is both decreasing and convex, coupled with the iid profitability draws, suggests that the probability of receiving a high enough value of $(\zeta_{Lt1} - \zeta_{Lt0})$ to induce adoption approaches one. In other words, the right-hand side of the aforementioned inequality decreases with time and the support of distribution from which the $\zeta$'s are drawn is unbounded. Combining these two facts, the probability of receiving a value of $(\zeta_{Lt1} - \zeta_{Lt0})$ favorable enough to induce adoption must increase as $t$ increases.

[24]The use of static pricing strategies is prevalent in the majority of computational models of dynamic oligopoly in the industrial organization literature, such as in Ericson and Pakes (1995), where firms make dynamic entry/exit and investment decisions but play a static pricing equilibrium in each period.

The date-dependent nature of $C(\Delta_t)$ and the resulting inclusion of $t$ in the state space forces me to solve for the full backwards-induction solution to the dynamic game. The solution method to the standard Ericson and Pakes (1995) dynamic oligopoly model is developed in Pakes and McGuire (1994) (and discussed in Doraszelski and Pakes (2007)). The algorithm uses value function iteration to solve for the fixed point of both an expected value function and a policy function, for every firm, *in each potential state.* Given that each state is date-dependent in my model, employing this algorithm would force me to solve for an exorbitantly large number fixed points which is likely computationally intractable. Instead, I simply fix an ending point to the game, solve for each firm's best response by comparing the values of adopting and not adopting, calculate expected continuation values conditional on these choices, and carry this process backward until the beginning of the game. In essence, the fact that each $\psi_t$ is a function of $t$ prohibits me from grouping states into equivalence classes and bounding the size of the state space. Thus, as the number of technologies and/or firms grows, the model suffers from a curse of dimensionality.

Given the timing and specification of the model, the Bellman equation can be written as:

$$\begin{aligned} V_j(\psi_t) = \max_{a_{jt} \in A_{jt}} & - \mathbb{1}_{[a_{jt}=\theta_{Bt} \text{ \& } a_{jt-1} \neq \theta_{Bt}]} C(\Delta_t) + \zeta_{jta_{jt}} + \\ & E_{\zeta_{\bar{j}t}} \left[ \pi_{jt}(a_{jt}, \Theta^*_{-jt}) + \beta[\rho EV_j(t+1, T_{\theta_{Bt}+1}, \Theta^*_t) + \right. \\ & \left. (1-\rho) EV_j(t+1, T_{\theta_{Bt}}, \Theta^*_t)]\right], \end{aligned} \tag{3.12}$$

where $\beta$ is the common discount factor, $\rho = 0$ for all $t \geq T_N$, $\mathbb{1}_{[\cdot]}$ is an indicator function that equals one if the firm upgrades its technology, and in a slight abuse of notation, $\zeta_{jta_{jt}} = \zeta_{jt0}$ if the firm chooses not to adopt $\theta_{Bt}$ and $\zeta_{jta_{jt}} = \zeta_{jt1}$ if it adopts or has previously adopted $\theta_{Bt}$. I define $\Theta^*_{-jt}$ as a $(J-1) \times 1$ vector containing the equilibrium actions of all firms but $j$ in period $t$ such that $\Theta^*_{-jt} = (a_{1t}, a_{2t}, \ldots, a_{(j-1)t}, a_{(j+1)t}, \ldots, a_{Jt})$. Similarly, $\Theta^*_t$ is a $J \times 1$ vector including all firms' equilibrium actions in period $t$ (including $j$). The $\zeta$'s generate an information asymmetry so that when each firm (except the last) acts in order, it must form

A notable exception is Goettler and Gordon (2011), in which competing firms make dynamic pricing and R&D investment decisions in a durable goods market.

an expectation, $E_{\zeta_{\bar{j}t}}(\cdot)$, about the equilibrium flow profit it will attain in the current period and the technology vector that will transition into the next period $(\Theta_t^*)$.[25] This expectation is only taken over the set of firms moving *after* $j$, which I denote as $\bar{j}$.

### 3.2.3 Backwards-Induction Algorithm

In this section I discuss the backwards-induction algorithm utilized to solve for the unique Markov perfect equilibrium of the dynamic game where firms act sequentially in each period but with asymmetric information regarding competitors' profitabilities. I discuss the three-firm case because it is sufficient and notationally much less cumbersome. To further simplify the exposition I also assume that conditional on the vector of firms' technologies, flow profits are time-invariant.[26] Without loss of generality I assume that in each period firm 1 moves first, firm 2 moves second, and firm 3 moves third. As discussed in footnote 23, it is not straightforward to solve for the "final" period of this dynamic game due to the profitability shocks ($\zeta$). Schmidt-Dengler (2006) assumes flow profits are such that all firms can be ranked according their marginal benefit of adoption. This, coupled with a decreasing returns assumption (i.e. the marginal increase in flow profit is always greater for an individual firm if it adopts $(n-1)$-th rather than $n$-th) and no uncertainty imply that the last (potential) period of the game can be calculated as the earliest point in time when the least profitable firm would choose to adopt the new technology, conditional on it being the last adopter. In contrast, I make no assumptions on the flow profit function that would allow me to rank firms in a similar manner. Further, even if I could rank firms by marginal increase in flow profit from adoption, the presence of the $\zeta$'s could change this ranking each period. To alleviate this issue I simply assume that at some point in time far after the release of each technology $\theta = 1, 2, \ldots, N$, $C(\Delta_t)$ has declined sufficiently so that all firms have a strictly dominant strategy to adopt $\theta$. For $\theta = N$, this

[25] In an alternative specification it could be assumed that there is a one period lag between the date when a technology is adopted and the date when it is implemented. In this case a firm's flow profit in period $t$ would be a function of $\Theta_{t-1}$ and each firm would know its flow profit when making its adoption decision. While this specification might quantitatively alter firms' equilibrium adoption dates it would not qualitatively distort the dynamics of the model.

[26] This is equivalent to assuming that $\omega_{jt} = 0 \forall j, t$ and $w_{jt}$ and $x_{jt}$ are both constant across time.

assumption allows me to generate an ending point to the game. For $\theta = 1, 2, \ldots, N-1$, the assumption enables me to calculate "pseudo-continuation values" that are necessary for the algorithm.

Let $\overline{T}_\theta$ define the "end date" for technology $\theta$ at which point all firms will adopt the technology if they haven't done so already. Also, let $\pi_j(a_{1t}, a_{2t}, a_{3t})$ denote firm $j$'s flow profit given the three firms' technology choices in the current period $t$. Suppose firm $j$ has not adopted $\theta = N$ entering period $\overline{T}_N$. In this case firm $j$'s value is given by:

$$V_j(\psi_{\overline{T}_N}) = \pi_j(N, N, N) - C(\Delta_{\overline{T}_N}) + \zeta_{j\overline{T}_N 1} + \beta EV_j(\overline{T}_N + 1, T_N, (N, N, N)). \tag{3.13}$$

The value for a firm entering period $\overline{T}_N$ having already adopted $\theta = N$ is the same as in (3.13) less the cost term. Employing the logit inclusive value property, $EV_j(\overline{T}_N + 1, T_N, (N, N, N))$ is given by:

$$EV_j(\overline{T}_N + 1, T_N, (N, N, N)) = \ln \left[ \exp(\pi_j(N, N, N) + \beta EV_j(\overline{T}_N + 2, T_N, (N, N, N))) \right]. \tag{3.14}$$

Beginning in period $\overline{T}_N + 1$ actions are stationary because all firms have adopted $\theta = N$ and can take no further action. As a result, it must be that the expected continuation values are equal in all periods beginning in $\overline{T}_N + 1$:

$$EV_j(\overline{T}_N + 1, T_N, (N, N, N)) = EV_j(\overline{T}_N + 2, T_N, (N, N, N)) = \frac{\pi_j(N, N, N)}{1 - \beta}. \tag{3.15}$$

Given these expected continuation values, (3.13) can now be calculated for all firms and all states entering period $\overline{T}_N$. Additionally, from the perspective of period $\overline{T}_N - 1$ it is now possible to calculate $EV_j(\overline{T}_N, T_N, \Theta_{\overline{T}_N - 1})$ as

$$\begin{aligned} EV_j(\overline{T}_N, T_N, \Theta_{\overline{T}_N - 1}) = \ln \Bigg[ \exp \Bigg[ & \pi_j(N, N, N) - \mathbb{1}_{\left[a_{j\overline{T}_N - 1} \neq N\right]} C(\Delta_{\overline{T}_N}) + \\ & \beta EV_j(\overline{T}_N + 1, T_N, (N, N, N)) \Bigg] \Bigg]. \end{aligned} \tag{3.16}$$

I can now initiate the backwards-induction algorithm in period $\overline{T}_N - 1$ by solving for the probability that firm 3 adopts $\theta = N$ in every state. Recall that firm 3 moves last in each period and as a result, its information set includes $\psi_{\overline{T}_N-1}$ plus the actions of firms 1 and 2 *in the current period*. Consider a state $\psi_{\overline{T}_N-1}$ where firm 3 has yet to adopt $\theta = N$. The firm compares the value of adopting:

$$\begin{aligned}V_3(a_{3\overline{T}_N-1} = N|\psi_{\overline{T}_N-1}, a_{1\overline{T}_N-1}, a_{2\overline{T}_N-1}) =&\pi_3(a_{1\overline{T}_N-1}, a_{2\overline{T}_N-1}, N) - C(\Delta_{\overline{T}_N-1}) + \zeta_{3,\overline{T}_N-1,1}+\\ &\beta EV_3(\overline{T}_N, T_N, (a_{1\overline{T}_N-1}, a_{2\overline{T}_N-1}, N)),\end{aligned} \tag{3.17}$$

with the value of not adopting,

$$\begin{aligned}V_3(a_{3\overline{T}_N-1} = a_{3\overline{T}_N-2}|\psi_{\overline{T}_N-1}, a_{1\overline{T}_N-1}, a_{2\overline{T}_N-1}) =&\pi_3(a_{1\overline{T}_N-1}, a_{2\overline{T}_N-1}, a_{3\overline{T}_N-1}) + \zeta_{3,\overline{T}_N-1,0}+\\ &\beta EV_3(\overline{T}_N, T_N, (a_{1\overline{T}_N-1}, a_{2\overline{T}_N-1}, a_{3\overline{T}_N-1})).\end{aligned} \tag{3.18}$$

I define the deterministic portion of the value function as $\overline{V}_3(\cdot|\cdot)$ so that

$$\overline{V}_3(a_{3\overline{T}_N-1}|\psi_{\overline{T}_N-1}, a_{1\overline{T}_N-1}, a_{2\overline{T}_N-1}) = V_3(a_{3\overline{T}_N-1}|\psi_{\overline{T}_N-1}, a_{1\overline{T}_N-1}, a_{2\overline{T}_N-1}) - \zeta_{3,\overline{T}_N-1}. \tag{3.19}$$

Since the $\zeta$'s are distributed Type I EV, the conditional probability that firm 3 adopts $\theta = N$ in $t = \overline{T}_N - 1$ is

$$\mathbf{Pr}_3(a_{3t} = N|\psi_t, a_{1t}, a_{2t}) = \frac{\exp(\overline{V}_3(a_{3t} = N|\psi_t, a_{1t}, a_{2t}))}{\sum\limits_{z\in A_{3t}} \exp(\overline{V}_3(a_{3t} = z|\psi_t, a_{1t}, a_{2t}))}, \tag{3.20}$$

and $\mathbf{Pr}_3(a_{3t} \neq N|\cdot) = 1 - \mathbf{Pr}_3(a_{3t} = N|\cdot)$. If firm 3 has already adopted $\theta = N$ then $\mathbf{Pr}_3(a_{3t} = N|\cdot) = 1$. Since firm 2 does not know the realization of firm 3's $\zeta$'s when it acts, it must integrate out over firm 3's conditional choice probabilities when deciding whether or not to adopt $\theta = N$. Thus,

$$\mathbf{Pr}_2(a_{2t} = N|\psi_t, a_{1t}) = \frac{\exp\left[\sum_{z\in A_{3t}} \left[\mathbf{Pr}_3(a_{3t} = z|\psi_t, a_{1t}, a_{2t} = N)\overline{V}_2(a_{2t} = N|\psi_t, a_{1t}, a_{3t} = z)\right]\right]}{\sum_{y\in A_{2t}} \exp\left[\sum_{z\in A_{3t}} \left[\mathbf{Pr}_3(a_{3t} = z|\psi_t, a_{1t}, a_{2t} = y)\overline{V}_2(a_{2t} = y|\psi_t, a_{1t}, a_{3t} = z)\right]\right]}. \tag{3.21}$$

I let $y$ and $z$ denote firm 2 and firm 3's potential actions, respectively. Firm 2's expected value from adoption is a weighted average where the weights are firm 3's conditional choice probabilities. Note that $\overline{V}_2(\cdot|\cdot)$ is conditional on firm 3's technology choice, *even though firm 3 has yet to act*. Similarly, firm 1's conditional choice probabilities are a function of both firm 2 and firm 3's probabilities and its choice-specific value is conditional on both firm 2 and 3's subsequent actions:

$$\mathbf{Pr}_1(a_{1t} = N|\psi_t) = \frac{\exp\left[\sum_{y\in A_{2t}}\sum_{z\in A_{3t}} \left[\mathbf{Pr}_2(a_{2t} = y|\psi_t, a_{1t} = N)\cdot\right.\right.}{\sum_{x\in A_{1t}} \exp\left[\sum_{y\in A_{2t}}\sum_{z\in A_{3t}} \left[\mathbf{Pr}_2(a_{2t} = y|\psi_t, a_{1t} = x)\cdot\right.\right.} \cdots$$

$$\cdots \frac{\left.\left.\mathbf{Pr}_3(a_{3t} = z|\psi_t, a_{1t} = N, a_{2t} = y)\overline{V}_1(a_{1t} = N|\psi_t, a_{2t} = y, a_{3t} = z)\right]\right]}{\left.\left.\mathbf{Pr}_3(a_{3t} = z|\psi_t, a_{1t} = x, a_{2t} = y)\overline{V}_1(a_{1t} = x|\psi_t, a_{2t} = y, a_{3t} = z)\right]\right]}, \tag{3.22}$$

where firm 1's potential actions are denoted by $x$. I calculate these conditional choice probabilities for each $\psi_t$ and all permutations of the firms' potential actions in period $\overline{T}_N - 1$. Given these probabilities I can calculate the expected continuation values for period $\overline{T}_N - 1$ from the viewpoint of period $\overline{T}_N - 2$. The standard logit inclusive value term must be augmented with the conditional choice probabilities that I just calculated. To better explain the intuition underlying these continuation values, suppose period $\overline{T}_N - 1$ begins in some state $\psi_{\overline{T}_N - 1}$. Firm 1 makes its adoption decision in this state with probability one. However, after making its adoption decision, its flow profit in period $\overline{T}_N - 1$ is contingent on firm 2 and 3's decisions. Firm 2's situation is slightly different. Firm 1's action dictates the state it faces when called to act and firm 3's action determines its flow profit. Finally, firm 3's "state" is a function of both firm 1 and firm 2's choices but its flow profit for each choice is known with certainty. Put differently, the firm moving first knows with certainty the existing state of the world when acting but not its ultimate payoff from any action. The firm moving last is faced with the exact opposite situation–it is uncertain what state it will face when called to act but knows with certainty the outcome (in terms of flow profits) resulting from its decision. A firm moving not first or last is subjected to both types of uncertainty. The expected continuation values for all three firms are shown below:

$$EV_1(\psi_t) = \ln\left[\sum_{x\in A_{1t}} \exp\left[\sum_{y\in A_{2t}}\sum_{z\in A_{3t}} \mathbf{Pr}_2(a_{2t}=y|\psi_t, a_{1t}=x)\mathbf{Pr}_3(a_{3t}=z|\psi_t, a_{1t}=x, a_{2t}=y)\cdot \right.\right.$$
$$\left.\left. \overline{V}_1(a_{1t}=x|\psi_t, a_{2t}=y, a_{3t}=z)\right]\right], \tag{3.23}$$

$$EV_2(\psi_t) = \sum_{x\in A_{1t}} \mathbf{Pr}_1(a_{1t}=x|\psi_t) \ln\left[\sum_{y\in A_{2t}} \exp\left[\sum_{z\in A_{3t}} \mathbf{Pr}_3(a_{3t}=z|\psi_t, a_{1t}=x, a_{2t}=y)\cdot \right.\right.$$
$$\left.\left. \overline{V}_2(a_{2t}=y|\psi_t, a_{1t}=x, a_{3t}=z)\right]\right], \tag{3.24}$$

$$EV_3(\psi_t) = \sum_{x\in A_{1t}}\sum_{y\in A_{2t}} \mathbf{Pr}_1(a_{1t}=x|\psi_t)\mathbf{Pr}_2(a_{2t}=y|\psi_t, a_{1t}=x, a_{2t}=y)\cdot$$
$$\ln\left[\sum_{z\in A_{3t}} \exp\left[\overline{V}_3(a_{3t}=z|\psi_t, a_{1t}=x, a_{2t}=y)\right]\right]. \tag{3.25}$$

Now the expected continuation values for period $\overline{T}_N - 1$ are fully characterized from the perspective of $\overline{T}_N - 2$. I can continue this process of solving for the conditional choice probabilities and continuation values recursively for all periods $t = \overline{T}_N - 2, \overline{T}_N - 3 \ldots, T_N$. Next, consider period $T_N - 1$. I illustrate the timing and transition in this period in Figure 3.1 where

$t = T_N - 1$. Once all three firms have acted and flow profits are realized, there is uncertainty

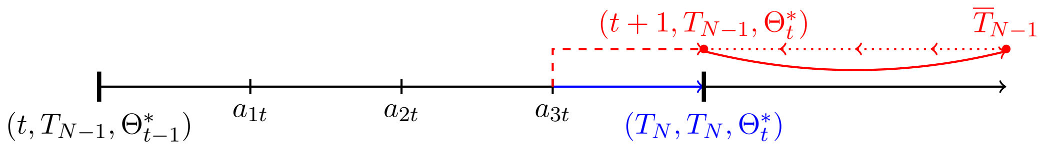


Figure 3.1: Calculating Expected Continuation Values in $T_N - 1$

regarding whether or not $\theta = N$ will be released in the next period. All firms believe that it will be released in the subsequent period with probability $\rho$ (denoted by the blue line), so that the state transitions to $(T_N, T_N, \Theta^*_{T_N-1})$. With probability $(1-\rho)$, the firms believe that they will transition to state $(t+1, T_{N-1}, \Theta^*_{T_N-1})$, where the final technology is not released (indicated by the red dashed line). Ex ante I know that the release date of $\theta = N$ occurs in period $T_N$ so that the state transitions according to the blue line. And, through the backwards-induction algorithm I have already calculated expected continuation values associated with state $(T_N, T_N, \Theta^*_{T_N-1})$. So, while the "red state" $(t+1, T_{N-1}, \Theta^*_{T_N-1})$ can obviously never be reached, I still need to calculate the "pseudo-continuation value," $EV_j(T_N, T_{N-1}, \Theta^*_{T_N-1})$, to proceed with the backwards-induction algorithm. To perform this task I define $\overline{T}_{N-1}$ as the "end date" for technology $\theta = N-1$ when, if hypothetically reached, all firms have a strictly dominant strategy to adopt $\theta = N-1$. In other words, if, hypothetically, $\theta = N$ was not released in all periods $t = T_N, T_N+1, \ldots, \overline{T}_{N-1}$, all firms would find it optimal to adopt $\theta = N-1$ in $\overline{T}_{N-1}$ (if they had not already adopted the technology by that time). So, I move forward to this hypothetical point in time and then recursively work backwards until I reach $T_N$. Suppose firm $j$ enters $t = \overline{T}_{N-1}$ having not adopted $\theta = N-1$. Similarly to (3.13), firm $j$'s value in the period is:

$$\begin{aligned} V_j(\psi_{\overline{T}_{N-1}}) =& \pi_j(N-1, N-1, N-1) - C(\Delta_{\overline{T}_{N-1}}) + \zeta_{j\overline{T}_{N-1}1} + \\ & \beta \left[ \rho EV_j(T_N, T_N, (N-1, N-1, N-1)) \right. \\ & \left. (1-\rho) EV_j(\overline{T}_{N-1}+1, T_{N-1}, (N-1, N-1, N-1)) \right], \end{aligned} \tag{3.26}$$

where $EV_j(T_N, T_N, (N-1, N-1, N-1))$ has already been calculated in the backwards-induction process. Due to the fact that actions are stationary in all hypothetical periods $t = \overline{T}_{N-1}, \overline{T}_{N-1}+1, \dots$ until $\theta = N$ is released, it can be shown that

$$
\begin{aligned}
EV_j(\overline{T}_{N-1}+1, T_{N-1}, (N-1, N-1, N-1)) =& EV_j(\overline{T}_{N-1}+2, T_{N-1}, (N-1, N-1, N-1)) \\
=& \frac{\pi_j(N-1, N-1, N-1) + \beta\rho EV_j(T_N, T_N, (N-1, N-1, N-1))}{1-\beta(1-\rho)}. \qquad (3.27)
\end{aligned}
$$

This expected continuation value differs from (3.15) because here each firm only continues to receive a flow profit of $\pi_j(N-1, N-1, N-1)$ as long as $\theta = N$ is not released (and this event occurs with probability $(1-\rho)$ in each period). Now that (3.26) is fully characterized, I can begin the backwards-induction process of calculating conditional choice probabilities and expected continuation values in the hypothetical period $\overline{T}_{N-1} - 1$ and continue the process backward until reaching period $T_N$. Again, defining $\overline{V}_j(\cdot|\cdot)$ as firm $j$'s value less the $\zeta$ shock, the conditional choice probabilities can be calculated using the same equations (3.20)–(3.22). The expected continuation values are similar to equations (3.23)–(3.25) except that there is now an additional term due to the uncertain state transition. Slightly abusing notation, let $\widetilde{EV}_j(\psi_t, \widetilde{\psi}_t)$ be the "total" expected continuation value for firm $j$ in period $t$ (from the perspective of period $t-1$) *prior to knowing whether or not a new technology is released in* $t$. Let $\psi_t$ be the state where a new technology is *not* released in period $t$ and $\widetilde{\psi}_t$ denote the state where a new technology *is* released. Then,

$$
\begin{aligned}
\widetilde{EV}_1(\psi_t, \widetilde{\psi}_t) =& \rho EV_1(\widetilde{\psi}_t) + (1-\rho)\ln\left[\sum_{x\in A_{1t}} \exp\left[\sum_{y\in A_{2t}}\sum_{z\in A_{3t}} \mathbf{Pr}_2(a_{2t}=y|\psi_t, a_{1t}=x)\cdot\right.\right. \\
&\left.\left.\mathbf{Pr}_3(a_{3t}=z|\psi_t, a_{1t}=x, a_{2t}=y)\overline{V}_1(a_{1t}=x|\psi_t, a_{2t}=y, a_{3t}=z)\right]\right], \qquad (3.28)
\end{aligned}
$$

$$
\begin{aligned}
\widetilde{EV}_2(\psi_t, \widetilde{\psi}_t) =& \rho EV_1(\widetilde{\psi}_t) + (1-\rho)\left[\sum_{x\in A_{1t}} \mathbf{Pr}_1(a_{1t}=x|\psi_t)\ln\left[\sum_{y\in A_{2t}} \exp\left[\sum_{z\in A_{3t}}\right.\right.\right. \\
&\left.\left.\left.\mathbf{Pr}_3(a_{3t}=z|\psi_t, a_{1t}=x, a_{2t}=y)\cdot\overline{V}_2(a_{2t}=y|\psi_t, a_{1t}=x, a_{3t}=z)\right]\right]\right], \qquad (3.29)
\end{aligned}
$$

$$\widetilde{EV}_3(\psi_t, \widetilde{\psi}_t) = \rho EV_1(\widetilde{\psi}_t) + (1-\rho)\left[\sum_{x \in A_{1t}} \sum_{y \in A_{2t}} \mathbf{Pr}_1(a_{1t} = x|\psi_t)\mathbf{Pr}_2(a_{2t} = y|\psi_t, a_{1t} = x, a_{2t} = y) \cdot \right.$$
$$\left. \ln\left[\sum_{z \in A_{3t}} \exp\left[\overline{V}_3(a_{3t} = z|\psi_t, a_{1t} = x, a_{2t} = y)\right]\right]\right]. \tag{3.30}$$

I recursively calculate these conditional choice probabilities and expected "total" continuation values in all $t = \overline{T}_{N-1} - 1, \ldots, T_N$ (the dotted red line in Figure 3.1). At that point I have fully characterized each firm's expected continuation value in period $T_N$ (from the perspective of period $T_N - 1$). Given this value I can continue the backwards-induction process for periods $t = T_N - 1, \ldots, T_{N-1}$. I then repeat the process for all earlier technologies until I reach $t = 0$, at which point I have calculated each firm's conditional choice probability and expected continuation value in every state of the game. Next, I draw values of $\zeta_{jt0}$ and $\zeta_{jt1}$ for each firm in each period and simulate choices under (3.12) in every state. Finally, I start in period 0 in state $\psi_0 = (0, 0, (0, 0, 0))$ and work forward, noting each firm's optimal action and transitioning the state accordingly, to generate the unique Markov perfect equilibrium of the game.

### 3.2.4 Simulations

To illustrate the equilibrium properties of the dynamic game I run a variety of simulations with different parameterizations of the model. Not surprisingly, different parameterizations yield different equilibrium outcomes. In certain instances firms exhibit "leap-frogging" behavior while in others a single firm may preempt its competitors in the adoption of all of the technologies. Further, shifting different parameters can cause adoption dates to be more condensed or dispersed. In what follows I use the "base" parameterization summarized in Table 3.1. Notice that since $\phi_2 = \xi_j = \omega_{jt} = 0$ and $x_{jt}$ is constant across firms and time, this implies that firms are *ex-ante identical.* In fact, the only way that firms differ is in their predetermined order of moves and $\zeta$ draws each period. $RD(\theta = n)$ denotes the "release date" of $\theta = n$, so here new technologies are released at ten-period intervals. The firms' commonly held belief that a new technology will be released in each period ($\rho$) is "consistent" in the sense

| ***Parameter(s)*** | ***Value*** |
|---:|---:|
| $\phi_2$, $\xi_j$, $\omega_{jt}$ | 0 |
| $\phi_0$, $\phi_1$, $\alpha$, $\tau$, $x_{jt}$ | 1 |
| $\gamma$ | 6 |
| $\rho$ | 0.1 |
| $\beta$ | 0.95 |
| $RD(\theta = 2)$ | 10 |
| $RD(\theta = 3)$ | 20 |
| $C(\Delta_t)$ | $10/\sqrt{1+\Delta_t}$ |

Table 3.1: Base Parameterization

that the mean of the geometric distribution defined by $\rho$ is equal to the actual release date of each technology. Here, the chosen adoption cost function is consistent with the assumptions discussed in Schmidt-Dengler (2006). Table B.1 summarizes the calculated flow profit values for $1 \leq J \leq 3$ using the base parameterization.[27]

Tables B.2–B.3 summarize the results of 1,000 simulations using the base parameterization for different market sizes ($J$) and number of technologies ($N$). It is important to note that in Table B.2 firms are ordered by the exogenous *order of moves*. In other words, $j = 1$ denotes the firm acting first in each period, $j = 2$ denotes the firm moving second, and so on. While Table B.3 summarizes the same results as in Table B.2, firms are now ordered by the *order of adoption*. Here, $j = 1$ denotes the first firm to adopt a technology, $j = 2$ denotes the second firm to adopt, and so on. As an example, consider a duopoly market ($J = 2$) where the second firm to act in each period is the first adopter of a new technology. In Table B.2 the firm will contribute to the $j = 2$ columns because it moves second in each period. However, since it is

[27]The simulated flow profits satisfy some but not all of the assumptions in Schmidt-Dengler (2006). In both cases adoption is rivalrous but always increases the flow profit of the adopting firm. Additionally, there are "decreasing returns" in the sense that the marginal increase in flow profit from adopting is always smaller as the vector of competitors' technologies improves. However, unlike Schmidt-Dengler (2006), here I cannot exactly rank firms in a "profitability order." In other words, due to the time-varying $\zeta$-draws, the ranking of each firm's marginal benefit of adoption can vary by period. This randomness undoubtedly generates a much larger set of potential equilibrium outcomes than the Schmidt-Dengler (2006) model for a given parameterization. Put differently, fixing the parameterization, different realizations of the $\zeta$'s can potentially generate different equilibrium outcomes while in Schmidt-Dengler (2006), conditional on the parameterization an equilibrium is unique. Further, Schmidt-Dengler (2006) does not provide any simulated equilibria for different market structures that I could use as a basis for comparison here.

the first adopter, it will contribute to the $j = 1$ column in Table B.3. First consider Table B.3 where $N = 1$. On average, a monopolist adopts the new technology 1.53 periods after its release. In a duopoly market the preemption incentive drives the first adopter to adopt the technology relatively sooner (0.70). However, this preemption incentive is mitigated by the addition of competing firms. The marginal increase in flow profit for the first adopter in a duopoly is 1.37 and this value decreases to 1.21 in a triopoly. This, coupled with the fact that the first adopter's window of "monopoly power" is shortened, lessen the benefit of adopting first. As a result, adopting first does not warrant paying as high a cost as it does in a duopoly market. Once a fourth firm is added to the market the first adopter actually adopts later than a monopolist (on average).

The addition of a second technology ($N = 2$) further decreases competing firms' incentives to preempt, as is evidenced by the increase in the first adopter's average adoption date of $\theta = 1$. Again consider the duopoly case. When the leading firm adopts $\theta = 1$ it forms an expectation regarding the following firm's optimal adoption date for $\theta = 1$. However, it is uncertain how long it will be able to earn rents at its competitor's expense because with probability $\rho$, $\theta = 2$ is released in the subsequent period and a new adoption game commences. This uncertainty decreases the preemption incentive and, on average, drives the leading firm to adopt slightly later. Stated differently, the leading firm hedges against the additional risk posed by the potential release of a better technology by waiting and paying a lower cost for the current technology.[28] As a result, a model with only one new technology will tend to *overstate* the importance of the preemption incentive relative to a game with multiple advancements. In addition to the leading firm adopting later, the follower's average adoption date is earlier due to the fact that it only adopts $\theta = 1$ roughly 92% of the time (in essence, instances where $\theta = 2$ is released before the follower would optimally adopt $\theta = 1$ are being truncated). In the remaining 8% of the simulations, firms enter period $T_2$ in an asymmetric state where only one firm has adopted $\theta = 1$. In these states, the marginal increase in flow profit from adopting

[28]While Figure B.2 shows that the average adoption date of $\theta = 1$ across all firms is increasing in $\rho$, this relationship also holds for the leading firm's average adoption date alone. As $\rho$ increases the expected benefit from adopting relatively early shrinks, so firms are only willing to adopt $\theta = 1$ at a lower cost.

$\theta = 2$ is greater for the firm that has not adopted $\theta = 1$ (1.3 versus 1.1), which leads the $j = 2$ firm's average adoption date of $\theta = 2$ to come slightly before that of the $j = 1$ firm. This property is even more apparent in markets with additional firms ($J = 3$ and $J = 4$).

Tables B.4–B.5 are the analogs of Tables B.2–B.3 where each firm $j$ is now differentiated by its time-invariant value of $\xi_j \sim N(0, 1)$. Comparing Table B.2 with Table B.4 it is evident that the addition of time-invariant heterogeneity limits the importance of the imposed order of moves on the equilibrium outcome of the game, especially in the adoption of $\theta = 1$ (i.e. the average adoption dates and number of adoptions are closer in value across firms). However, a comparison of Table B.3 with Table B.5 illustrates that the equilibrium outcomes generated under the two parameterizations are significantly different. In particular, the heterogeneity generates a "ranking" of the firms' profitabilities that persists across technologies, so that the firm adopting $\theta = 1$ first will also likely adopt $\theta = 2$ and $\theta = 3$ before its competitors. Not surprisingly, the heterogeneity also creates greater variance in the average adoption dates across firms for a given technology.

Figure B.1 demonstrates how the uptake of $\theta = 1$ varies across different market structures with heterogeneous firms. Each line is a plot of the cumulative probability that $\theta = 1$ is adopted by period $t$ for a different market structure. As discussed in the homogenous firm case, fixing the number of technologies the duopoly market is first-order stochastically dominated by all other-sized markets. Fixing the number of firms, uptake is faster in the single technology game relative to the model with two technologies.

In general there is a large amount of adoption in the simulations run using the base parameterization. As a result, Tables B.6–B.9 recreate the results in Tables B.2–B.5 assuming that new technologies are released more quickly. Specifically, I assume that the new technologies are now released at five-period intervals (instead of ten-period intervals) and calibrate $\rho$ accordingly ($\rho = 0.2$). All other parameters of the model remain unchanged. When $N = 1$ the two sets of simulations are equivalent and the only difference across specifications in the average adoption dates and total number of adoptions is due to randomness in the $\zeta$'s and $\xi$'s (where applicable). For $N > 1$ there is less adoption of all technologies except $\theta = N$ when the time between release dates is shortened. Further, this difference is more pronounced as the number of firms increases. For instance, comparing Table B.2 with Table B.6, with $J = 1$ and $N = 3$ there is 90% as much adoption of $\theta = 1$ and $\theta = 2$ in the five-period-interval simulations compared with the ten-period-interval simulations. With $J = 3$, that percentage drops to 57%. The benefit from adopting a new technology is smaller in markets with more firms and when release dates are condensed this leads to fewer overall adoptions. Also, with less overall adoption of $\theta = 1$ and $\theta = 2$, $\theta = 3$ is adopted relatively earlier in the five-period-interval simulations. With heterogeneous firms the adoption patterns are roughly similar in both sets of simulations.

Figures B.2 and B.3 illustrate two comparative statics exercises where I vary the values of $\rho$ and the functional form of $C(\cdot)$, respectively. On average the first technology is adopted later as the common belief that a new technology will be released increases. If there is a greater probability of transitioning to state $\psi_t = (t, T_2, \Theta_{t-1})$ where a new game commences then the benefit from adopting $\theta = 1$ falls. Therefore, adopting $\theta = 1$ is only warranted at a lower cost. This is especially true in a monopoly market void of competitive pressures which dampen the benefit from adoption. Finally, Figure B.3 depicts the average adoption dates for the leader and follower (along the left vertical axis) and the average number of adoptions (along the right vertical axis) of $\theta = 1$ in duopoly markets with two technologies, for different cost structures. A lower value of $x$ denotes a relatively flatter cost function while a higher value is associated with a function that initially decreases faster. In the limiting case where $x = 0$ the cost of adopting a new technology is constant through time. When $x = 0$ there is no benefit from waiting to adopt and the preemption incentive drives a firm to adopt immediately.[29] The remaining firm only adopts $\theta = 1$ if it receives a very profitable $\zeta_1$ draw–otherwise it simply waits for the second technology to be released. As $x$ increases the difference between the leader's and follower's average adoption dates decreases.[30] If costs decrease faster then preemption becomes

[29]The average adoption date for the leader is slightly larger than zero because in some simulations both firms have low values of $(\zeta_1 - \zeta_0)$ in period 0 and neither firm finds it optimal to adopt the technology in that period.

[30]The initial increase in the follower's average date is due to the fact that its average date in the $x = 0$ case is essentially random. When $x = 1$ the follower has a greater incentive to actually adopt $\theta = 1$ but wants to do so at a later date.

increasingly more expensive. Thus, the leader adopts relatively later. At the same time, for higher values of $x$ the follower does not need to wait as long for adoption to be profitable and therefore adopts relatively sooner. This earlier adoption date also disincentivizes the leader to adopt because the benefits from being the only adopter of $\theta = 1$ are realized for a shorter period of time (on average).

## 3.3 Data

### 3.3.1 The Market for MRI

MRI is an advanced imaging technology that uses a magnetic field to produce highly-detailed pictures of human tissue. Unlike a computed tomography (CT or "Cat") scan, an MRI scan generates no radiation and is capable of producing an image in any plane. Due to its great precision and minimal side effects, MRI technology has steadily become more prevalent in the healthcare industry since its original introduction in the early 1980s. Bell (1996) estimates that approximately 350 MRI scanners were in operation in the US in 1985 and that number grew to almost 3,900 units by 1995. A more recent estimate by Aranibar (2013) suggests that more than 10,000 units were in use by hospitals and other imaging facilities in the US by 2011. These scanners now combine to produce roughly 30 million scans annually. As MRI technology has become more widespread in the healthcare industry, the technology itself has advanced. The strength of the scanner's main magnet, measured in "tesla" which is symbolized by "T," has grown from 0.15T in early models to 3.0T tesla in today's most advanced clinical models. Additionally, the advancement of the scanner's coils and the unit's software have enabled physicians to generate higher-resolution images and better diagnose a patient's condition.[31] In addition to improvements in image quality, MRI scanners have advanced along several other

[31] The main magnet, along with gradient magnets, radio frequency coils, and a computer system all work in conjunction to ultimately generate images of the body. Briefly, the main magnet produces a magnetic field that aligns the hydrogen atoms in the body. The coils then generate pulses which cause some of the atoms to spin in a different direction. When each pulse is stopped the atoms that were spinning in a different direction return to their original state and in doing so release energy. This energy is captured by the coils and processed by the computer to generate an image. The gradient magnets are used to shift the direction of the magnetic field generated by the main magnet which in turn alters the angle of final image.

dimensions. For instance, Frost and Sullivan (1998) notes that in 1985 an MRI scan of the brain would typically last an hour but that time was cut in half by 1997. Decreasing the time required per scan allows hospitals to run more scans each day and potentially generate higher revenue. The length and width of the MRI scanner bore has also changed over time.[32] Closed-bore MRI scanners are not conducive for examining claustrophobic and/or overweight patients. In the 1990s manufacturers began developing short-bore (shorter-length cylinder) and open (no real cylinder) MRI scanners to alleviate these issues. While short-bore scanners can generate images comparable to those of closed-bore scanners, scans on open MRI machines are typically of lesser quality.[33] Finally, Frost and Sullivan (2000) notes that manufacturers are attempting to minimize the significant amount of noise that is generated during an MRI scan.

The costs of adopting an MRI scanner are substantial. A scanner itself can range in price from about half of a million dollars to more than two million dollars (Baker and Wheeler (1998)). Additionally, there are significant construction costs associated with modifying a facility so that it is capable of handling the strong magnetic field generated by the scanner. Often smaller healthcare facilities cannot warrant this type of spending to provide their patients with MRI and in many instances these facilities share a "mobile" MRI scanner with other local hospitals or imaging centers. A mobile MRI scanner is a scanner housed inside of a trailer that is transported between sites where each facility typically keeps the scanner for a specified number of days each week. Thus, the cost of purchasing/leasing the scanner is shared between several providers. Sometimes the scanners are purchased directly by a group of hospitals (or a healthcare system that owns and operates several hospitals) and other times they are owned and maintained by third-party organizations (for instance, Alliance Imaging). As noted in market research by Frost and Sullivan (1998), the cost of an individual scanner decreases with time. MRI manufacturers are constantly attempting to innovate and compete for patents on

[32]The "bore" of the MRI is the outer cylindrical tube that houses all of the magnets and coils. The patient slides inside the bore on a table for an MRI scan.

[33]However, over time the image quality of open MRI scanners has improved as the magnet strength has increased.

new technologies. I assume that competition between MRI manufacturers causes the cost of a particular type of MRI scanner to be decreasing and convex in the time since the scanner's original release. If a manufacturer is the first to bring a new type of scanner to market then it will enjoy a period of monopoly power. However, when competing manufacturers respond by releasing similar models the price of the scanner must fall. I assume that manufacturers release new scanners in close succession because they stand to lose significant market share by delaying the release of a new scanner, causing the price of a new scanner to initially fall faster before eventually leveling off. However, in this paper I abstract from modeling the R&D game played by MRI manufacturers and simply take the process that governs the release of new technologies (and the eventual decrease in their costs of adoption) as exogenous.[34]

Based on conversations with the University of North Carolina Radiology Department (and corroborated by Frost and Sullivan (1998)), there is evidence supporting the idea that the benefits received from a new MRI technology can vary between hospitals. In particular, Academic Medical Centers (AMCs) experience teaching and research spillovers that other hospitals and private imaging facilities do not enjoy. Purchasing state-of-the-art scanners can help to attract researchers conducting innovative research and medical students hoping to gain valuable training and experience. Thus, even if an AMC hypothetically conducts the same number of scans as a privately-owned hospital on a new machine, the AMC still has a higher (implicit) marginal benefit from the technology and therefore might be incentivized to adopt it sooner.

### 3.3.2 Data Collection and Sample Selection

#### Data Collection

To track hospitals' purchases of MRI scanners I have collected data from three main sources. The MRI purchase data is collected from the state Certificate of Need (CON) programs in Mississippi, Michigan, Tennessee, and Virginia. CON programs vary by state and are intended

[34]Originally there were a large number of MRI manufacturers but over time the market became more concentrated. According to Frost and Sullivan (1998), by the 1990s the combined market share of GE Healthcare, Siemens Healthcare, and Philips Healthcare was approximately 70% and according to Aranibar (2013) that share rose to more than 80% by 2011.

to limit unnecessary healthcare expenditures. Suppose a hospital wants to purchase a new MRI scanner in a state where MRI is regulated by a CON law. The hospital must prove to the state that there is a need for the new scanner (through a demand calculation that includes the current number of MRI scans conducted in the market). The hospital is granted a CON if the state decides that there is sufficient demand to warrant the purchase of a new MRI scanner. 21 states in the US currently regulate MRI purchases through a CON program. However, some of these programs are relatively new and others have minimum spending thresholds that must be met to require a CON (i.e. if the purchase of an MRI scanner costs less than \$3 million then it is not regulated by a CON). Critics of CON laws argue that they act as entry deterrents for hospitals holding CONs, therefore limiting competition and leading to higher prices. For instance, Ford and Kaserman (1993) use changes in CON laws in several states to argue that these laws significantly inhibit entry in the dialysis industry, leading to highly concentrated markets. Sloan (1981) finds no evidence that CON laws actually reduce hospital costs.

Since my data comes exclusively from states with CON laws, one could argue that my sample is not representative of the market for MRI technology in the US, and therefore, the estimated replacement process is a direct result of regulation. However, Conover and Sloan (1998) survey the results from more than seventy studies and note that the effect of CON laws on the diffusion of technology is very inconclusive. They assert that in the majority of these studies, CON laws are found to have no effect on the rate of diffusion. Additionally, in all of the states in my sample, the requirements that must be met to warrant the replacement of an existing MRI scanner are much less stringent than the CON requirements for the purchase of a new (or an additional) scanner.[35] As a result, while CON laws may generate a barrier

[35]These policies differ by state but in general the process of replacing/upgrading an MRI scanner is more straightforward than initiating MRI service at an existing facility. In Michigan, while a replacement scanner requires a CON, rather than proving that there is a need for additional MRI capacity (as would be true to initiate MRI service) it must only be demonstrated that the existing scanner meets a minimum usage requirement. If the scanner meets this requirement it can be replaced if it is fully depreciated, poses a safety hazard, or "the proposed replacement equipment offers a significant technological improvement which enhances quality of care, increases efficiency, and reduces operating costs." In informal conversations with the Michigan Department of Community Health it was suggested that this last provision offers a lot of latitude for hospitals hoping to upgrade. In Mississippi, a hospital hoping to replace/upgrade an MRI scanner must simply contact the Mississippi State Department of Health (MSDH) and receive a "declaratory ruling" which is an acknowledgement that the MSDH has

to entry in the market for MRI scans, I argue that the regulations are less prohibitive when hospitals decide to upgrade their scanners.

The detail of the MRI purchase data varies by state and is summarized in Table 3.2. There is a significant amount of variability in the data collection protocols utilized in each state. For instance, the Michigan Department of Community Health (MDCH) has organized a database containing summary information on all CON applications dating back to the program's inception in 1972. Since the purchase of MRI equipment has always required CON authorization in the State of Michigan, I am able to track the entire history of MRI purchases in the state. However, very little information is provided regarding the scanners themselves. In contrast, the documentation in the Mississippi State Department of Health's (MSDH) CON program is significantly more complicated. Older files are only available in hard copies and the organization of newer digital files is somewhat muddled. Yet, I was able to obtain more detailed information about MRI scanners' characteristics than was available through the MDCH. Each state's data posed different challenges which I discuss in appendix B.2. However, in all states I am able to determine the purchase date of MRI scanners and whether they are mobile or fixed scanners.[36] These are the main variables that I will employ in the estimation routine.

In addition to the state CON data I also collect hospital-level data through the American Hospital Association (AHA) annual surveys from 1987 to 2009. The annual surveys provide information for all hospitals in the US regarding hospital location, ownership, size, utilization,

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been properly notified and that the purchase does not require a CON. The policy in Tennessee is similar to that in Mississippi–the replacement or upgrade of existing major medical equipment requires "a notice or prior approval by the Tennessee Health Services and Development Agency (but not a CON)." In Virginia a facility must register any replacement major medical equipment purchase with the state Certificate of Public Need Program within thirty days of the capital expenditure but is not required to apply for a new CON.

[36]In some instances these variables were missing for observations and I was forced to deduce the appropriate values. For instance, the project description on a CON might simply indicate that a hospital was "initiating MRI service" without specifying whether the project involved a fixed or mobile MRI service. However, the cost of the project might be in excess of $2 million, indicating that the project likely involved a fixed scanner. Or, several years later the same facility might have another observation indicating that it was "replacing a mobile scanner," which implied the type of the original machine. In instances where I could not comfortably deduce the type of scanner I contacted the facility in question. Observations with missing purchase dates were incredibly rare. However, I could easily impute these dates using information from CON applications (or applicable registrations/notifications) with adjacent reference numbers.

| | MI | MS | TN | VA |
|---|---|---|---|---|
| *Facility Name* | ✓ | ✓ | ✓ | ✓ |
| *Facility Type* | ∼ | | ✓ | |
| *Facility County* | ✓ | ✓ | ✓ | |
| *Purchase Date* | ✓ | ✓ | ✓ | ✓ |
| *Total Cost* | ∼ | ∼ | ∼ | ∼ |
| *Owned/Leased* | | | ✓ | |
| *Fixed/Mobile* | ✓ | ✓ | ✓ | ✓ |
| *Scanner Brand* | | ∼ | ✓ | |
| *Magnet Strength* | | ∼ | ✓ | |
| *Magnet Type* | | ∼ | ✓ | |
| *Shared?* | | ✓ | ✓ | |
| *Active?* | | | ✓ | |
| *Annual # Scans* | ∼ | ∼ | ∼ | |

✓ indicates the variable was available for nearly all obs.
∼ indicates the variable was available for only some obs.

Table 3.2: Variables Collected Through State CON Programs

and services offered, along with many additional variables. To link the AHA data with the state MRI purchase data I manually code the seven-digit AHA ID Number for each hospital in the CON data. While the AHA data do include a variable indicating whether or not a hospital provides MRI services, I am only able to distinguish between fixed and mobile MRI services for four years in the panel (1990–1993). I elaborate on this issue in appendix B.2. Finally, I collect county-level demographic data (i.e. population and per capita income) from the Area Resource Files (ARF) for 1983 to 2010 that is used to control for variability across markets. To form markets I follow Schmidt-Dengler (2006) and aggregate counties into healthcare service areas (HSAs) as designated in Makuc, Haglund, Ingram, Kleinman, and Feldman (1991). Each HSA is a group of several contiguous counties that "are relatively self-contained with respect to the provision of routine hospital care." The land area of an HSA will typically be larger in more rural regions and smaller in metropolitan areas where the population (and set of hospitals) is more condensed. There are a total of 802 HSAs in the US which I assume remain fixed through time.[37]

[37] I recognize that due to the length of my panel (1983–2010) it is possible that the appropriate boundaries of these HSAs may have changed over time because of the opening/closure of hospitals and

### Sample Selection

As previously mentioned, I restrict the sample to only include hospitals that purchased at least one fixed MRI scanner between 1983 and 2010. I omit hospitals that provide MRI service (solely) with a mobile scanner for several reasons. First, the investment required for a hospital to utilize a mobile scanner is far less substantial than the cost of purchasing and installing a fixed scanner. As a result, the decision to operate a mobile scanner, as opposed to a fixed scanner, is less binding. Second, anecdotal evidence from the healthcare industry and several sources at state health departments suggests that mobile MRI scanners frequently are not at the frontier of MRI technology. Often mobile MRI scanners are used to provide MRI service in an area that otherwise would not have convenient access to a scanner. Thus, hospitals operating with mobile MRI scanners are hoping to minimize costs rather than maximize efficiency or reap the benefits of better MRI technologies.[38] As a result, I argue that hospitals with mobile MRI scanners are not actively engaged in the dynamic technology upgrading game.

In restricting the sample to include only *hospitals* with fixed MRI scanners, I also omit all non-hospital imaging facilities. This simplification is made because it is incredibly difficult to track these facilities through time. Unfortunately there is no comprehensive listing of outpatient imaging facilities in the US that I can couple with the state CON data. As a result, changes in a facility's name, ownership, and/or location are nearly impossible to validate. Since there is significant turnover in the names of these facilities over time, I cannot confidently build accurate MRI scanner purchase histories. As noted in Frost and Sullivan (1998), part of this difficulty is likely the result of the fact that many outpatient imaging facilities closed in the mid-1990s due to excess capacity. By excluding outpatient imaging facilities from the analysis I recognize that I may overstate the amount of competition between hospitals alone. However, it is not immediately clear that hospitals and outpatient imaging facilities are competing for the same pool of potential patients.

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the migration of the US population. I abstract from these issues in the analysis.

[38]Further, the same sources suggested to me that third-party owners of mobile MRI scanners tend to delay replacing scanners in order to maximize profits.

In addition to restricting attention solely to hospitals, I also assume the number of hospitals competing in each market remains fixed through time, so there is no entry or exit in the model. Modeling endogenous entry/exit in a dynamic discrete choice game greatly complicates the state space as firms are forced to form expectations over the set of potential market participants in the subsequent period. And while a significant amount of turnover has occurred in the hospital industry over the length of my panel, this is not the case for the firms in my sample. Of the 255 hospitals in the sample, only nine entered the market after 1987 and three exited before 2010. For simplicity I assume that these hospitals were in existence for the entire length of my panel. While entry and exit does not occur frequently in my sample, 34 hospitals took part in a merger during the sample period. In essence I ignore these mergers and assume merged hospitals continue operating independently. In most cases even if hospitals have merged I can still determine exactly which of the merged hospitals purchase new MRI scanners. Whenever I cannot distinguish between merged hospitals I simply assume that *all* of the merged hospitals receive a new scanner.[39] I recognize that in ignoring mergers I may be overstating the number of independent decision-makers in certain markets.

Finally, due to data limitations I assume that all fixed MRI scanners purchased in the sample are at the technological frontier at the time of the purchase. In other words, at any point in time hospitals are only capable of purchasing *the best technology available*. While this assumption is admittedly a simplification, I am forced to make it for several reasons. I originally intended to categorize all scanners by the strength of the main magnet. However, this information is not available for all purchases in the data and differences exist between scanners with the same magnet strength (for instance, a short-bore scanner versus a closed-bore scanner). Attempting to use the purchase price as a proxy for a scanner's quality is also problematic because as I show in Figure B.6, these values are relatively noisy.[40] Further,

[39]For instance, in 1995 Chippenham Medical Center and Johnston-Willis Hospital merged in Virginia. In 2008, "Chippenham & Johnston-Willis Hospitals, Inc." added a second MRI scanner but it is unclear at which facility the scanner is located. So, I simply assume that both facilities added an MRI scanner in 2008. This type of situation is rare, only occurring with three sets of merged firms in the data.

[40]The cost measure is noisy for several reasons. First, a specific CON may include other medical services regulated by CON laws so that I cannot disentangle the exact amount spent on a new MRI scanner. Second, certain CONs may include construction costs associated with preparing a hospital to

as noted by Aranibar (2013), not all facilities purchase scanners with the highest tesla main magnet. He estimates that in 2011, 3.0T scanners (currently the highest-tesla clinical scanners available) only accounted for roughly 36% of total MRI market revenue in the US.

Given these assumptions, Table B.11 presents summary statistics for the sample and the contiguous US. All of the variables are averaged over the duration of my panel (1983–2010) so that I have a single, time-invariant measure for each market (or hospital).[41] Relative to the set of all HSAs, the markets in my sample are slightly smaller in terms of population. However, the hospitals in my sample, on average, are larger in terms of bed capacity. I also include a dummy variable equal to one if the hospital utilized a mobile scanner at some point in time prior to adopting its first fixed MRI scanner. Roughly half of the hospitals in my sample offered mobile MRI services before purchasing a fixed scanner. To account for the use of mobile scanners I will include this dummy variable in the flow profit function when $\theta = 0$ in my empirical model. Figure B.4 plots the market size distribution of the sample. I observe a significant number of monopoly markets (42) and a single market with 26 different hospitals each owning a fixed MRI scanner at some point during the panel (the Greater Detroit Area which extends as far west as Ann Arbor). Figure B.5 plots the total number of scanner adoptions in each year. Prior to 1990 there are very few adoptions but over time the number of purchases steadily increases as MRI technology becomes more prevalent in the healthcare industry. I obviously do not have access to a dataset that would allow me to compare this sample distribution of purchases with the distribution for the entire United States. However, market research by Aranibar (2013) suggests that Figure B.5 roughly parallels the overall trends in the industry since 2002. He claims that "MRI shipments peaked during 2002–2004" and shipments declined from 2008

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handle the strong magnetic field generated by the MRI scanner. And finally, the total cost is simply missing from certain data points.

[41] I use time-invariant observables in my estimation routine to limit the size of the state space. If hospitals were forced to form expectations regarding the transitions of market- and hospital-level observables then the state space would grow exponentially. Further, the focus of the empirical analysis is on how hospitals dynamically upgrade their MRI technology as both the vector of technologies in each market and the technological frontier evolve. The additional effects of changes in market- and hospital-level observables are beyond the scope of the analysis and would be difficult to identify in the empirical model.

to 2010 "due to budget freezes and limited access to capital during the economic crisis and (the) introduction of plans to reform healthcare." Table B.12 summarizes the average amount of time that elapses before a hospital adopts its first fixed MRI scanner for different market sizes. On average, MRI technology diffuses more slowly in markets with only a single adopter (during the panel). In these monopoly markets no firm adopts MRI prior to 1991. As market size increases hospitals adopt faster on average. Figure B.7 plots the Kaplan-Meier failure function for the same market-size bins used in Table B.12. Here a "failure" is the first MRI purchase by each hospital. The probability of adoption is initially greater in larger markets. However, later in the sample the probability of adoption in monopoly markets eclipses the respective probabilities in larger markets. This shift is generated by the fact that there are smaller hospitals in the larger markets that do not adopt a fixed MRI scanner until toward the end of the sample. Finally, Table B.13 extends Table B.12 and summarizes the average purchase dates of the second and third MRI scanner purchases for each hospital (if they exist). It is important to note that these dates are for *any* scanner purchases, not necessarily scanners with improved MRI technologies.[42] Nevertheless, on average subsequent MRI purchases occur faster in markets with more hospitals.

## 3.4 Estimation

### 3.4.1 Descriptive Results

Before discussing the estimation routine for the full dynamic game, it is instructive to consider the results from some preliminary, reduced-form specifications. First I run several multinomial logistic regressions where the dependent variable is the initial adoption date for each hospital.[43]

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[42] In the empirical model I set the release date for each MRI technology and once a firm adopts that technology it can take no further action until an improved technology is released. Suppose that $N = 2$, $\theta = 1$ is released in $t = 0$, and $\theta = 2$ is released in $t = 10$ and I observe MRI purchases for a hospital in $t = 8$, $t = 12$, and $t = 18$. In Table B.13 the first adoption would occur in $t = 8$, the second in $t = 12$, and the third in $t = 18$. However, in the empirical model I would consider $t = 8$ as the hospital's adoption date for $\theta = 1$ and $t = 12$ as the hospital's adoption date for $\theta = 2$, dropping the $t = 18$ adoption.

[43] Alternatively I could employ an ordered logit model in this instance. Ordered response models are only applicable if the alternatives can be ranked because it is assumed that there is only one latent

The adoption dates are grouped into three bins: 1983–1992 (outcome 1), 1993–2001 (outcome 2), and 2002–2010 (outcome 3). The results are reported in Table B.14 with outcome 1 set as the base outcome. In specifications (1) and (2) I calculate a z-score of the number of firms in each market to act as a proxy for the amount of competition that a hospital faces. In specifications (3) and (4) I replace this z-score with dummy variables denoting whether there are between two and four hospitals in the market ($2 \leq J \leq 4$) or more than four hospitals in the market ($J > 4$), where monopoly markets are the omitted group. Finally, in specifications (2) and (4) I include *had mobile?*, a dummy variable equal to one if a hospital utilized a mobile MRI scanner at some point in time before purchasing its first fixed MRI scanner. The strong significance of the mobile scanner dummy suggests that specifications (1) and (3) are suffering from omitted variable bias. Operating a mobile scanner seems to be correlated with delayed adoption which confirms a trend in the data–many late adopters of fixed MRI converted from some sort of mobile MRI service. In general the presence of greater competition from additional hospitals (especially when $J > 4$) increases the odds of earlier adoption. However, the competitive effect is mitigated by the inclusion of the mobile scanner dummy. In all four regressions I use a hospital-level z-score of number of beds (*z-beds*) as a proxy for hospital size which is always negative and significant for both outcomes. Thus, not surprisingly, larger hospitals seem to adopt fixed MRI relatively sooner. Both *for-profit* and *non-profit* are dummy variables for hospital ownership, where non-federal government hospitals are omitted (there are no federal government hospitals in the sample). The positive significance of the non-profit parameter estimate for outcome 3 suggests that relative to government hospitals, non-profits are more likely to adopt very late. This result is in contrast to the findings in Schmidt-Dengler (2006). The *medical school?* variable is a dummy variable equal to one if the hospital is affiliated with a medical school. The parameter estimate on this variable is insignificant across outcomes and specifications. Finally, *z-pop.* and *z-real-inc.* are market-level z-scores for population and real income, respectively. The positive values of *z-pop.* are somewhat

variable underlying the choices of interest. Here there is a chronological ranking of first adoptions. While I choose to illustrate the results from an unordered logit model, the results from an ordered logit estimation were qualitatively very similar.

confounding for outcome 3, especially since the market-competition variables are negative.[44]

Table B.15 presents results from several proportional hazard models of the hospitals' initial adoption dates. I assume that the underlying hazard rate follows a Weibull distribution, thus enabling it to vary monotonically over time. The different specifications correspond with different definitions of "adopting." In specifications (1) and (2) I do not censor any hospitals so each hospital's initial fixed MRI adoption is included in the model. Specifications (3) and (4) censor all hospitals who do not adopt a fixed MRI scanner until after 2001 and specifications (5) and (6) do the same for 1991. A positive parameter estimate increases the hazard rate, meaning that there is a greater likelihood of adoption conditional on no adoption up to that point. Confirming the results from Table B.14, larger hospitals (in terms of average bed size) have a faster adoption rate. Further, the use of a mobile scanner decreases the adoption rate but this effect decreases as the definition of an adoption is relaxed. Put differently, if a hospital uses a mobile scanner it is much less likely to adopt relatively early in the panel. Isolating the "early adopters" in specifications (5) and (6) we see that hospitals affiliated with a medical school have a higher adoption rate than non-academic hospitals. This result seems to confirm the idea that academic hospitals potentially had an incentive to adopt the original MRI scanners due to spillover effects. By and large the results in regressions (1)–(4) confirm those in Table B.14. Finally, it is important to note that $p$, a parameter of the Weibull distribution, is greater than one which indicates that the hazard rate is monotonically increasing in time. This result is consistent with the increased diffusion of MRI in the healthcare industry as a whole over time.

Both of the reduced-form analyses in Tables B.14 and B.15 focus on each hospital's *initial* fixed MRI purchase. In contrast, Table B.16 and Table B.17 examine the factors influencing a hospital's MRI technology later in the panel through an ordered probit model. The dependent

[44] This result could in part be attributed to the Detroit-area market, where the population z-score is almost four times as large as the value in the next-largest market, but the difference in the number of hospitals is relatively smaller in magnitude. Here, half of the firms in the market do not adopt a fixed MRI scanner until a year in the outcome 3 window. Alternatively, the positive value for the population parameter could be due to endogeneity.

variable in these regressions is the hospital's technology entering 2008.[45] This technology is a function of the hospital's adoption dates and the release dates of each technological improvement. Each specification corresponds with a different vector of release dates (where in all cases I assume that $\theta = 1$ is released in 1983). Due to a combination of data limitations and the fact that MRI scanners have improved along several dimensions since their clinical inception, I cannot define a single "true" vector of release dates for new technologies to be used in all of the estimation routines. Instead I vary both the assumed number of technologies and their release dates to see how parameter estimates change. Varying the number of technologies and their release dates will also potentially alter each hospital's observed adoption date(s). As a result, I define a hospital's adoption date of technology $\theta_{Bt}$ as the first period $t$ that a hospital purchases a fixed MRI scanner such that $T_{\theta_{Bt}} \leq t < T_{\theta_{Bt}+1}$. To illustrate how altering the release dates changes a hospital's observed adoption dates, consider a hospital that purchases MRI scanners in 1991, 1996, and 2003. In specification (1) the hospital is considered to not adopt $\theta = 1$, adopt $\theta = 2$ two years after its release (1991-1989), and adopt $\theta = 3$ five years after its release (2003-1998). However, in specification (4) the same hospital would be assumed to adopt $\theta = 1$ eight years after its release (1991-1983), adopt $\theta = 2$ four years after its release (1996-1992), and adopt $\theta = 3$ five years after its release (2003-1998). Thus, in changing the release dates I alter each hospital's adoption date of each technology relative to its release and can examine how sensitive the model is to the definition of the set of new technologies.[46] In the first nine specifications of Tables B.16 and B.17 I assume that there are three waves of technological advancements while in specifications (10)–(12) I assume that there are only two different technologies. The reported cuts are the values of "$x\beta$" corresponding to the cutoffs for each MRI technology.[47] The first result to notice is that the prior presence of a mobile scanner seems to be irrelevant in determining a hospital's MRI technology late in the panel.

[45]I choose not to use the MRI technology entering 2010 because at that point almost all firms have adopted the best technology available.

[46]I will employ this strategy throughout the remainder of paper.

[47]There are only two cutoffs for specifications (1)–(3) because in these instances no firms enter 2008 with $\theta = 1$ (i.e. all of the early adopters have subsequently upgraded to $\theta = 2$ or $\theta = 3$ by 2008).

This result suggests that the hospitals that converted from mobile to fixed MRI service did so over an extended period of time rather than all at once. Second, the medical school dummy variable is insignificant across all of the specifications. So, while hospitals affiliated with medical schools tended to be early adopters of the technology, the increased rate of adoption by *all* hospitals later in the panel diminishes the appearance of spillover effects.[48] Finally, an interesting pattern develops in the three-technology models: fixing the release date of $\theta = 2$, as the release date of $\theta = 3$ increases the market-competition variables gain significance while the market-population variable's significance falls. A potential explanation might be that competition is actually strongest in smaller, non-monopoly markets where the preemption incentive is significant but there are still gains from adoption for preempted firms. In larger markets, once several firms have adopted a new technology the marginal benefit from upgrading may be smaller due to the sheer number of firms in the market, pushing preempted firms' adoption dates further into the future. When the difference between the release date of $\theta = 3$ and the year under examination (2008) is large, this competitive effect is masked by the fact that more firms in all markets are adopting in a larger window.

Finally, Tables B.18 and B.19 present results from a hospital-level hazard model of the adoption of $\theta = N$ using the same release dates as in Tables B.16 and B.17. In these models *tech. entering* denotes the hospital's technology entering the $T_N$. In all cases but one an increase in a hospital's technology entering $T_N$ has a negative effect on its hazard rate of adopting the last advancement. In other words, the smaller the discrepancy between a hospital's existing fixed MRI technology and the latest advancement, the lower the hazard rate of adopting. This relationship only does not hold in specification (10) where the last advancement ($\theta = 2$) is released very early when relatively few hospitals have purchased $\theta = 1$. Figure B.9 plots the estimated hazard functions for specifications (8) and (9) for different market sizes and technologies entering period $T_N$. In all plots the values of all unspecified covariates are set equal to their mean values. In panels (a) and (c) the blue line corresponds to a monopoly

[48]This result is also likely due to the assumption that all MRI scanners purchased in the same year are equivalent. Hospitals with medical school affiliations seem to own more 3.0T scanners than non-academic hospitals. However, due to data limitations I simply cannot make this type of distinction in the empirical model.

market, the red line to a market with $2 \leq J \leq 4$ firms, and the green line to a market with $J > 4$ firms. As discussed in the results in ables B.16 and B.17, the hazard function is greatest in the intermediate-sized markets. Panels (b) and (d) both illustrate the fact that the hazard function is decreasing in the technology owned entering $T_3$. And, comparing (a) with (c) and (b) with (d), the differences in the hazard rates are more marked when $T_2$ is closer in value to $T_3$.

### 3.4.2 Empirical Model

Unfortunately due to data limitations I cannot employ the full Berry (1994) demand specification discussed in Section 2. Specifically, I do not observe quantities and prices of MRI scans at the hospital level for all hospital-years in the CON data.[49] As result, in the empirical model I specify a hospital's flow profit to be a reduced-form function of hospital- and market-level covariates, the hospital's own technology, and the sum of all competitors' technologies:

$$\pi(\theta_{jm}, \Theta_{-jm}) = \left[\kappa x_{jm} + \lambda z_m + \nu \sum_{\forall j' \neq j \in J_m} \theta_{j'm}\right] ln(2 + \theta_{jm}), \tag{3.31}$$

where slightly abusing notation, $\theta_{jm}$ denotes hospital $j$'s technology in market $m$, $\Theta_{-jm}$ denotes the vector of all competitors' technologies, $x_{jm}$ is a vector of hospital-level variables, $z_m$ is vector of market-level variables, and $\kappa$, $\lambda$, and $\nu$ are (potentially) vectors of parameters to be estimated. The "2" is included in the $ln(2+\theta_{jm})$ term to allow for heterogeneity in firms' flow profits when operating with $\theta_{jm} = 0$.[50] As previously mentioned I assume that flow profits are time-invariant for tractability. Note that while the flow profit function is deterministic, the idiosyncratic $\zeta$-draws that each hospital receives in each period introduce a stochastic error term into the model. In addition to the flow profit function I also must parameterize the cost

[49] While I do observe hospital-level annual MRI scan totals for most years in Mississippi and some years in Tennessee, I have no price data. Prices are complicated by hospitals' agreements with health insurance companies, HMOs, and PPOs, along with Medicare reimbursement rates which vary through time. Further, prices typically vary by the type of MRI scan (i.e. brain, chest, abdomen, etc.) and the quantity data that I have collected do not distinguish between these different scan types.

[50] In other words, if $ln(1 + \theta_{jm})$ was utilized instead of $ln(2 + \theta_{jm})$ then all firms operating with $\theta_{jm} = 0$ would earn $\pi(\theta_{jm}, \Theta_{-jm}) = 0$ regardless of firm- and market-level characteristics.

function associated with adopting a new technology. I choose the following functional form:

$$C(\Delta_t) = \eta(\chi^{\Delta_t}). \tag{3.32}$$

While both $\eta$ and $\chi$ are identified in the model, I will typically fix the value of $\chi = 0.98$ to correspond with the value estimated by Schmidt-Dengler (2006).[51]

Identification in the model is achieved through a combination of variations in the data and the choice of functional form for $\pi(\cdot)$. As in any discrete choice model, only differences in flow profit parameters are identified. Put differently, suppose that I attempted to specify the flow profit function as

$$\pi(\theta_{jm}, \Theta_{-jm}) = \upsilon_{\theta_{jm}} + \kappa_{\theta_{jm}} x_{jm} + \lambda_{\theta_{jm}} z_m + \nu_{\theta_{jm}} \sum_{\forall j' \neq j \in J_m} \theta_{j'm}, \tag{3.33}$$

where $\upsilon_{\theta_{jm}}$ is a different constant for each technology. Without any normalization, none of the parameters would be identified. In other words, there exists an infinite number of sets of $\{\kappa, \lambda, \nu\}$ that could generate the same differences in flow profit levels and describe the same data generating process. To alleviate this issue without normalizing the flow profit level associated with one of the technologies I interact all of the covariates with the technology choice. I choose not to normalize the flow profit associated with one technology and estimate a different set of parameters for each of the remaining technologies in order to limit the total number of parameters in the model. As I will discuss briefly below, the model suffers from a curse of dimensionality and estimating a larger set of parameters typically requires more evaluations of the likelihood function, which can increase the run time of the estimation routine exponentially. The values of $\kappa$, $\lambda$, and $\nu$ are identified through differences in adoption choices both between firms within the same market and across different markets. For example, differences in adoption dates of similarly sized hospitals located in different markets can identify

[51] In order for the adoption cost to fall with time, it must be that $\chi \in (0, 1)$. When the estimation routine tests values for $\chi$ outside of this range it can often generate "NaN" values for the log-likelihood function which immediately the stop the routine from converging. To limit this occurrence I simply fix the value of $\chi$.

$\kappa$. Identification of $\nu$ is also aided by the fact that I often observe multiple technology adoption decisions by the same firm in the same market over time.

The remaining "dynamic" parameters in the model are the discount factor ($\beta$), the commonly-held belief regarding the release of a new technology ($\rho$), and the scale parameter in the cost function ($\eta$). In a single-agent dynamic optimization problem the discount factor can sometimes be identified if inter-period transitions are affected by something outside of utility. In this dynamic game inter-period transitions are technically a function of intra-period decisions by all hospitals acting after the hospital of interest. However, the transition is also directly a function of $\rho$, which complicates the potential identification argument for $\beta$. For simplification I choose to fix the values of $\beta$ and $\rho$ and estimate the value of $\eta$, which given the distributional assumptions on the $\zeta$'s, is identified through the different adoption dates of the same technology by competing firms.

### Estimation Routine

Given specifications for the flow profit and cost functions, below I discuss the algorithm utilized to estimate the parameters of the dynamic technology adoption game. I define the set of parameters to be estimated as $\Lambda := \{\kappa, \lambda, \nu, \eta\}$.

1. Set the release dates of all new technologies, random order of action in each period, $\beta$, and $\rho$ and make an initial guess at $\Lambda$

2. Calculate flow profit levels in market $m$ for all firms $j = 1, \ldots, J_m$ and all potential technology vectors $\Theta$

3. Beginning in period $\overline{T}_N$, recursively calculate expected continuation values and conditional choice probabilities using the algorithm in Section 2.3

4. Calculate market $m$'s contribution to the log-likelihood function. Beginning in state $(0, 0, 0, 0)$, if the first hospital to act chooses $a_{1t} = \theta_{Bt}$ then its contribution to the log-likelihood function is $\ln(\mathbf{Pr}_1(a_{1t} = \theta_{Bt}|\psi_t))$. Otherwise, its contribution is $\ln(\mathbf{Pr}_1(a_{1t} = 0|\psi_t))$. If there is more than one hospital in the market, the second hospital to act

views the first hospital's decision and its contribution is $\ln(\mathbf{Pr}_2(a_{2t}|\psi_t, a_{1t}))$. This process continues for all firms for all periods in the sample where the state is adjusted accordingly between periods. As a result, the contribution of market $m$ to the likelihood function is:

$$LL_m(\Lambda) = \sum_{t=0}^{27} \sum_{j=1}^{J_m} \ln(\mathbf{Pr}_j(a_{jt}|\cdot))$$

5. Repeat steps (2) to (4) for all remaining markets $m = 2, \ldots, M$

6. Summing over markets, calculate the total log-likelihood function:

$$LL(\Lambda) = \sum_{m=1}^{M} LL_m(\Lambda)$$

7. Maximize the log-likelihood function using a combination of both a direct search polytope algorithm and a simulated annealing algorithm, which perturbs the parameter vector $(\Lambda)$ and repeats steps (2)–(6) until the parameter estimates converge.

8. Once the estimated parameter vector converges, calculate standard errors for the parameter estimates using the "Outer Product of the Gradient Method" originally proposed in Berndt, Hall, Hall, and Hausman (1974)

An increase in the maximum number of firms in a market and/or the number of new technologies causes the state space to grow which in turn increases the runtime for a single log-likelihood evaluation. As the number of parameters in the model increases, more log-likelihood function evaluations are typically required for convergence. Thus, the model suffers from a curse of dimensionality similar to that encountered in most dynamic games.[52] To mitigate this issue I restrict the maximum number of firms in each market to four by choosing the largest four firms in terms of bed size or the first four adopters of fixed MRI. While these restrictions are suboptimal, the reduced-form hazard results suggest that strategic interactions between

[52] If there are two technologies and a maximum of four firms in each market then a single log-likelihood evaluation takes roughly 4 seconds. Adding a third technology into the model increases the runtime to 52 seconds. However, allowing for five firms in each market drastically increases the runtimes: 90 seconds for the two-technology game and roughly 35 *minutes* for the three-technology model.

hospitals may be greatest in relatively small, non-monopoly markets. In markets with more than four hospitals I include a variable equal to the log of the number of hospitals excluded from the analysis to account for the censoring.

### Results

Parameter estimates are presented in Tables B.20–B.23. In each specification I rescale the z-scores for population and bed size so that they only take on positive values and then subsequently take the natural logarithm of the rescaled values (*ln(1+z-pop)* and *ln(1+z-beds)*). I take the natural logarithm of these variables along with the sum of all competitors' technologies and number of censored firms (where applicable) simply to limit the value of the flow profits.[53] In the displayed results I typically do not vary the value of $\rho$ so that it is consistent with the chosen release dates for each specification. I choose not to calibrate $\rho$ for each specification for several reasons. First, if there are three new technologies a "consistent" value of $\rho$ might be different for $\theta = 2$ versus $\theta = 3$ depending on their release dates and I assume that $\rho$ is time-invariant in the model.[54] Second, in preliminary estimations of the two-technology model where $\rho$ was calibrated specifically for each parameterization the results were qualitatively very similar to those presented here. So, to simplify the exposition I typically present results where $\rho = 0.1$ which is roughly consistent in most situations. Finally, in markets with more than four adopting firms I restrict the sample to include the four largest firms in terms of average number of beds across the length of the entire panel (sample: *beds*) or the first four adopters of fixed MRI scanners (sample: *first4*). In any market with more than four firms I proxy for the potential additional competition posed by all firms omitted from the sample through the inclusion of the *ln(1+extra-hosp.)* variable, where *extra-hosp.* equals the total number of hospitals in a market that adopt a fixed MRI scanner at some point during the panel minus four.

Table B.20 presents parameter estimates assuming that there are no strategic effects (i.e.

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[53] If flow profits become too large then the $\exp(\cdot)$ terms in the expected continuation values and conditional choice probabilities can explode which causes issues for the optimization routine.

[54] However, it would be a relatively straightforward extension to allow $\rho$ to vary by technology.

every hospital is a monopolist). As a result, all 255 hospitals in the sample are included in the estimation. In all three specifications it is assumed that there are two technologies and the only difference between the specifications is the release date of $\theta = 2$. In general the results align relatively well with the reduced-form results which is not surprising–in both cases I do not explicitly model the within-market strategic interactions between hospitals. The negative sign on the *had mobile?* parameter (where *had mobile?* is constructed the same as in the reduced-form regressions) suggests that the benefit of adoption is smaller for hospitals that operated a mobile MRI scanner compared with those that did not utilize a mobile scanner. This result is straightforward as hospitals with mobile MRI tend to adopt fixed MRI scanners relatively later. The positive and strongly significant estimate for the *ln(1+z-beds)* parameter supports the results from the descriptive analysis suggesting that larger hospitals tend to have a greater benefit from MRI technology and thus tend to adopt earlier. Again, the *ln(1+z-pop)* parameter is significant and negative. In a true monopoly one would imagine that greater demand would increase profits. So, potentially the negative sign indicates that the assumption of monopoly markets is erroneous because there are fewer gains to be had from purchasing a newer MRI scanner in larger markets where there are likely more scanners in operation. The magnitudes of all of the parameters increase as the release date of $\theta = 2$ is pushed further into the future. Fixing each covariate at its mean value, this result seems to be a direct consequence of the fact that more firms adopt $\theta = 1$. Moving from specification (1) to (3) the difference between $\pi(1)$ and $\pi(0)$ is increasing, meaning that there is a greater marginal benefit of adopting. As $\eta$ increases the convexity of the cost function increases suggesting that there are gains from delaying adoption. Combining these two facts can potentially explain the additional "late" adoptions of $\theta = 1$ as $T_2$ increases.

Tables B.21 and B.22 present results for different parameterizations of the two-technology dynamic game. The most striking result is the consistently positive and significant parameter on the competing hospitals' technologies variable (*ln(1+comp-tech)*). This result suggests that an increase in a hospital's competitors' MRI technologies increases the hospital's own flow profit and its marginal benefit from adopting an improved technology. This type of positive spillover effect between competing hospitals is the opposite of what Schmidt-Dengler (2006) finds. However, it is important to note that Schmidt-Dengler (2006) places restrictions on his parameters so that they satisfy the underlying assumptions of the Fudenberg and Tirole (1985) model. In essence, he forces competing firms to engage in the preemption equilibrium so it is not surprising that his parameter estimates suggest this is the case. In contrast, I use a much more flexible flow profit specification that does not impose these types of ex ante restrictions. While the positive effect on a competitors' flow profits is admittedly unexpected, the positive interaction between a hospital's own technology with its competitors' technologies could imply some sort of learning effect. Alternatively, this positive effect could result from limitations inherent in the data.[55] Comparing (7) with (8) the flow profit becomes more negative as $\rho$ increases. Thus, fixing the covariates, if hospitals believe that the release of the second technology is more imminent, the model predicts that flow profits will be lower. This result is in line with the simulation results in Figure B.2 where increases in $\rho$ lead to later adoption dates of $\theta = 1$ (on average). However, as previously noted, the changes in $\rho$ do not qualitatively alter the predictions of the empirical model. Finally, Table B.23 shows parameter estimates for a model with three technological advancements. The results are largely the same as those in Tables B.21 and B.22 except that here the parameter on the *ln(1+extra-hosp.)* variable becomes insignificant while the constant term gains significance.

## 3.5 Conclusion

This paper develops and analyzes an innovative technology upgrading game. I find that including additional advancements into the standard technology adoption model (with a single technology) alters firms' adoption incentives. The extent of the difference in equilibrium adoption dates is a function of several factors including the speed of technological advancement, firm beliefs, and market size and composition. In addition to solving for the equilibrium of the dynamic game I also estimate the model using a novel dataset that captures repeated adoption decisions over an extended period of time. The empirical analysis of the dynamic tradeoffs be-

[55] It would be interesting to see if the positive effect persisted when using a dataset with more detailed information on MRI scanner characteristics.

tween adopting a new technology versus waiting to adopt a future advancement in the presence of strategic interactions is a significant contribution to the literature. While parameter estimates from the empirical model are in contrast to those developed by Schmidt-Dengler (2006), there is a significant difference in the underlying assumptions and set of potential strategies in the two models. Extending a single-technology model to include multiple advancements is a complex task and thus the results from this analysis should be viewed as a first step in the process of better modeling and understanding technology upgrading games. Using data with more detailed firm and product characteristics, I am confident that this basic framework can continue to advance the frontier of this strand in the literature.

The need to better understand the process by which firms upgrade their technologies is very important from a policy perspective. Technological advancement is pervasive in all sectors of the economy and consumers and firms continue to anticipate future progress. This forward-looking behavior across multiple waves of advancements necessitates more complex economic modeling techniques. For instance, suppose firms are delaying the adoption of a new technology because an even better technology is on the horizon. A policymaker must decide whether or not to incentivize current investment at a lower cost and potentially increase total surplus in the short term or attempt to limit current investment because the gains from waiting outweigh the costs. This type of policy experiment simply cannot be addressed in a single-technology model. In the healthcare industry if there are indeed positive spillover effects from increased technological diffusion then states with CON programs might be significantly impeding healthcare efficiency by focusing on the significant fixed costs of new medical equipment. From a broader perspective there are also policy implications for the innovating firms investing in R&D. If marginal improvements to existing technologies can be patented then markets may become saturated with too many advancements resulting in suboptimal upgrading patterns (or vice versa). As technologies continue to evolve the relationship between innovation rates and technological uptake has large implications for informed welfare analysis.

# Appendix A

# Chapter 2 Appendices

## A.1 Tables and Figures

| | Joint Adoption | | Firm 1 Leader | | Firm 2 Leader | |
|---|---|---|---|---|---|---|
| $n$ | $M_1$ | $M_2$ | $L_1$ | $F_2$ | $L_2$ | $F_1$ |
| 0 | 0.111 | 0.111 | 0.359 | 0.655 | 0.234 | 0.785 |
| 1 | 0.673 | 0.573 | 0.829 | 0.667 | 0.660 | 0.853 |
| 2 | 0.863 | 0.673 | 0.937 | 0.679 | 0.728 | 0.914 |
| 3 | 0.960 | 0.689 | 0.960 | 0.689 | 0.715 | 0.969 |
| 4 | 1.019 | 0.675 | 1.019 | 0.675 | 0.675 | 1.019 |
| 5 | 1.059 | 0.650 | 1.059 | 0.650 | 0.650 | 1.059 |
| 6 | 1.089 | 0.620 | 1.089 | 0.620 | 0.620 | 1.089 |
| 7 | 1.111 | 0.589 | 1.111 | 0.589 | 0.589 | 1.111 |
| 8 | 1.128 | 0.559 | 1.128 | 0.559 | 0.559 | 1.128 |
| 9 | 1.142 | 0.530 | 1.142 | 0.530 | 0.530 | 1.142 |
| 10 | 1.154 | 0.502 | 1.154 | 0.502 | 0.502 | 1.154 |

Table A.1: Continuation Values in Figure A.6 where $n = t - T$

| | $c_1 = 0.30$ | | | | $c_1 = 0.20$ | | | | $c_1 = 0.10$ | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $j = 1$ | | $j = 2$ | | $j = 1$ | | $j = 2$ | | $j = 1$ | | $j = 2$ | |
| *Firm* | 1 | 2 | 1 | 2 | 1 | 2 | 1 | 2 | 1 | 2 | 1 | 2 |
| $x = 0$ | 500 | 500 | 10 | 10 | 500 | 500 | 10 | 10 | 500 | 500 | 10 | 10 |
| 0.1 | 500 | 500 | 10 | 13 | 500 | 500 | 10 | 13 | 0 | 62 | 510 | 12 |
| 0.2 | 500 | 500 | 10 | 13 | 30 | 500 | 10 | 13 | 1 | 15 | 116 | 12 |
| 0.3 | 106 | 208 | 10 | 13 | 8 | 66 | 17 | 12 | 1 | 10 | 38 | 13 |
| 0.4 | 90 | 90 | 11 | 13 | 5 | 21 | 16 | 12 | 1 | 7 | 14 | 26 |
| 0.5 | 38 | 38 | 11 | 13 | 3 | 13 | 15 | 12 | 1 | 5 | 14 | 21 |
| 0.6 | 23 | 23 | 11 | 13 | 3 | 9 | 12 | 15 | 1 | 5 | 14 | 19 |
| 0.7 | 16 | 16 | 11 | 13 | 3 | 7 | 13 | 14 | 2 | 4 | 17 | 17 |
| 0.8 | 12 | 12 | 11 | 13 | 3 | 6 | 12 | 14 | 2 | 4 | 14 | 17 |
| 0.9 | 10 | 10 | 11 | 13 | 3 | 5 | 12 | 14 | 2 | 3 | 14 | 16 |
| 1.0 | 8 | 8 | 12 | 13 | 3 | 5 | 13 | 13 | 2 | 3 | 15 | 15 |

*Parameterization:* $C(n) = 1/((1+n)^x)$, $c_0 = 0.40$, $\rho = 0.1$, $\beta = 0.9$, *and* $T = 10$

Table A.2: Duopoly Adoption Dates for Different Parameterizations of $C(n)$

| | $c_1 = 0.30$ | | | | $c_1 = 0.20$ | | | | $c_1 = 0.10$ | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $j = 1$ | | $j = 2$ | | $j = 1$ | | $j = 2$ | | $j = 1$ | | $j = 2$ | |
| *Firm* | 1 | 2 | 1 | 2 | 1 | 2 | 1 | 2 | 1 | 2 | 1 | 2 |
| $x = 0.5,\ \rho = 0$ | 7 | 20 | 13 | 11 | 2 | 8 | 12 | 15 | 2 | 4 | 14 | 21 |
| 0.1 | 38 | 38 | 11 | 13 | 3 | 13 | 15 | 12 | 1 | 5 | 14 | 21 |
| 0.2 | 74 | 74 | 11 | 13 | 6 | 19 | 15 | 12 | 2 | 6 | 14 | 21 |
| 0.3 | 120 | 120 | 11 | 13 | 8 | 25 | 15 | 12 | 2 | 7 | 14 | 21 |
| 0.4 | 174 | 174 | 11 | 13 | 10 | 31 | 13 | 11 | 2 | 8 | 14 | 21 |
| 0.5 | 236 | 236 | 11 | 13 | 12 | 37 | 13 | 11 | 2 | 8 | 14 | 21 |
| 0.6 | 303 | 303 | 11 | 13 | 14 | 43 | 13 | 11 | 3 | 9 | 14 | 21 |
| 0.7 | 374 | 374 | 11 | 13 | 16 | 48 | 13 | 11 | 3 | 9 | 14 | 21 |
| 0.8 | 449 | 449 | 11 | 13 | 17 | 52 | 13 | 11 | 3 | 10 | 21 | 13 |
| 0.9 | 500 | 500 | 11 | 13 | 18 | 57 | 13 | 11 | 3 | 10 | 21 | 13 |
| 1.0 | 500 | 500 | 11 | 13 | 19 | 61 | 13 | 11 | 3 | 10 | 21 | 13 |
| $x = 1.0,\ \rho = 0$ | 5 | 7 | 12 | 13 | 3 | 4 | 13 | 13 | 2 | 3 | 15 | 15 |
| 0.1 | 8 | 8 | 12 | 13 | 3 | 5 | 13 | 13 | 2 | 3 | 15 | 15 |
| 0.2 | 10 | 10 | 11 | 13 | 3 | 5 | 13 | 13 | 2 | 3 | 15 | 15 |
| 0.3 | 12 | 12 | 11 | 13 | 3 | 5 | 13 | 13 | 2 | 3 | 15 | 15 |
| 0.4 | 14 | 14 | 11 | 13 | 3 | 5 | 13 | 13 | 2 | 3 | 15 | 15 |
| 0.5 | 16 | 16 | 11 | 13 | 4 | 5 | 13 | 13 | 2 | 3 | 15 | 15 |
| 0.6 | 16 | 16 | 11 | 13 | 4 | 5 | 13 | 13 | 2 | 3 | 15 | 15 |
| 0.7 | 16 | 16 | 11 | 13 | 4 | 6 | 13 | 13 | 2 | 3 | 15 | 15 |
| 0.8 | 17 | 17 | 11 | 13 | 4 | 6 | 13 | 13 | 2 | 3 | 15 | 15 |
| 0.9 | 17 | 17 | 11 | 13 | 4 | 6 | 13 | 13 | 2 | 3 | 15 | 15 |
| 1.0 | 17 | 17 | 11 | 13 | 4 | 6 | 13 | 13 | 2 | 3 | 15 | 15 |

*Parameterization:* $C(n) = 1/((1+n)^x)$, $c_0 = 0.40$, $\beta = 0.9$, *and* $T = 10$

Table A.3: Duopoly Adoption Dates for Different Firm Beliefs ($\rho$)

| | $c_0 = 0.40$ | | | | | | | | $c_0 = 0.25$ | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $j = 1$ | | | | $j = 2$ | | | | $j = 1$ | | | | $j = 2$ | | | |
| *Firm* | $P$ | $M$ | $D_1$ | $D_2$ | $P$ | $M$ | $D_1$ | $D_2$ | $P$ | $M$ | $D_1$ | $D_2$ | $P$ | $M$ | $D_1$ | $D_2$ |
| $x = 0.2$, $c_1 = 35$ | 500 | 500 | 500 | 500 | 10 | 11 | 10 | 13 | | | | | | | | |
| 30 | 217 | 500 | 500 | 500 | 10 | 11 | 10 | 13 | | | | | | | | |
| 25 | 27 | 346 | 500 | 500 | 10 | 11 | 10 | 13 | | | | | | | | |
| 20 | 6 | 61 | 30 | 500 | 11 | 11 | 10 | 13 | 500 | 500 | 500 | 500 | 10 | 13 | 10 | 17 |
| 15 | 2 | 15 | 5 | 108 | 12 | 11 | 34 | 12 | 51 | 438 | 211 | 500 | 10 | 13 | 10 | 17 |
| 10 | 1 | 5 | 1 | 15 | 15 | 59 | 116 | 12 | 7 | 35 | 12 | 95 | 15 | 13 | 10 | 17 |
| 5 | 0 | 2 | 0 | 5 | 54 | 510 | 510 | 510 | 2 | 7 | 1 | 15 | 54 | 510 | 510 | 16 |
| $x = 1.0$, $c_1 = 35$ | 8 | 13 | 18 | 18 | 11 | 12 | 11 | 13 | | | | | | | | |
| 30 | 4 | 7 | 8 | 8 | 11 | 12 | 12 | 13 | | | | | | | | |
| 25 | 3 | 5 | 5 | 5 | 11 | 12 | 12 | 13 | | | | | | | | |
| 20 | 2 | 4 | 3 | 5 | 12 | 13 | 13 | 13 | 6 | 10 | 7 | 12 | 12 | 12 | 13 | 13 |
| 15 | 2 | 3 | 2 | 4 | 12 | 14 | 14 | 14 | 3 | 6 | 6 | 6 | 12 | 14 | 14 | 14 |
| 10 | 1 | 2 | 2 | 3 | 13 | 15 | 15 | 15 | 2 | 4 | 3 | 5 | 13 | 15 | 15 | 15 |
| 5 | 1 | 2 | 1 | 3 | 15 | 18 | 18 | 18 | 2 | 3 | 3 | 3 | 15 | 18 | 18 | 18 |

*Parameterization:* $C(n) = 1/((1+n)^x)$, $\beta = 0.9$, $\rho = 0.1$, *and* $T = 10$

Table A.4: Monopoly, Duopoly, and Efficient Adoption Dates for Different Marginal Cost Vectors and Adoption Costs

| | $j=1$ | | | $j=2$ | | | $\sigma$ | | $\Delta_\sigma$ |
|---|---|---|---|---|---|---|---|---|---|
| *Firm* | $P$ | $D_1$ | $D_2$ | $P$ | $D_1$ | $D_2$ | $\sigma_P$ | $\sigma_D$ | |
| $c_1=0.3,\ \rho=0.1$ | 10 | 38 | 38 | 11 | 11 | 13 | 2.58 | 2.10 | 0.48 |
| 0.4 | 28 | 174 | 174 | 11 | 11 | 13 | 2.58 | 2.10 | 0.48 |
| 0.7 | 47 | 374 | 374 | 11 | 11 | 13 | 2.58 | 2.10 | 0.48 |
| $c_1=0.2,\ \rho=0.1$ | 3 | 3 | 13 | 12 | 15 | 12 | 2.80 | 2.09 | 0.71 |
| 0.4 | 6 | 10 | 31 | 12 | 11 | 13 | 2.69 | 2.10 | 0.59 |
| 0.7 | 10 | 16 | 48 | 11 | 11 | 13 | 2.58 | 2.10 | 0.48 |
| $c_1=0.1,\ \rho=0.1$ | 1 | 1 | 5 | 14 | 14 | 21 | 3.30 | 2.33 | 0.97 |
| 0.4 | 2 | 2 | 8 | 14 | 14 | 21 | 3.27 | 2.38 | 0.89 |
| 0.7 | 3 | 3 | 9 | 14 | 14 | 21 | 3.19 | 2.36 | 0.83 |

*Parameterization:* $C(n)=1/((1+n)^{0.5})$, $c_0=0.40$, $\beta=0.9$, *and* $T=10$

Table A.5: Duopoly and Socially Optimal Adoption Dates and Total Surplus for Different Beliefs ($\rho$)

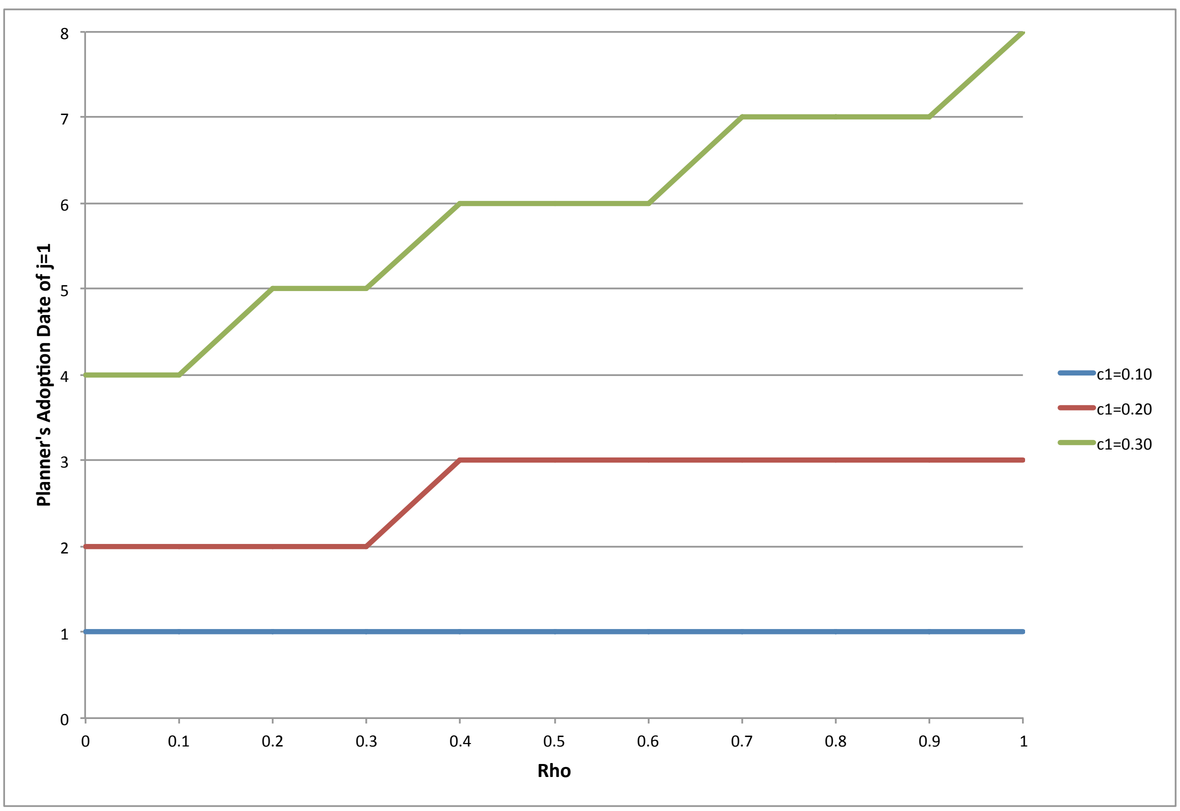



Figure A.1: Planner's Adoption Date of $j=1$ for Different Values of $\rho$ and $c_1$ (where $c_0=0.4$, $\beta=0.9$, and $C(n)=1/(1+n)$)

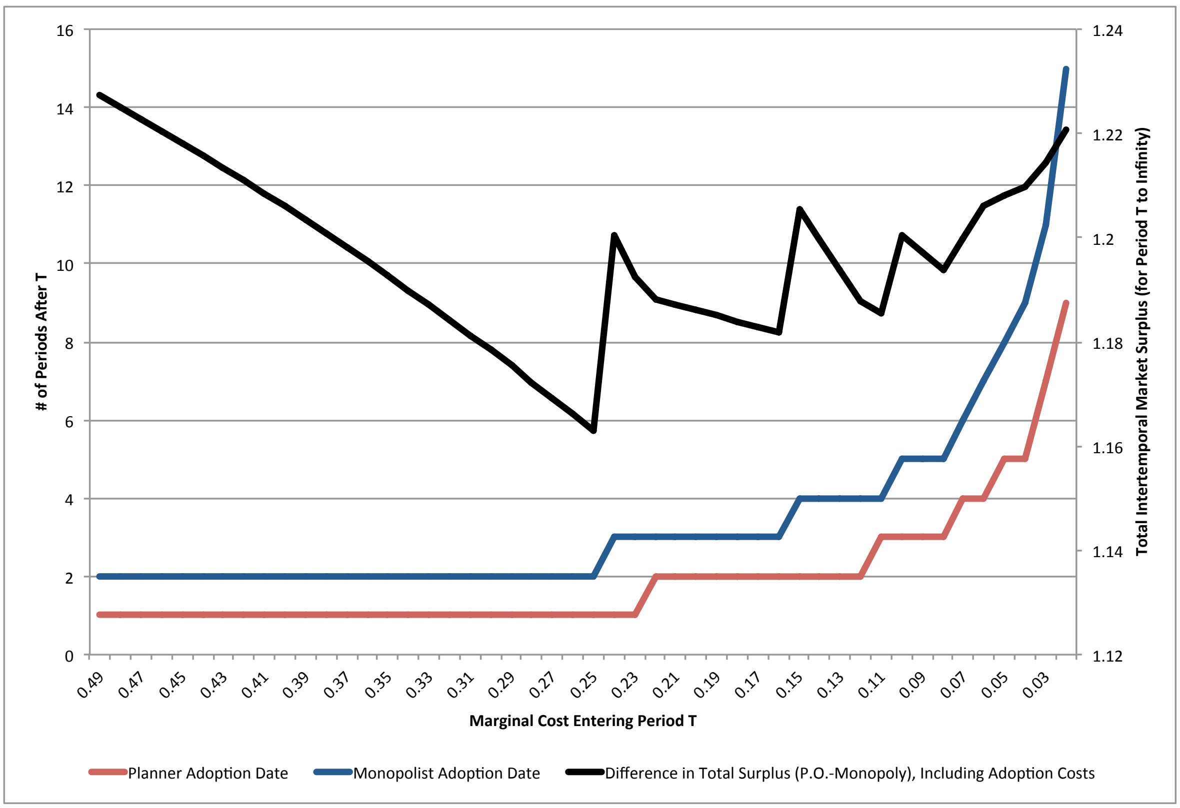



Figure A.2: Efficient and Monopoly Adoption Dates for j=2 (where $\beta = 0.9$ and $C(n) = 1/(1+n)$)

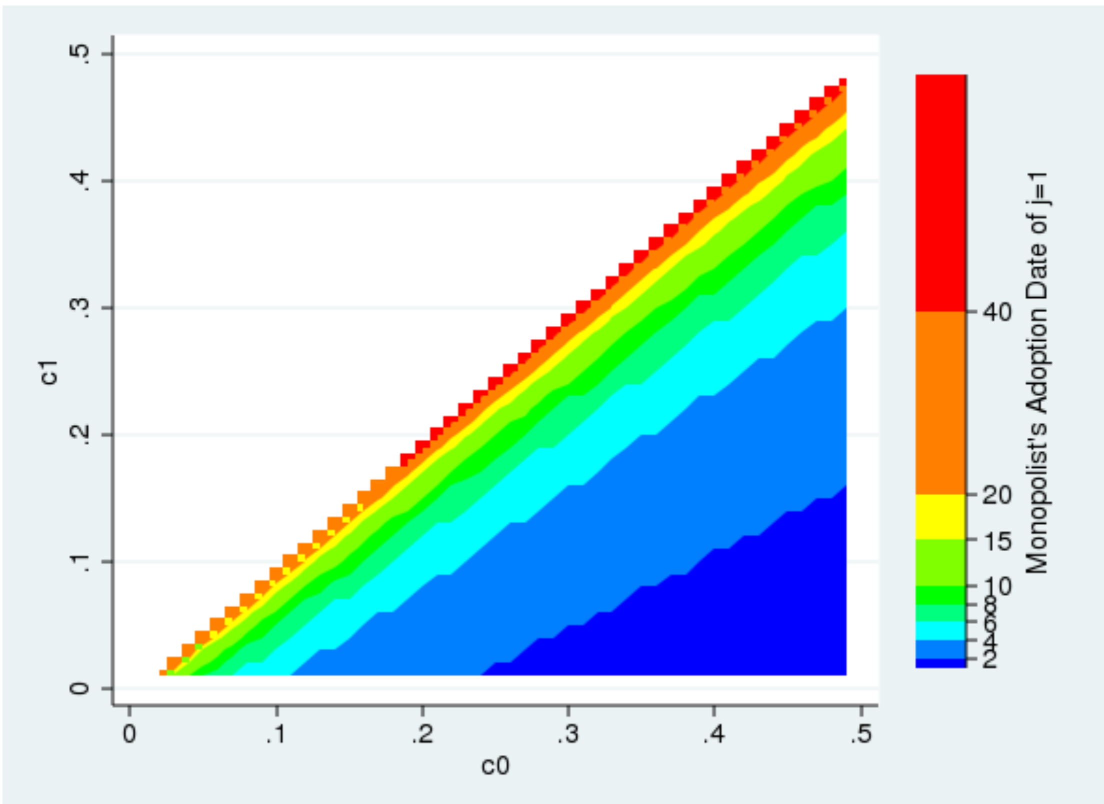



Figure A.3: Monopoly Adoption Dates for j=1 ($\beta = 0.9, p = 0.1$)

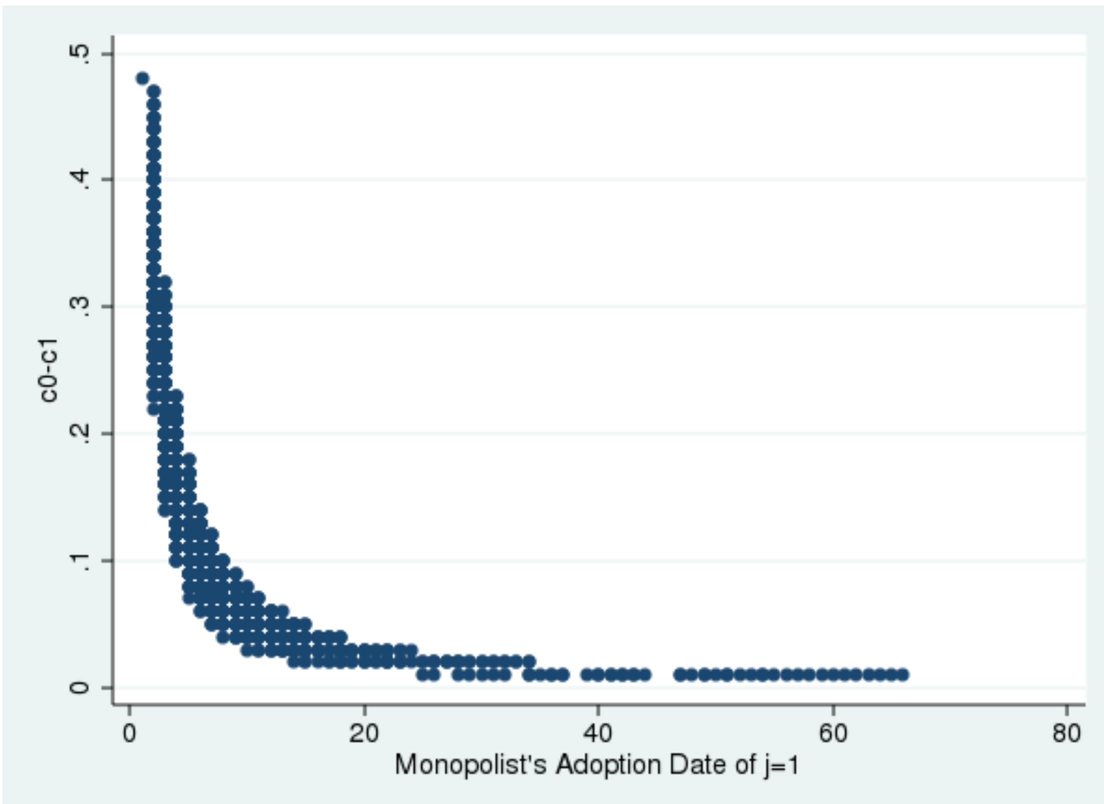



Figure A.4: Scatter Plot of $c_0 - c_1$ versus Monopoly Adoption Dates for j=1

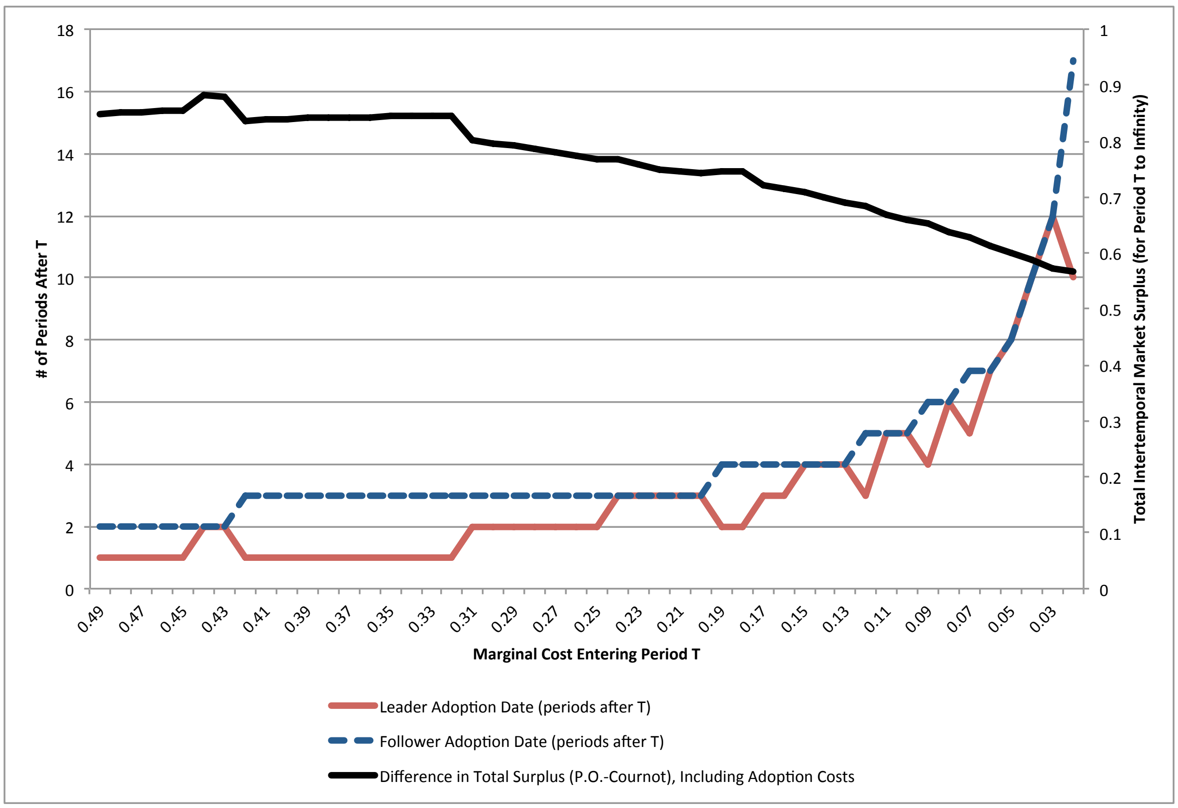



Figure A.5: Cournot Adoption Dates for $j = 2$ in States $(T, 0, a, a)$

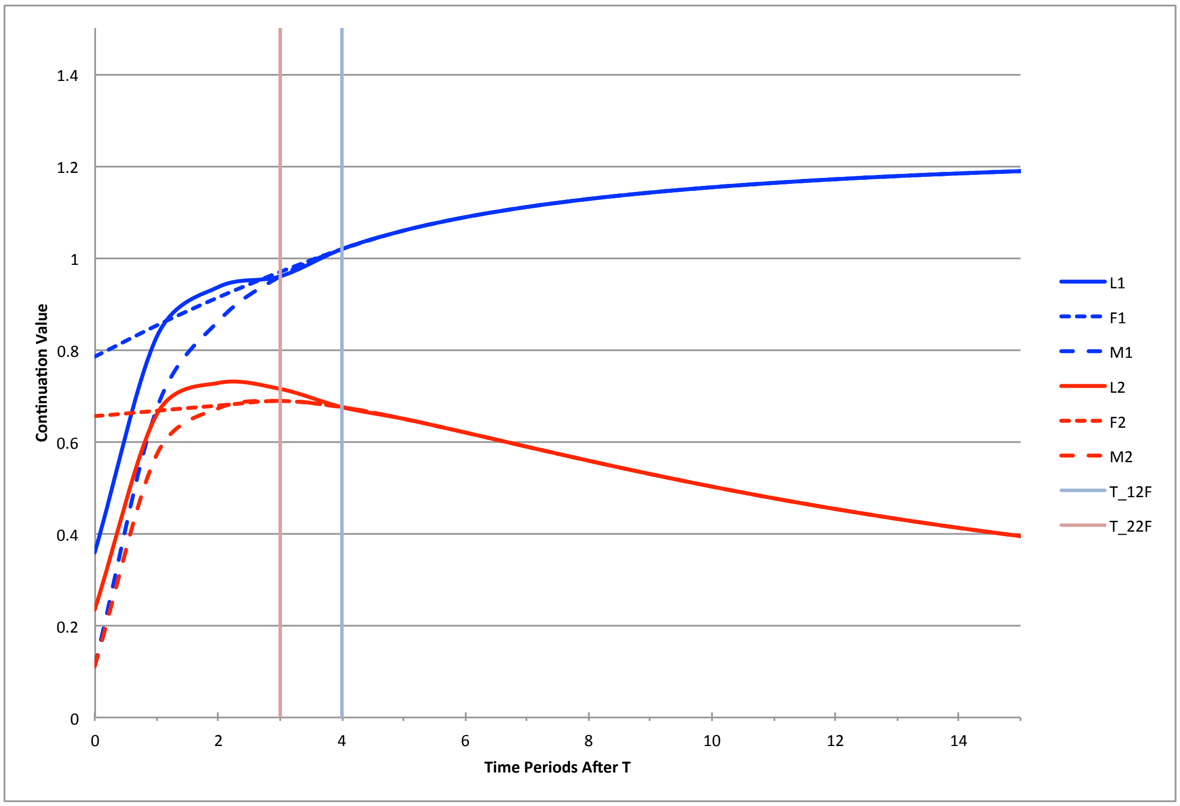
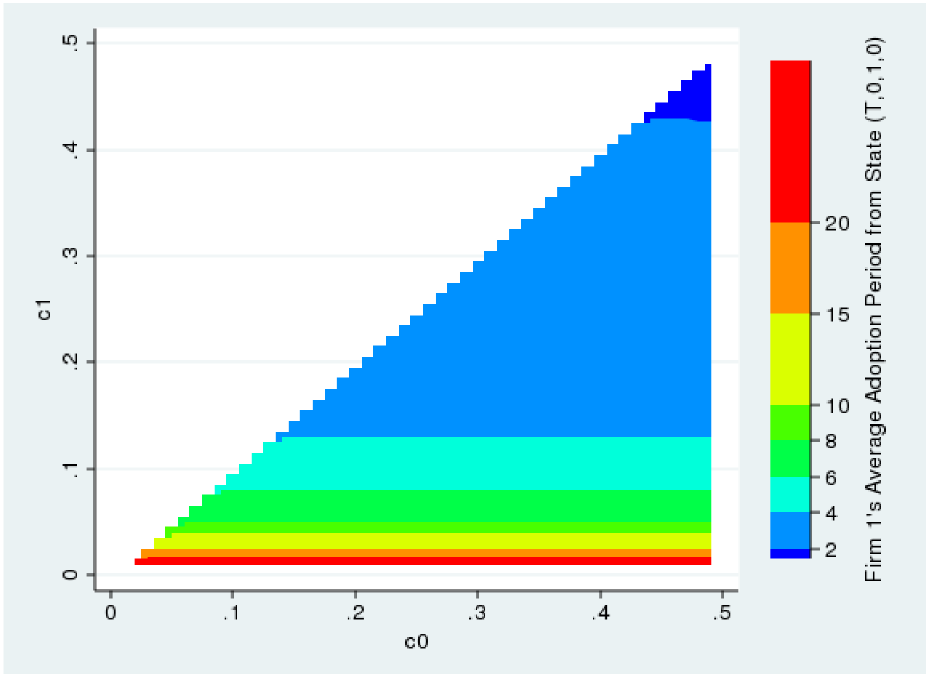
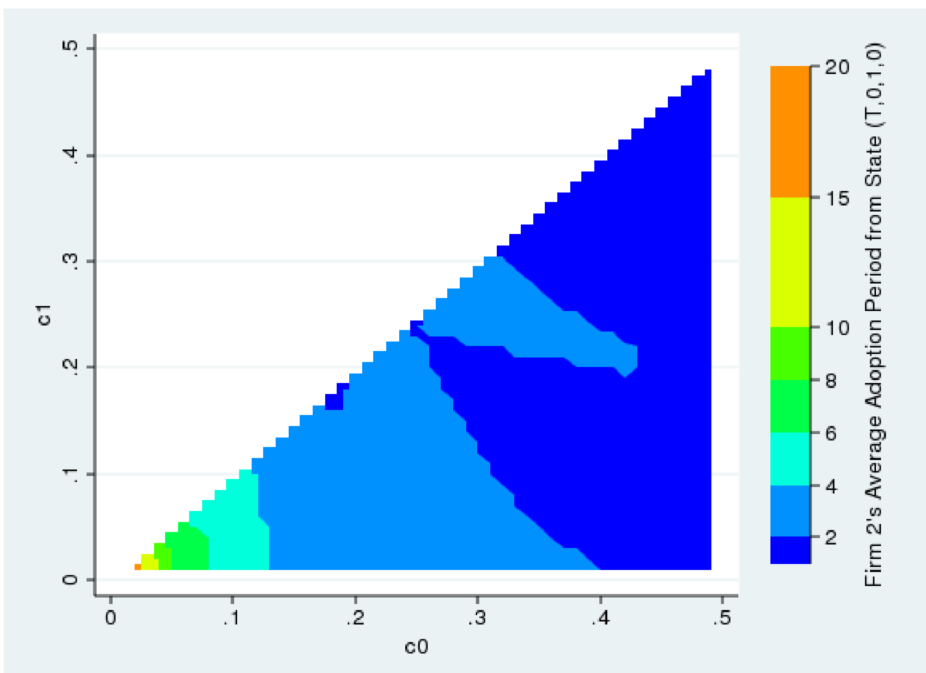



Figure A.6: Example Continuation Game Beginning in State $(T, 0, 1, 0)$ where $(\beta = 0.9, c_0 = 0.35, c_1 = 0.15)$

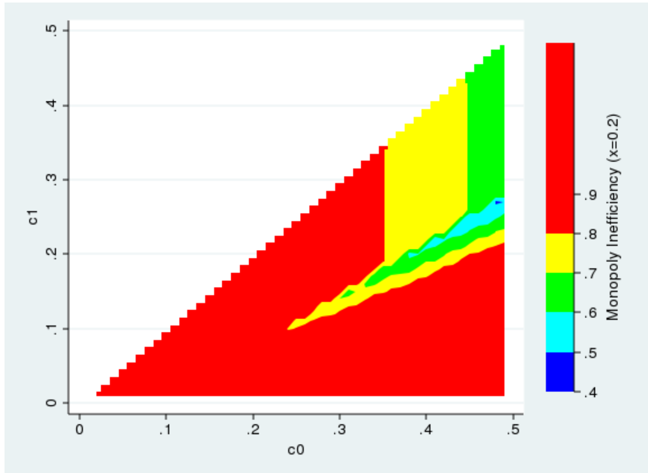



(a) Firm 1's Average Adoption Period

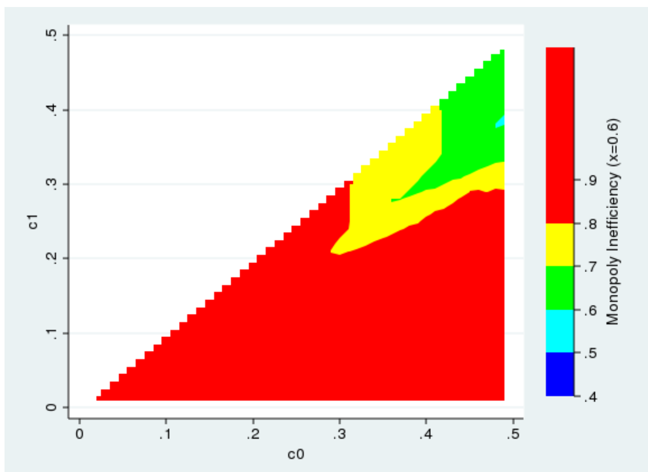



(b) Firm 2's Average Adoption Period

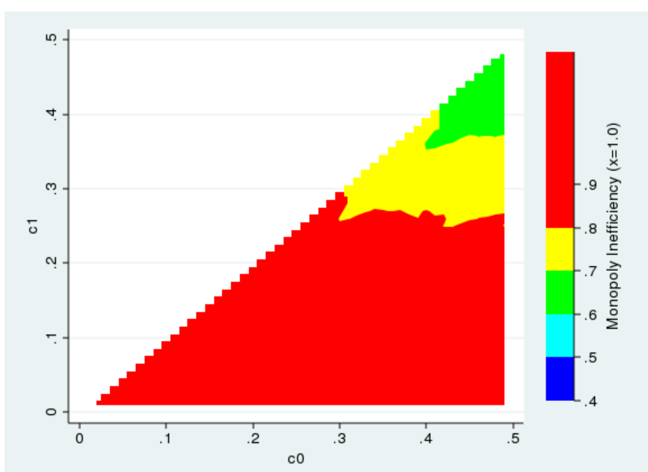
Figure A.7: Cournot Adoption Dates (# of Periods After $T$) in State $(T, 0, 1, 0)$




(a) $x = 0.2$

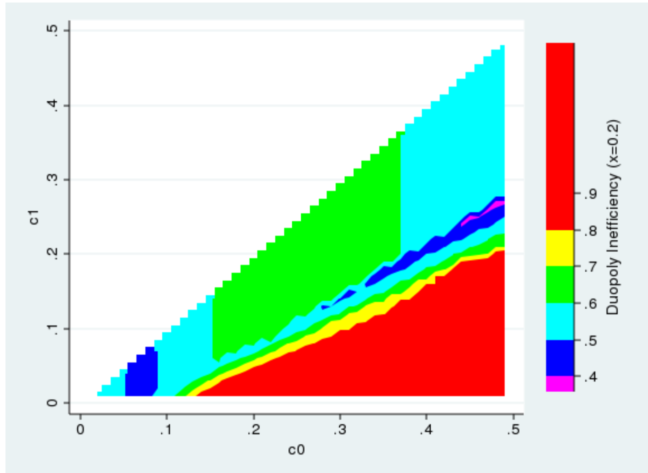



(b) $x = 0.6$

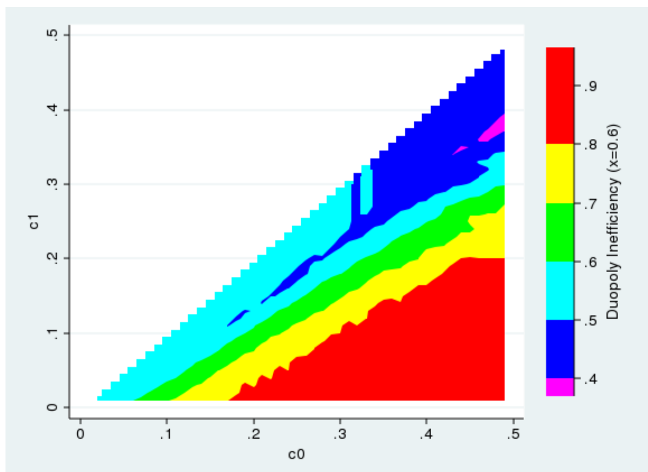



(c) $x = 1.0$

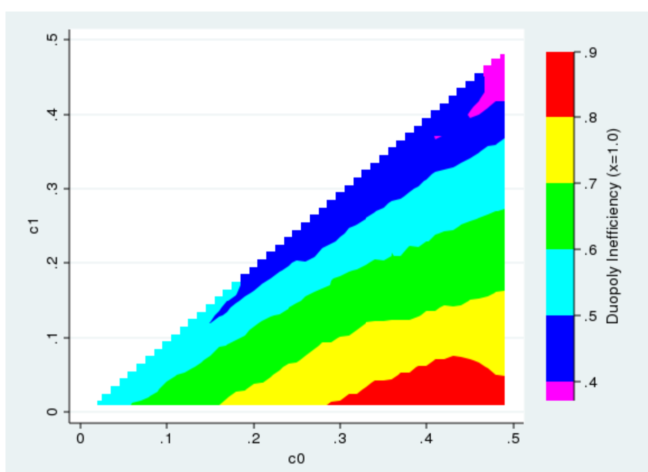
Figure A.8: Total Monopoly Inefficiency, Including Adoption Costs (where $C(n) = \frac{1}{(1+n)^x}$)




(a) $x = 0.2$

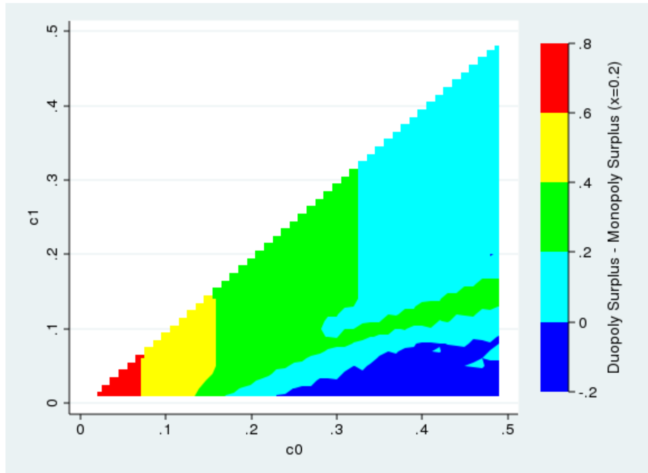



(b) $x = 0.6$

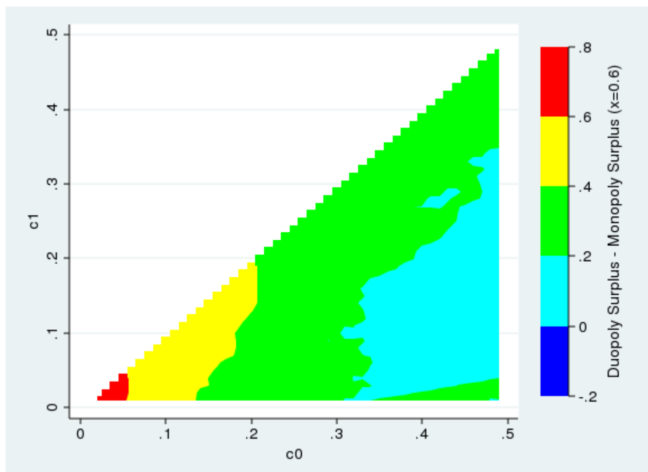



(c) $x = 1.0$

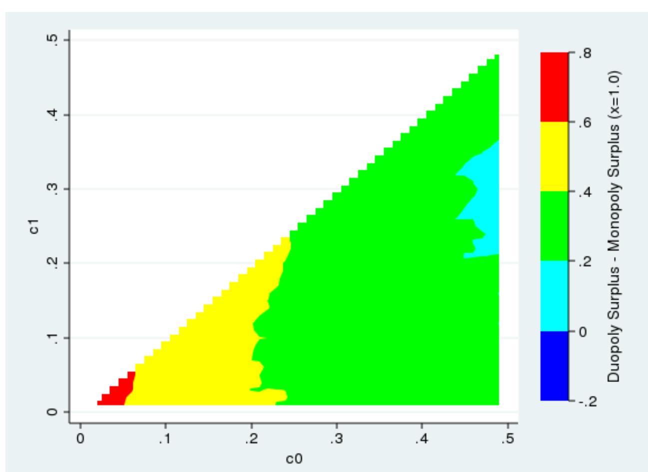
Figure A.9: Total Duopoly Inefficiency, Including Adoption Costs (where $C(n) = \frac{1}{(1+n)^x}$)




(a) $x = 0.2$

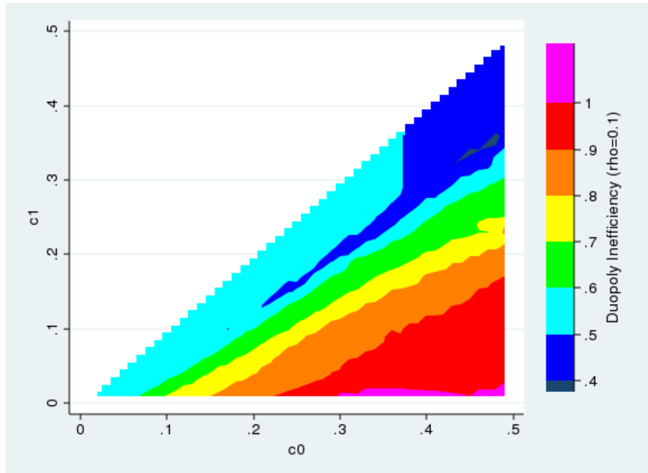



(b) $x = 0.6$

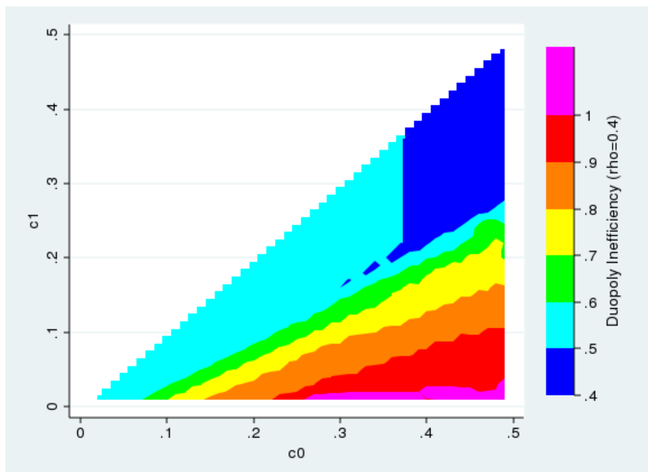



(c) $x = 1.0$

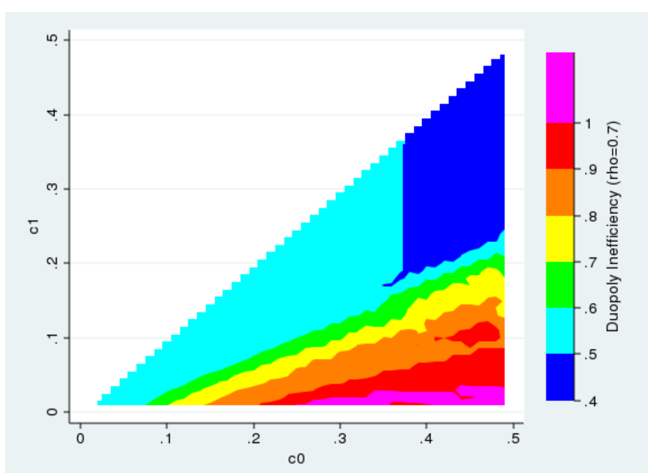
Figure A.10: Difference in Total Intertemporal Surplus (Duopoly − Monopoly), Including Adoption Costs (where $C(n) = \frac{1}{(1+n)^x}$)




(a) $\rho = 0.1$

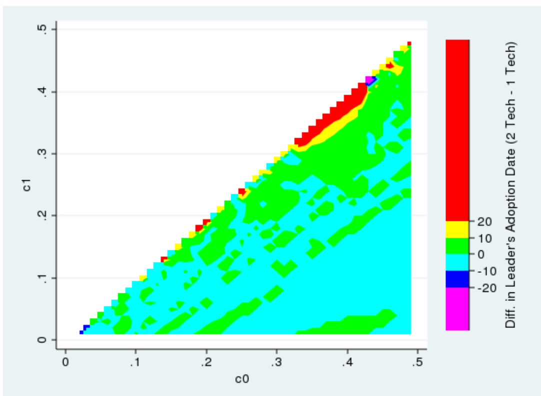



(b) $\rho = 0.4$

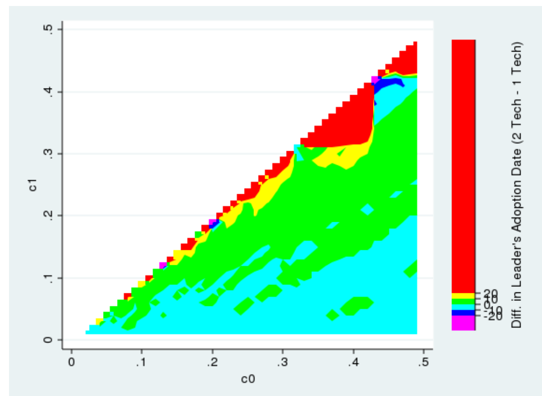



(c) $\rho = 0.7$

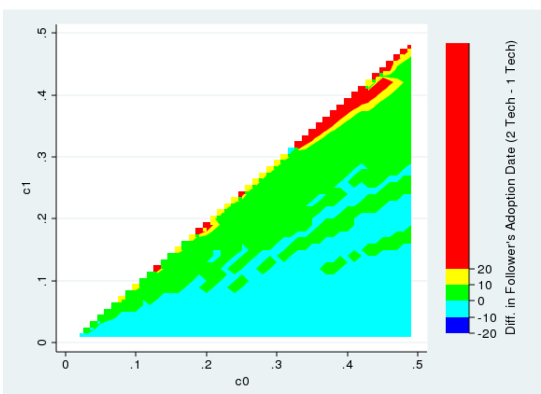
Figure A.11: Total Duopoly Inefficiency, Including Adoption Costs for Different Values of $\rho$ (where $C(n) = \frac{1}{(1+n)^{0.5}}$)



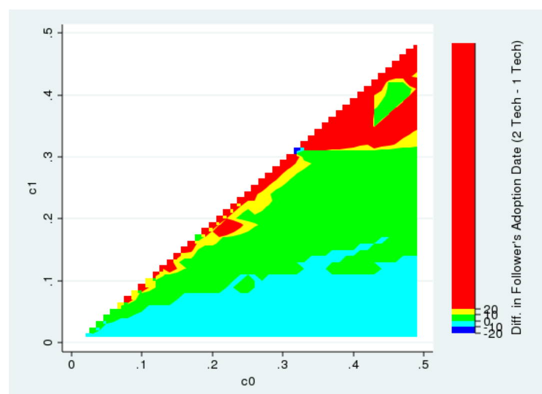

(a) Leader ($\rho = 0.1$)




(b) Leader ($\rho = 0.7$)

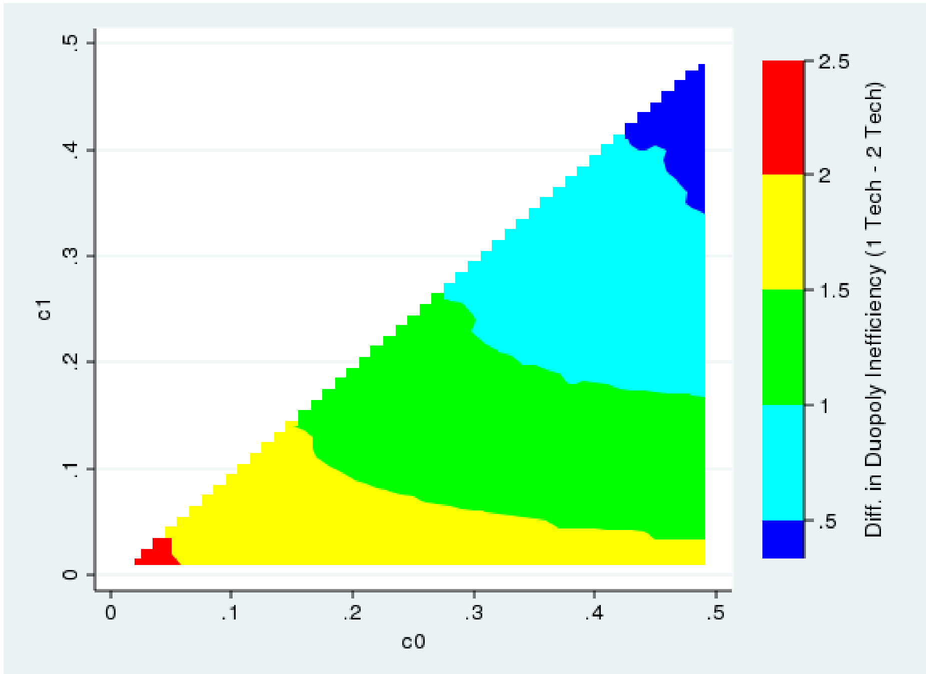



(c) Follower ($\rho = 0.1$)

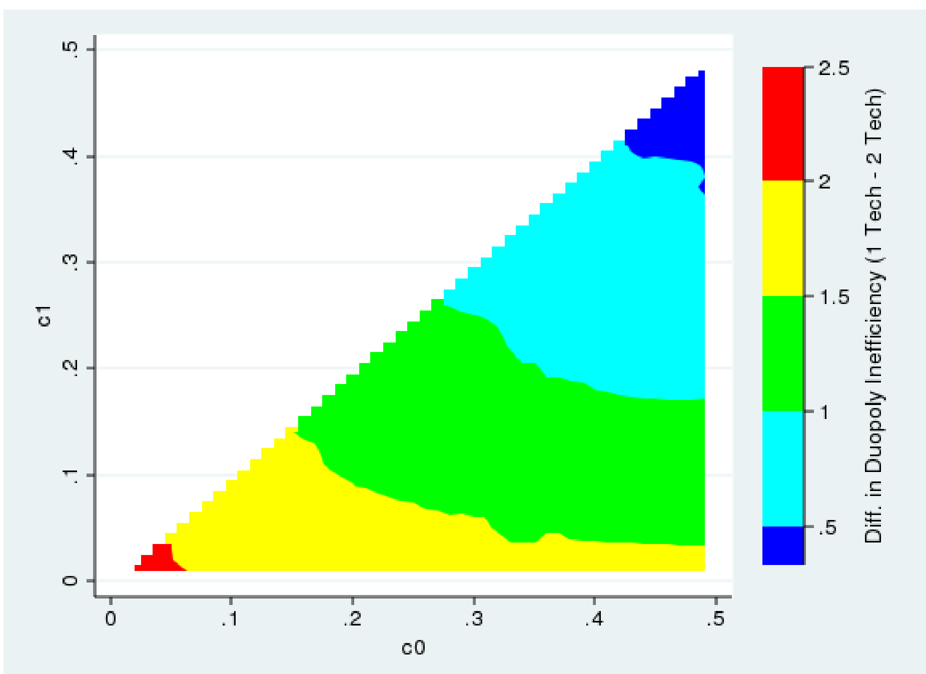



(d) Follower ($\rho = 0.7$)

Figure A.12: Difference in Adoption Dates of $j = 1$ for a Two- vs. One-Technology Model (Two-Technology Date – One-Technology Date, Color Scale Maintained Throughout)




(a) $\rho = 0.1$




(b) $\rho = 0.7$

Figure A.13: Difference in Total Inefficiency (One-Technology Model – Two-Technology Model)

## A.2 Bertrand Stage Game

In this section we examine the dynamic game under the assumption that in each period firms compete in prices rather than quantities. We find that the unique equilibrium exhibits "increasing dominance" as in Vickers (1986) and Riordan and Salant (1994).[1] Suppose that rather than competing in quantities, the two firms engage in a Bertrand pricing game in the second stage of each period. Output is assumed to be homogeneous between the two firms and all other assumptions from the previous analysis are still maintained. Conditional on the firms' technology choices in a given period, flow profits are given by:

$$\pi(a_i, a_{-i}) = \begin{cases} (1 - c_{a_{-i}})(c_{a_{-i}} - c_{a_i}) & \text{if } a_i > a_{-i} \\ 0 & \text{if } a_i \leq a_{-i} \end{cases}.$$

Here a firm's flow profit is positive only if its technology is strictly better than its competitor's technology. Below we show that as periods become shorter, this "all or nothing" payoff structure yields a unique equilibrium where only *one* firm (potentially) adopts the new technologies. The proof is illustrated through a series of lemmas.

**Lemma 1.** *Consider the continuation game beginning in period $T$ (when $j = 2$ is released). In this continuation game no joint-adoption equilibrium exists.*

*Proof.* It suffices to show that a profitable one-shot deviation exists in all states $(t, n, a_i^{t-1}, a_{-i}^{t-1})$ where $t \geq T$ and both $a_i^{t-1}$ and $a_{-i}^{t-1}$ are strictly less than $j = 2$. In each pertinent state a firm's value under joint-adoption is given by:

$$V(t, n, a_i^{t-1}, a_{-i}^{t-1}) = 0 - C(n) + \beta\left[V(t+1, n+1, 2, 2)\right] = -C(n),$$

[1] Vickers (1986) examines a sequence of patent races between duopoly firms. In each period a cost-reducing technology is released that is won by the highest bidder in second-price auction. He shows that if profits are determined via a Bertrand equilibrium then only one of the two firms will ever purchase the new technologies. Riordan and Salant (1994) show that a similar result holds in the Nash equilibrium of a continuous-time game dynamic duopoly game where adoption costs are constant. They also utilize an alternating-move framework. Here, we show that if firms compete in prices the unique subgame-perfect Nash equilibrium of our dynamic game involves only one firm adopting when adoption costs decrease with time.

noting that the continuation value $V(t+1, n+1, 2, 2)$ is equal to zero because both firms set $p = c_2 = 0$. Now assume that one firm deviates by choosing $a_i^t = a_i^{t-1}$ in the current period. The value of this one-shot deviation is given by:

$$V(t, n, a_i^{t-1}, a_{-i}^{t-1}) = 0 + \beta \left[ V(t+1, n+1, \hat{a}_i^t, 2) \right] = 0.$$

Here, firm $i$'s equilibrium strategy in each period after $t$ induced by the one-shot deviation involves choosing $\hat{a}_i^{\tilde{t}} = \hat{a}_i^{\tilde{t}-1}$, $\forall \tilde{t} \geq t$. In other words, once firm $i$ deviates and chooses not to adopt $j = 2$, it is optimal to never adopt $j = 2$ at any point in the future. As a result, the continuation value under the one-shot deviation, $V(t+1, n+1, \hat{a}_i^t, 2)$, is equal to zero. Thus, the value of not adopting is strictly greater than the value of adopting and a one-shot deviation always exists. □

**Lemma 2.** *Consider the continuation game beginning in period $T$ (when $j = 2$ is released). In this continuation game exactly one firm adopts technology $j = 2$.*

*Proof.* Entering period $T$ there are four potential states: $(T, 0, 0, 0)$, $(T, 0, 1, 1)$, $(T, 0, 1, 0)$, and $(T, 0, 0, 1)$. The analysis of the first two states is analogous and so is the analysis of the latter two states. Consider state $(T, 0, 0, 0)$. We have already shown that no joint-adoption equilibrium exists. Below we show that once one of the firms adopts $j = 2$ the remaining firm responds optimally by never adopting $j = 2$. Suppose firm $-i$ has already adopted $j = 2$. Firm $i$'s continuation payoff from adopting in the current period is $-C(n)$. However, firm $i$ guarantees itself a continuation payoff of zero by deciding never to adopt. Thus, once preempted, firm $i$'s optimal strategy is to never adopt $j = 2$. The adopting firm's payoff is maximized by waiting until the first period where the flow profit from adopting exceeds the cost benefit from delaying adoption. This occurs at the first date $n$ periods after $T$ when the following inequality holds:

$$(1 - c_0)(c_0 - c_2) > C(n) - \beta C(n+1).$$

However, the non-adopting firm has an incentive to preempt its competitor if the continuation value from doing so is greater than zero. This preemption incentive drives the period in which the adopting firm actually adopts $j = 2$ back to the first point in time where the value of adopting exceeds the value of never adopting. Specifically, this is the first period $t \geq T$ where

$$\frac{(1-c_0)(c_0-c_2)}{1-\beta} \geq C(n).^2 \tag{A.1}$$

The analysis in the asymmetric states is similar. However, in these states there is a unique outcome–the firm entering period $T$ with technology $j = 1$ always acts as the sole adopter of $j = 2$. The firm entering with $j = 1$ has a greater incentive to adopt $j = 2$ because it attains a higher flow profit in each period after adopting, $(1 - c_0)(c_0 - c_2)$, than the firm entering with $j = 0$ ($(1 - c_1)(c_1 - c_2)$). Thus, the preemption incentive drives the $j = 1$ firm's adoption time back to the latest period where

$$\frac{(1-c_1)(c_1-c_2)}{1-\beta} \leq C(n).^3$$

Stated differently, the $j = 1$ firm delays adoption until the last period before it becomes optimal for the $j = 0$ firm to adopt. □

Lemma 2 essentially states that if the firms enter period $T$ with the same technology, the incentive to preempt one another drives each firm's equilibrium continuation value toward zero. In fact, as the length of each time period decreases, (1) gets closer and closer to holding with equality. In other words, the adopter of $j = 2$ generates rents at the competing firm's expensive solely due to the fact that both firms are restricted to act at discrete points in time. If time periods are sufficiently short, only one firm can ever adopt the new technologies in equilibrium.

[2] It is important to note that the adopter's continuation value is greater than the non-adopter's continuation value solely because time is discrete. In continuous time the preemption incentive drives both firms' continuation values to zero.

[3] While the adopting firm would prefer to act like a monopolist and set price equal to 1/2, this cannot be an equilibrium because the non-adopting firm would undercut the price until it once again reached $c_0$.

**Lemma 3.** *Suppose time periods are sufficiently short so that $V(T, 0, 0, 0) = V(T, 0, 1, 1) = 0$. In this situation there is a unique class of equilibria where only one firm (potentially) adopts the new technologies.*[4]

*Proof.* First suppose that both firms have adopted $j = 1$ when $j = 2$ is released. In this situation each firm's continuation value beginning in period $T$ is equal to zero. Next, suppose that one firm has adopted $j = 1$ and the remaining firm is deciding whether or not to adopt $j = 1$ in some period $t < T$. Whether the firm adopts $j = 1$ or not, its flow profit in the current period and its continuation value are both equal to zero. Thus, it is never profitable for the firm to adopt $j = 1$ and incur a cost of $C(t)$. By Lemma 1 (substituting the correct continuation values) there also cannot be a joint-adoption equilibrium for $j = 1$. Thus, by logic similar to that developed in Lemma 2, the preemption incentive drives exactly one firm to adopt $j = 1$ in the first period $t$ where

$$(1 - c_0)(c_0 - c_1) - C(t) + \beta \left[\rho V(T, 0, 1, 0) + (1 - \rho)V(t + 1, t + 1, 1, 0)\right] \geq 0. \tag{A.2}$$

By Lemma 2 the firm adopting $j = 1$ is the only firm to subsequently adopt $j = 2$. If $j = 2$ is released before (2) holds, then neither firm adopts $j = 1$ and by Lemma 2, a single firm adopts $j = 2$. □

[4]This wording is admittedly poor. What we are trying to say is that if both technologies are adopted, they are adopted by the same firm. However, it is possible that if $j = 2$ is released early enough, neither firm adopts $j = 1$ in equilibrium.

## A.3 Issues with Discrete Time

The use of discrete time can generate equilibrium outcomes different from those developed in Fudenberg and Tirole (1985). In section 2.2.3 we show why there are no "true" late joint-adoption equilibria in discrete time. However, there are values of $c$ where what would be a diffusion equilibrium in continuous time is transformed into a joint-adoption equilibrium in $T_{2F}$ in discrete time. Consider Figure A.14. The black line plots the leader's value of adopting

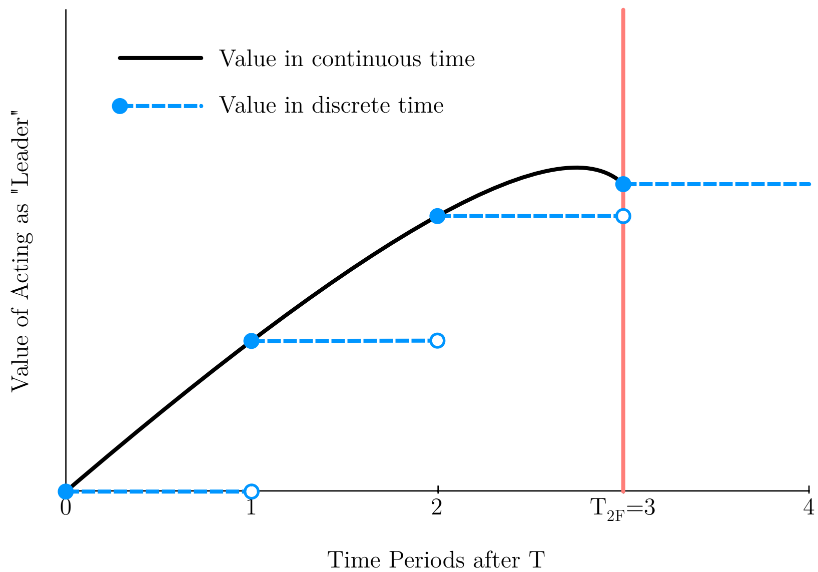



Figure A.14: A Situation where a Diffusion Equilibrium in Continuous Time Appears to be a Joint-Adoption Equilibrium in Discrete Time

in continuous time and the blue dots signify the values that the function takes at each point in discrete time. As explained in section 2.2.3, the leader's value reaches a maximum at a point in time before $T_{2F}$. However, that point in time lies between $T_{2F} - 1 = 2$ and $T_{2F} = 3$. As a result, in discrete time the value of leading in period 2 is less than the value of following in period 3. Thus, in discrete time, neither firm wants to adopt the technology at any point in time before $T_{2F}$ and a joint-adoption equilibrium ensues in period 3. This issue is an obvious shortcoming of modeling the dynamic technology adoption game in discrete time and is exacerbated in situations where there is less incentive to act as "leader."

Even when $T_{2L}$ is strictly less than $T_{2F}$, the use of discrete time can alter each firm's incentive to preempt one another, causing the leader to adopt in a different period than he would in continuous time. Consider Figure A.15. We suppose that both firms enter period $T$ with the same technology so that the game is analogous to that discussed in Fudenberg and Tirole (1985). The blue (red) line denotes the leader's (follower's) continuation value from period $T$ on, *conditional on the leader adopting* $j = 2$ *in period* $n$ *and the follower responding optimally by adopting in period* $T_{2F}$. For instance, suppose that the leader chooses to adopt in period $n = 3$. In this case the leader would receive a continuation value of "C" while the follower would delay adoption until $T_{2F}$ and receive "E." In the example, $T_{2F} = 6$, and at

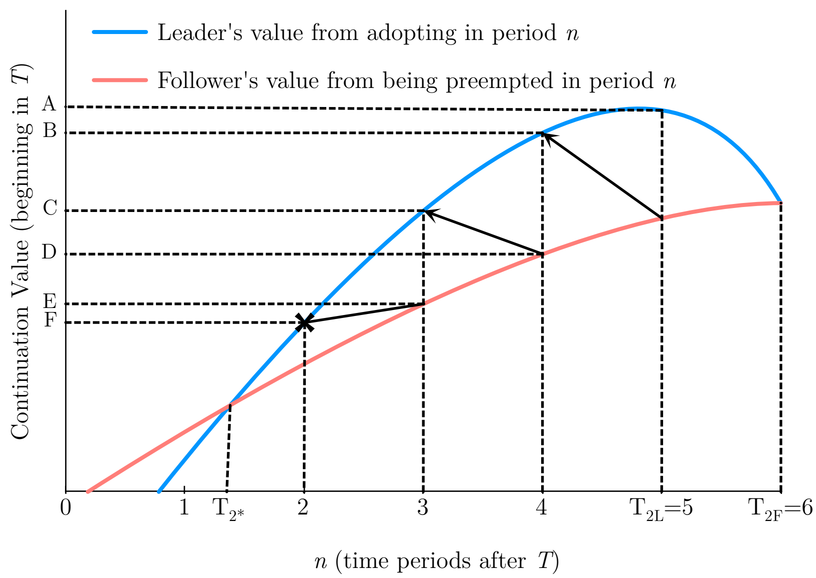



Figure A.15: Discrete Time Preemption Does Not Lead to Equal Continuation Values

that point the leader's and follower's continuation values are equal (because if the "leader" delays adoption until $T_{2F}$ the "follower" adopts in the same period, generating a joint-adoption equilibrium). In discrete time the leader's optimal adoption date is $T_{2L} = 5$ (and it is slightly before $n = 5$ in continuous time). However, if the leader adopts in $n = 5$, the follower can do better than simply adopting in $T_{2F}$ and earning a value slightly more than "C" by preempting the leader in $n = 4$ and getting a value of "B." The original leader, now acting as the follower and earning "D" is better served to preempt his competitor, lead in period $n = 3$ and earn a value of "C." At this point in discrete time the preemption ceases. The follower in $n = 3$ is made strictly worse off by preempting the leader in period $n = 2$ ($F < E$) and thus chooses to act as the follower and adopt in $T_{2F}$. As a result of the preemption incentive, the leader's equilibrium adoption date is $n = 3$, the follower's adoption date is $n = 6$, and the leader earns a greater continuation value than the follower ($C > E$). In continuous time, each firm's incentive to preempt its competitor drives the leader's adoption time back to the point where the value of leading equals the value of following ($T_{2*}$). Thus, forcing firms to adopt at discrete points in time allows the leader to earn rents at the follower's (and the consumers') expense. Entering any state $(T, 0, a, a)$ the two firms are ex ante identical, so each is equally likely to play the role of leader. As a result, when optimizing in all $t < T$, each firm's expected value of entering period $T$ with the same technology as its competitor is given by $EV(T, 0, a, a) = 0.5C + 0.5E$.

# Appendix B

# Chapter 3 Appendices

## B.1 Simulation Results

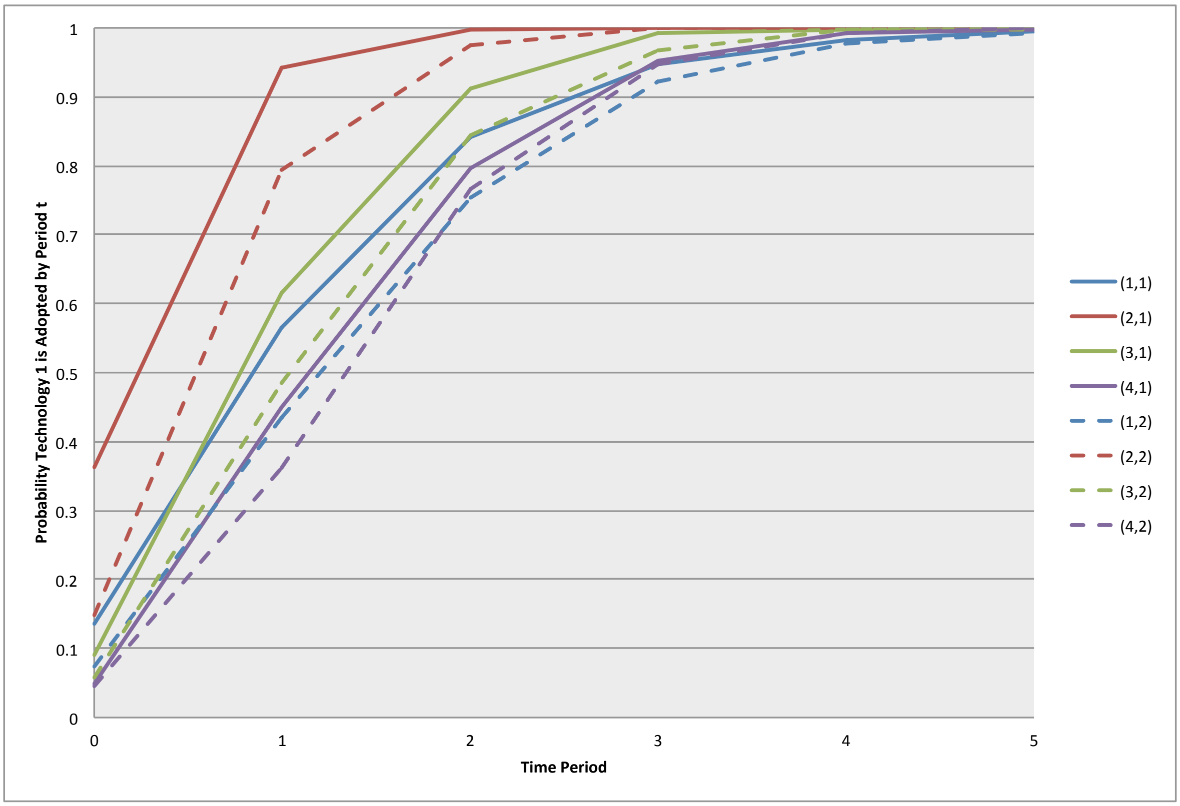



Figure B.1: Cumulative Probability of $\theta = 1$ Uptake for Different $(J, N)$ Pairs

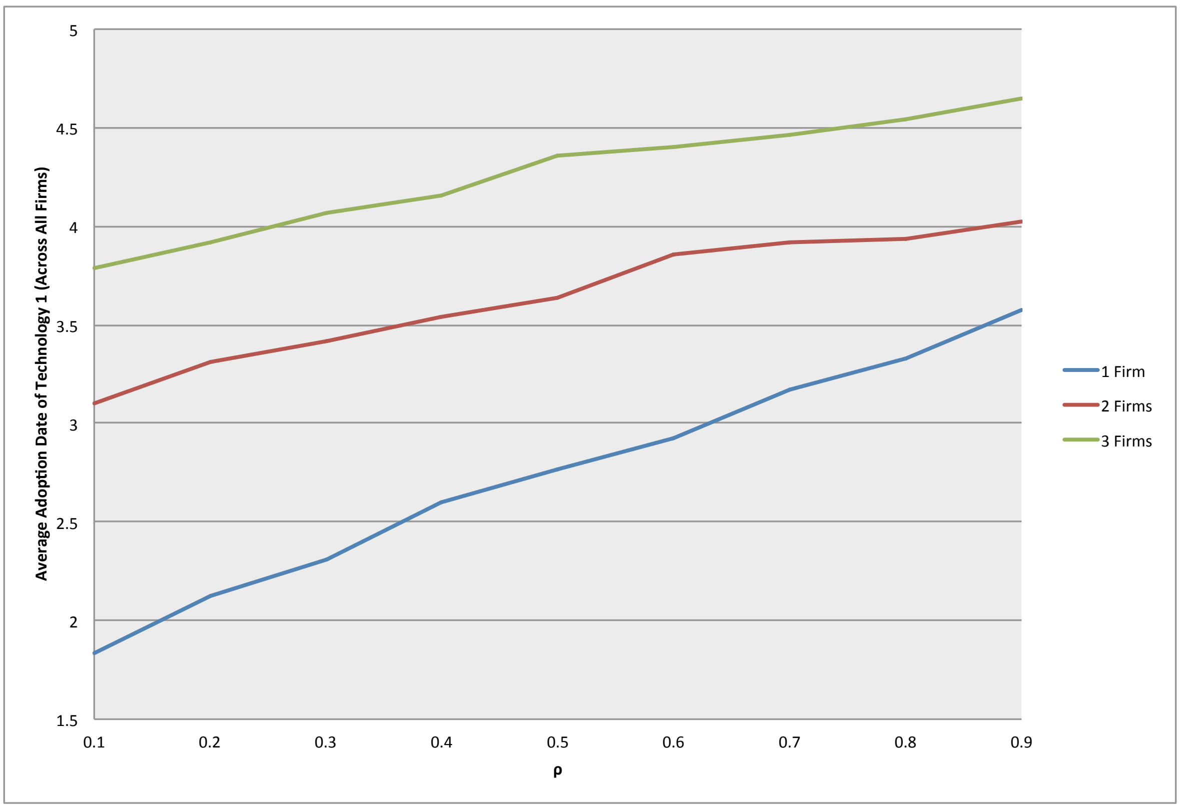



Figure B.2: Average Adoption Date of $\theta = 1$ for Different Values of $\rho$ ($N = 2$)

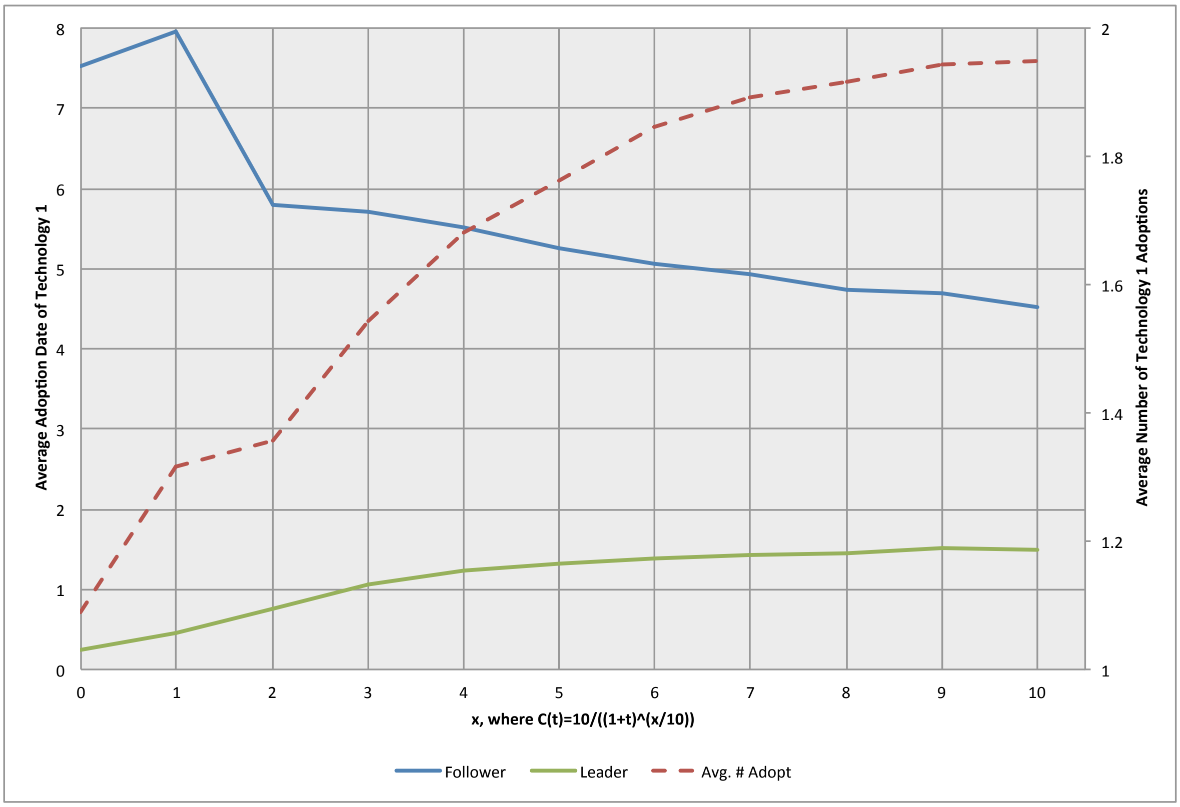



Figure B.3: Average Adoption Date of $\theta = 1$ for Different Values of $x$, where $C(t) = 10/(1 + t)^{x/10}$ $(J = 2, N = 2)$

| | | | | |
|---|---|---|---|---|
| $N = 1$ | | | | |
| $\theta_1 = 0$ | 1.73 | | | |
| $\theta_1 = 1$ | 3.69 | | | |
| $\theta_1 = 2$ | 5.02 | | | |
| $\theta_1 = 3$ | 6.06 | | | |
| $N = 2$ | | | | |
| | $\theta_2 = 0$ | $\theta_2 = 1$ | $\theta_2 = 2$ | $\theta_2 = 3$ |
| $\theta_1 = 0$ | (0.81, 0.81) | | | |
| $\theta_1 = 1$ | (2.18, 0.38) | (0.98, 0.98) | | |
| $\theta_1 = 2$ | (3.29, 0.26) | (1.68, 0.58) | (1.00, 1.00) | |
| $\theta_1 = 3$ | (4.23, 0.20) | (2.39, 0.41) | (1.49, 0.67) | (1.00, 1.00) |
| $N = 3$ | | | | |
| | | $\theta_3 = 0$ | | |
| | $\theta_2 = 0$ | $\theta_2 = 1$ | $\theta_2 = 2$ | $\theta_2 = 3$ |
| $\theta_1 = 0$ | (0.46, 0.46, 0.46) | | | |
| $\theta_1 = 1$ | (1.67, 0.21, 0.21) | (0.86, 0.86, 0.07) | | |
| $\theta_1 = 2$ | (2.74, 0.14, 0.14) | (1.59, 0.53, 0.04) | (0.96, 0.96, 0.02) | |
| $\theta_1 = 3$ | (3.65, 0.11, 0.11) | (2.31, 0.38, 0.03) | (1.47, 0.65, 0.01) | (0.99, 0.99, 0.01) |
| | | $\theta_3 = 1$ | | |
| | $\theta_2 = 0$ | $\theta_2 = 1$ | $\theta_2 = 2$ | $\theta_2 = 3$ |
| $\theta_1 = 0$ | | | | |
| $\theta_1 = 1$ | | (0.50, 0.50, 0.50) | | |
| $\theta_1 = 2$ | | (1.12, 0.31, 0.31) | (0.74, 0.74, 0.17) | |
| $\theta_1 = 3$ | | (1.80, 0.22, 0.22) | (1.26, 0.52, 0.11) | (0.88, 0.88, 0.06) |
| | | $\theta_3 = 2$ | | |
| | $\theta_2 = 0$ | $\theta_2 = 1$ | $\theta_2 = 2$ | $\theta_2 = 3$ |
| $\theta_1 = 0$ | | | | |
| $\theta_1 = 1$ | | | | |
| $\theta_1 = 2$ | | | (0.50, 0.50, 0.50) | |
| $\theta_1 = 3$ | | | (0.94, 0.35, 0.35) | (0.68, 0.68, 0.23) |
| | | $\theta_3 = 3$ | | |
| | $\theta_2 = 0$ | $\theta_2 = 1$ | $\theta_2 = 2$ | $\theta_2 = 3$ |
| $\theta_1 = 0$ | | | | |
| $\theta_1 = 1$ | | | | |
| $\theta_1 = 2$ | | | | |
| $\theta_1 = 3$ | | | | (0.50, 0.50, 0.50) |

Table B.1: Simulation Flow Profit Levels Using the Base Parameterization

| | *Average Adoption Date* | | | | *Total Number of Adoptions* | | | |
|---|---|---|---|---|---|---|---|---|
| | $j=1$ | $j=2$ | $j=3$ | $j=4$ | $j=1$ | $j=2$ | $j=3$ | $j=4$ |
| $J=1,\ N=1$ | | | | | | | | |
| $\theta=1$ | 1.53 | | | | 1000 | | | |
| $J=2,\ N=1$ | | | | | | | | |
| $\theta=1$ | 2.51 | 3.57 | | | 1000 | 1000 | | |
| $J=3,\ N=1$ | | | | | | | | |
| $\theta=1$ | 4.49 | 4.55 | 5.08 | | 999 | 1000 | 1000 | |
| $J=4,\ N=1$ | | | | | | | | |
| $\theta=1$ | 6.42 | 5.99 | 6.49 | 6.49 | 999 | 1000 | 1000 | 1000 |
| $J=1,\ N=2$ | | | | | | | | |
| $\theta=1$ | 1.85 | | | | 1000 | | | |
| $\theta=2$ | 12.52 | | | | 1000 | | | |
| $J=2,\ N=2$ | | | | | | | | |
| $\theta=1$ | 2.67 | 3.19 | | | 963 | 952 | | |
| $\theta=2$ | 14.56 | 15.34 | | | 1000 | 1000 | | |
| $J=3,\ N=2$ | | | | | | | | |
| $\theta=1$ | 3.71 | 3.73 | 3.88 | | 893 | 866 | 839 | |
| $\theta=2$ | 16.46 | 16.35 | 16.56 | | 1000 | 999 | 1000 | |
| $J=4,\ N=2$ | | | | | | | | |
| $\theta=1$ | 4.30 | 4.15 | 4.39 | 4.40 | 808 | 780 | 772 | 767 |
| $\theta=2$ | 17.88 | 18.10 | 17.98 | 18.03 | 998 | 996 | 999 | 996 |
| $J=1,\ N=3$ | | | | | | | | |
| $\theta=1$ | 1.75 | | | | 1000 | | | |
| $\theta=2$ | 12.81 | | | | 999 | | | |
| $\theta=3$ | 23.19 | | | | 1000 | | | |
| $J=2,\ N=3$ | | | | | | | | |
| $\theta=1$ | 2.58 | 3.13 | | | 962 | 949 | | |
| $\theta=2$ | 13.96 | 14.19 | | | 873 | 894 | | |
| $\theta=3$ | 26.22 | 26.70 | | | 1000 | 1000 | | |
| $J=3,\ N=3$ | | | | | | | | |
| $\theta=1$ | 3.49 | 3.86 | 4.00 | | 884 | 865 | 857 | |
| $\theta=2$ | 14.59 | 14.80 | 14.79 | | 785 | 800 | 773 | |
| $\theta=3$ | 27.73 | 27.96 | 27.96 | | 998 | 1000 | 1000 | |
| $J=4,\ N=3$ | | | | | | | | |
| $\theta=1$ | 4.18 | 4.19 | 4.46 | 4.47 | 802 | 763 | 766 | 738 |
| $\theta=2$ | 15.01 | 14.93 | 15.07 | 14.83 | 711 | 716 | 718 | 707 |
| $\theta=3$ | 29.27 | 29.66 | 29.37 | 29.21 | 997 | 991 | 997 | 992 |

*Parameterization:* $\phi_2=\xi_j=\omega_{jt}=0$, $\phi_0=\phi_1=\alpha=\tau=x_{jt}=1$, $\gamma=6$, $\rho=0.1$, $\beta=0.95$, $C(t)=10/\sqrt{(1+t)}$, *RD*($\theta=2$)*=10, and RD*($\theta=3$)*=20*

Table B.2: 1,000 Simulations with Homogeneous Firms (*by order of* ***moves***)

| | Average Adoption Date | | | | Total Number of Adoptions | | | |
|---|---|---|---|---|---|---|---|---|
| | $j=1$ | $j=2$ | $j=3$ | $j=4$ | $j=1$ | $j=2$ | $j=3$ | $j=4$ |
| $J=1,\ N=1$ | | | | | | | | |
| $\theta=1$ | 1.53 | | | | 1000 | | | |
| $J=2,\ N=1$ | | | | | | | | |
| $\theta=1$ | 0.70 | 5.39 | | | 1000 | 1000 | | |
| $J=3,\ N=1$ | | | | | | | | |
| $\theta=1$ | 1.40 | 3.89 | 8.84 | | 1000 | 1000 | 999 | |
| $J=4,\ N=1$ | | | | | | | | |
| $\theta=1$ | 1.76 | 3.85 | 7.10 | 12.68 | 1000 | 1000 | 1000 | 999 |
| $J=1,\ N=2$ | | | | | | | | |
| $\theta=1$ | 1.85 | | | | 1000 | | | |
| $\theta=2$ | 12.52 | | | | 1000 | | | |
| $J=2,\ N=2$ | | | | | | | | |
| $\theta=1$ | 1.08 | 4.94 | | | 1000 | 915 | | |
| $\theta=2$ | 15.08 | 14.81 | | | 1000 | 1000 | | |
| $J=3,\ N=2$ | | | | | | | | |
| $\theta=1$ | 1.65 | 4.14 | 6.66 | | 1000 | 990 | 608 | |
| $\theta=2$ | 16.99 | 16.80 | 15.59 | | 1000 | 1000 | 999 | |
| $J=4,\ N=2$ | | | | | | | | |
| $\theta=1$ | 1.89 | 4.06 | 6.34 | 7.57 | 1000 | 998 | 834 | 295 |
| $\theta=2$ | 18.73 | 18.49 | 17.95 | 16.83 | 995 | 997 | 998 | 999 |
| $J=1,\ N=3$ | | | | | | | | |
| $\theta=1$ | 1.75 | | | | 1000 | | | |
| $\theta=2$ | 12.81 | | | | 999 | | | |
| $\theta=3$ | 23.19 | | | | 1000 | | | |
| $J=2,\ N=3$ | | | | | | | | |
| $\theta=1$ | 1.00 | 4.90 | | | 1000 | 911 | | |
| $\theta=2$ | 13.93 | 14.22 | | | 880 | 887 | | |
| $\theta=3$ | 26.33 | 26.60 | | | 1000 | 1000 | | |
| $J=3,\ N=3$ | | | | | | | | |
| $\theta=1$ | 1.61 | 4.22 | 6.60 | | 1000 | 987 | 619 | |
| $\theta=2$ | 14.86 | 14.85 | 14.49 | | 780 | 741 | 837 | |
| $\theta=3$ | 27.96 | 27.64 | 28.04 | | 999 | 1000 | 999 | |
| $J=4,\ N=3$ | | | | | | | | |
| $\theta=1$ | 1.90 | 4.19 | 6.40 | 7.61 | 1000 | 993 | 814 | 262 |
| $\theta=2$ | 15.16 | 15.15 | 14.61 | 14.96 | 654 | 693 | 715 | 790 |
| $\theta=3$ | 29.31 | 29.11 | 29.67 | 29.43 | 998 | 995 | 992 | 992 |

*Parameterization:* $\phi_2 = \xi_j = \omega_{jt} = 0$, $\phi_0 = \phi_1 = \alpha = \tau = x_{jt} = 1$, $\gamma = 6$, $\rho = 0.1$, $\beta = 0.95$, $C(t) = 10/\sqrt{(1+t)}$, *RD*($\theta = 2$)=10, *and RD*($\theta = 3$)=20

Table B.3: 1,000 Simulations with Homogeneous Firms (*by order of* ***adoption***)

| | Average Adoption Date | | | | Total Number of Adoptions | | | |
|---|---|---|---|---|---|---|---|---|
| | $j=1$ | $j=2$ | $j=3$ | $j=4$ | $j=1$ | $j=2$ | $j=3$ | $j=4$ |
| $J=1,\ N=1$ | | | | | | | | |
| $\theta=1$ | 1.59 | | | | 1000 | | | |
| $J=2,\ N=1$ | | | | | | | | |
| $\theta=1$ | 3.86 | 4.54 | | | 1000 | 1000 | | |
| $J=3,\ N=1$ | | | | | | | | |
| $\theta=1$ | 6.03 | 6.40 | 6.52 | | 999 | 998 | 1000 | |
| $J=4,\ N=1$ | | | | | | | | |
| $\theta=1$ | 7.89 | 8.04 | 8.27 | 8.50 | 988 | 992 | 987 | 991 |
| $J=1,\ N=2$ | | | | | | | | |
| $\theta=1$ | 1.81 | | | | 1000 | | | |
| $\theta=2$ | 12.47 | | | | 1000 | | | |
| $J=2,\ N=2$ | | | | | | | | |
| $\theta=1$ | 2.98 | 3.23 | | | 896 | 902 | | |
| $\theta=2$ | 16.12 | 15.63 | | | 1000 | 998 | | |
| $J=3,\ N=2$ | | | | | | | | |
| $\theta=1$ | 3.66 | 3.63 | 3.83 | | 770 | 772 | 770 | |
| $\theta=2$ | 17.68 | 17.55 | 17.97 | | 996 | 999 | 996 | |
| $J=4,\ N=2$ | | | | | | | | |
| $\theta=1$ | 4.21 | 4.08 | 4.05 | 4.19 | 692 | 663 | 687 | 651 |
| $\theta=2$ | 18.96 | 19.44 | 18.88 | 19.42 | 992 | 989 | 992 | 993 |
| $J=1,\ N=3$ | | | | | | | | |
| $\theta=1$ | 1.78 | | | | 1000 | | | |
| $\theta=2$ | 12.83 | | | | 1000 | | | |
| $\theta=3$ | 23.24 | | | | 1000 | | | |
| $J=2,\ N=3$ | | | | | | | | |
| $\theta=1$ | 2.98 | 3.21 | | | 893 | 889 | | |
| $\theta=2$ | 13.93 | 14.19 | | | 846 | 805 | | |
| $\theta=3$ | 27.05 | 27.32 | | | 1000 | 997 | | |
| $J=3,\ N=3$ | | | | | | | | |
| $\theta=1$ | 3.67 | 3.74 | 3.87 | | 788 | 766 | 774 | |
| $\theta=2$ | 14.48 | 14.62 | 14.74 | | 736 | 734 | 737 | |
| $\theta=3$ | 28.73 | 29.23 | 28.47 | | 993 | 995 | 995 | |
| $J=4,\ N=3$ | | | | | | | | |
| $\theta=1$ | 4.00 | 4.19 | 4.16 | 4.10 | 663 | 655 | 668 | 661 |
| $\theta=2$ | 14.87 | 15.05 | 14.75 | 14.81 | 663 | 637 | 644 | 629 |
| $\theta=3$ | 30.12 | 30.47 | 29.98 | 29.90 | 984 | 993 | 986 | 991 |

*Parameterization:* $\xi_j \sim N(0,1)$, $\phi_2 = \omega_{jt} = 0$, $\phi_0 = \phi_1 = \alpha = \tau = x_{jt} = 1$, $\gamma = 6$, $\rho = 0.1$, $\beta = 0.95$, $C(t) = 10/\sqrt{(1+t)}$, *RD*($\theta = 2$)=10, *and RD*($\theta = 3$)=20

Table B.4: 1,000 Simulations with Heterogeneous Firms (*by order of* ***moves***)

| | Average Adoption Date | | | | Total Number of Adoptions | | | |
|---|---|---|---|---|---|---|---|---|
| | $j=1$ | $j=2$ | $j=3$ | $j=4$ | $j=1$ | $j=2$ | $j=3$ | $j=4$ |
| $J=1,\ N=1$ | | | | | | | | |
| $\theta=1$ | 1.59 | | | | 1000 | | | |
| $J=2,\ N=1$ | | | | | | | | |
| $\theta=1$ | 1.06 | 7.34 | | | 1000 | 1000 | | |
| $J=3,\ N=1$ | | | | | | | | |
| $\theta=1$ | 1.31 | 5.19 | 12.48 | | 1000 | 1000 | 997 | |
| $J=4,\ N=1$ | | | | | | | | |
| $\theta=1$ | 1.47 | 4.68 | 9.57 | 17.35 | 1000 | 1000 | 999 | 959 |
| $J=1,\ N=2$ | | | | | | | | |
| $\theta=1$ | 1.81 | | | | 1000 | | | |
| $\theta=2$ | 12.47 | | | | 1000 | | | |
| $J=2,\ N=2$ | | | | | | | | |
| $\theta=1$ | 1.34 | 5.31 | | | 1000 | 798 | | |
| $\theta=2$ | 13.92 | 17.84 | | | 1000 | 998 | | |
| $J=3,\ N=2$ | | | | | | | | |
| $\theta=1$ | 1.52 | 4.78 | 6.82 | | 1000 | 927 | 385 | |
| $\theta=2$ | 15.32 | 17.94 | 19.96 | | 1000 | 997 | 994 | |
| $J=4,\ N=2$ | | | | | | | | |
| $\theta=1$ | 1.72 | 4.53 | 6.75 | 7.70 | 1000 | 962 | 606 | 125 |
| $\theta=2$ | 16.17 | 18.64 | 18.96 | 22.99 | 1000 | 994 | 990 | 982 |
| $J=1,\ N=3$ | | | | | | | | |
| $\theta=1$ | 1.78 | | | | 1000 | | | |
| $\theta=2$ | 12.83 | | | | 1000 | | | |
| $\theta=3$ | 23.24 | | | | 1000 | | | |
| $J=2,\ N=3$ | | | | | | | | |
| $\theta=1$ | 1.28 | 5.43 | | | 1000 | 782 | | |
| $\theta=2$ | 13.57 | 14.67 | | | 916 | 735 | | |
| $\theta=3$ | 24.98 | 29.39 | | | 1000 | 997 | | |
| $J=3,\ N=3$ | | | | | | | | |
| $\theta=1$ | 1.52 | 4.78 | 7.01 | | 1000 | 934 | 394 | |
| $\theta=2$ | 13.96 | 14.87 | 15.20 | | 856 | 725 | 626 | |
| $\theta=3$ | 26.28 | 28.90 | 31.27 | | 999 | 994 | 990 | |
| $J=4,\ N=3$ | | | | | | | | |
| $\theta=1$ | 1.69 | 4.60 | 6.79 | 7.72 | 1000 | 963 | 563 | 121 |
| $\theta=2$ | 14.26 | 15.01 | 14.89 | 15.82 | 824 | 670 | 665 | 414 |
| $\theta=3$ | 26.82 | 29.39 | 31.10 | 33.27 | 1000 | 994 | 990 | 970 |

*Parameterization:* $\xi_j \sim N(0,1)$, $\phi_2 = \omega_{jt} = 0$, $\phi_0 = \phi_1 = \alpha = \tau = x_{jt} = 1$, $\gamma = 6$, $\rho = 0.1$, $\beta = 0.95$, $C(t) = 10/\sqrt{(1+t)}$, *RD*($\theta = 2$)=10, *and RD*($\theta = 3$)=20

Table B.5: 1,000 Simulations with Heterogeneous Firms (*by order of* ***adoption***)

| | *Average Adoption Date* | | | | *Total Number of Adoptions* | | | |
|---|---|---|---|---|---|---|---|---|
| | $j=1$ | $j=2$ | $j=3$ | $j=4$ | $j=1$ | $j=2$ | $j=3$ | $j=4$ |
| $J=1,\ N=1$ | | | | | | | | |
| $\theta=1$ | 1.55 | | | | 1000 | | | |
| $J=2,\ N=1$ | | | | | | | | |
| $\theta=1$ | 2.50 | 3.74 | | | 1000 | 1000 | | |
| $J=3,\ N=1$ | | | | | | | | |
| $\theta=1$ | 4.63 | 4.68 | 4.84 | | 1000 | 1000 | 1000 | |
| $J=4,\ N=1$ | | | | | | | | |
| $\theta=1$ | 6.20 | 6.04 | 6.46 | 6.46 | 999 | 1000 | 999 | 1000 |
| $J=1,\ N=2$ | | | | | | | | |
| $\theta=1$ | 1.96 | | | | 968 | | | |
| $\theta=2$ | 7.39 | | | | 1000 | | | |
| $J=2,\ N=2$ | | | | | | | | |
| $\theta=1$ | 1.88 | 1.93 | | | 728 | 684 | | |
| $\theta=2$ | 8.50 | 9.34 | | | 1000 | 1000 | | |
| $J=3,\ N=2$ | | | | | | | | |
| $\theta=1$ | 2.34 | 2.43 | 2.40 | | 563 | 539 | 523 | |
| $\theta=2$ | 10.37 | 10.54 | 10.56 | | 999 | 1000 | 1000 | |
| $J=4,\ N=2$ | | | | | | | | |
| $\theta=1$ | 2.57 | 2.50 | 2.56 | 2.55 | 428 | 419 | 418 | 405 |
| $\theta=2$ | 11.36 | 11.64 | 12.15 | 12.07 | 998 | 997 | 998 | 999 |
| $J=1,\ N=3$ | | | | | | | | |
| $\theta=1$ | 1.90 | | | | 980 | | | |
| $\theta=2$ | 7.45 | | | | 823 | | | |
| $\theta=3$ | 12.76 | | | | 1000 | | | |
| $J=2,\ N=3$ | | | | | | | | |
| $\theta=1$ | 1.60 | 1.89 | | | 759 | 612 | | |
| $\theta=2$ | 7.03 | 7.11 | | | 642 | 638 | | |
| $\theta=3$ | 14.70 | 15.49 | | | 999 | 1000 | | |
| $J=3,\ N=3$ | | | | | | | | |
| $\theta=1$ | 2.32 | 2.41 | 2.37 | | 570 | 522 | 502 | |
| $\theta=2$ | 7.38 | 7.38 | 7.40 | | 504 | 495 | 518 | |
| $\theta=3$ | 16.41 | 16.45 | 17.04 | | 998 | 999 | 1000 | |
| $J=4,\ N=3$ | | | | | | | | |
| $\theta=1$ | 2.48 | 2.55 | 2.49 | 2.60 | 435 | 409 | 429 | 391 |
| $\theta=2$ | 7.42 | 7.43 | 7.47 | 7.50 | 433 | 458 | 399 | 416 |
| $\theta=3$ | 17.82 | 17.67 | 17.95 | 17.69 | 999 | 997 | 999 | 998 |

*Parameterization:* $\phi_2 = \xi_j = \omega_{jt} = 0$, $\phi_0 = \phi_1 = \alpha = \tau = x_{jt} = 1$, $\gamma = 6$, $\rho = 0.2$, $\beta = 0.95$, $C(t) = 10/\sqrt{(1+t)}$, *RD*($\theta = 2$)=5, *and RD*($\theta = 3$)=10

Table B.6: 1,000 Simulations with Homogeneous Firms (*by order of* ***moves***)

| | *Average Adoption Date* | | | | *Total Number of Adoptions* | | | |
|---|---|---|---|---|---|---|---|---|
| | $j=1$ | $j=2$ | $j=3$ | $j=4$ | $j=1$ | $j=2$ | $j=3$ | $j=4$ |
| $J=1,\ N=1$ | | | | | | | | |
| $\theta=1$ | 1.55 | | | | 1000 | | | |
| $J=2,\ N=1$ | | | | | | | | |
| $\theta=1$ | 0.66 | 5.58 | | | 1000 | 1000 | | |
| $J=3,\ N=1$ | | | | | | | | |
| $\theta=1$ | 1.41 | 3.93 | 8.81 | | 1000 | 1000 | 1000 | |
| $J=4,\ N=1$ | | | | | | | | |
| $\theta=1$ | 1.67 | 3.85 | 6.99 | 12.66 | 1000 | 1000 | 1000 | 998 |
| $J=1,\ N=2$ | | | | | | | | |
| $\theta=1$ | 1.96 | | | | 968 | | | |
| $\theta=2$ | 7.39 | | | | 1000 | | | |
| $J=2,\ N=2$ | | | | | | | | |
| $\theta=1$ | 1.40 | 3.14 | | | 999 | 413 | | |
| $\theta=2$ | 8.75 | 9.09 | | | 1000 | 1000 | | |
| $J=3,\ N=2$ | | | | | | | | |
| $\theta=1$ | 1.85 | 3.18 | 3.70 | | 991 | 564 | 70 | |
| $\theta=2$ | 11.61 | 9.75 | 10.10 | | 1000 | 999 | 1000 | |
| $J=4,\ N=2$ | | | | | | | | |
| $\theta=1$ | 2.04 | 3.21 | 3.67 | 3.67 | 986 | 585 | 96 | 3 |
| $\theta=2$ | 13.55 | 10.55 | 9.11 | 14.03 | 995 | 1000 | 1000 | 997 |
| $J=1,\ N=3$ | | | | | | | | |
| $\theta=1$ | 1.90 | | | | 980 | | | |
| $\theta=2$ | 7.45 | | | | 823 | | | |
| $\theta=3$ | 12.76 | | | | 1000 | | | |
| $J=2,\ N=3$ | | | | | | | | |
| $\theta=1$ | 1.21 | 3.14 | | | 1000 | 371 | | |
| $\theta=2$ | 6.88 | 7.23 | | | 588 | 692 | | |
| $\theta=3$ | 15.02 | 15.17 | | | 1000 | 999 | | |
| $J=3,\ N=3$ | | | | | | | | |
| $\theta=1$ | 1.82 | 3.22 | 3.79 | | 995 | 541 | 58 | |
| $\theta=2$ | 7.46 | 7.07 | 7.74 | | 405 | 628 | 484 | |
| $\theta=3$ | 16.47 | 17.27 | 16.16 | | 999 | 998 | 1000 | |
| $J=4,\ N=3$ | | | | | | | | |
| $\theta=1$ | 2.00 | 3.19 | 3.65 | 3.75 | 974 | 570 | 112 | 8 |
| $\theta=2$ | 7.46 | 7.01 | 7.64 | 8.27 | 329 | 582 | 630 | 165 |
| $\theta=3$ | 18.02 | 18.57 | 17.64 | 16.89 | 997 | 999 | 999 | 998 |

*Parameterization:* $\phi_2=\xi_j=\omega_{jt}=0$, $\phi_0=\phi_1=\alpha=\tau=x_{jt}=1$, $\gamma=6$, $\rho=0.2$, $\beta=0.95$, $C(t)=10/\sqrt{(1+t)}$, *RD*$(\theta=2)$=5, *and RD*$(\theta=3)$=10

Table B.7: 1,000 Simulations with Homogeneous Firms (*by order of **adoption***)

| | *Average Adoption Date* | | | | *Total Number of Adoptions* | | | |
|---|---|---|---|---|---|---|---|---|
| | $j=1$ | $j=2$ | $j=3$ | $j=4$ | $j=1$ | $j=2$ | $j=3$ | $j=4$ |
| $J=1,\ N=1$ | | | | | | | | |
| $\theta=1$ | 1.58 | | | | 1000 | | | |
| $J=2,\ N=1$ | | | | | | | | |
| $\theta=1$ | 3.83 | 4.70 | | | 1000 | 1000 | | |
| $J=3,\ N=1$ | | | | | | | | |
| $\theta=1$ | 6.19 | 6.58 | 6.68 | | 999 | 997 | 999 | |
| $J=4,\ N=1$ | | | | | | | | |
| $\theta=1$ | 8.08 | 7.83 | 8.20 | 8.37 | 990 | 993 | 992 | 990 |
| $J=1,\ N=2$ | | | | | | | | |
| $\theta=1$ | 1.90 | | | | 966 | | | |
| $\theta=2$ | 7.43 | | | | 1000 | | | |
| $J=2,\ N=2$ | | | | | | | | |
| $\theta=1$ | 1.95 | 1.83 | | | 647 | 618 | | |
| $\theta=2$ | 9.28 | 9.84 | | | 998 | 1000 | | |
| $J=3,\ N=2$ | | | | | | | | |
| $\theta=1$ | 2.16 | 2.25 | 2.20 | | 488 | 483 | 477 | |
| $\theta=2$ | 11.56 | 11.48 | 12.18 | | 997 | 999 | 999 | |
| $J=4,\ N=2$ | | | | | | | | |
| $\theta=1$ | 2.30 | 2.38 | 2.33 | 2.34 | 384 | 408 | 359 | 364 |
| $\theta=2$ | 13.06 | 13.26 | 13.63 | 13.53 | 996 | 994 | 991 | 991 |
| $J=1,\ N=3$ | | | | | | | | |
| $\theta=1$ | 1.88 | | | | 965 | | | |
| $\theta=2$ | 7.51 | | | | 832 | | | |
| $\theta=3$ | 12.85 | | | | 1000 | | | |
| $J=2,\ N=3$ | | | | | | | | |
| $\theta=1$ | 1.85 | 1.71 | | | 644 | 609 | | |
| $\theta=2$ | 7.11 | 7.17 | | | 634 | 599 | | |
| $\theta=3$ | 15.47 | 15.87 | | | 998 | 1000 | | |
| $J=3,\ N=3$ | | | | | | | | |
| $\theta=1$ | 2.09 | 2.10 | 2.19 | | 482 | 513 | 437 | |
| $\theta=2$ | 7.34 | 7.36 | 7.37 | | 487 | 480 | 403 | |
| $\theta=3$ | 17.49 | 17.32 | 17.52 | | 998 | 992 | 996 | |
| $J=4,\ N=3$ | | | | | | | | |
| $\theta=1$ | 2.33 | 2.35 | 2.33 | 2.34 | 391 | 365 | 396 | 364 |
| $\theta=2$ | 7.40 | 7.50 | 7.46 | 7.48 | 398 | 349 | 368 | 360 |
| $\theta=3$ | 19.31 | 19.23 | 18.60 | 19.06 | 992 | 992 | 993 | 996 |

*Parameterization:* $\xi_j \sim N(0,1)$, $\phi_2 = \omega_{jt} = 0$, $\phi_0 = \phi_1 = \alpha = \tau = x_{jt} = 1$, $\gamma = 6$, $\rho = 0.2$, $\beta = 0.95$, $C(t) = 10/\sqrt{(1+t)}$, *RD*($\theta = 2$)=5, *and RD*($\theta = 3$)=10

Table B.8: 1,000 Simulations with Heterogeneous Firms (*by order of* ***moves***)

| | Average Adoption Date | | | | Total Number of Adoptions | | | |
|---|---|---|---|---|---|---|---|---|
| | $j=1$ | $j=2$ | $j=3$ | $j=4$ | $j=1$ | $j=2$ | $j=3$ | $j=4$ |
| $J=1,\ N=1$ | | | | | | | | |
| $\theta=1$ | 1.58 | | | | 1000 | | | |
| $J=2,\ N=1$ | | | | | | | | |
| $\theta=1$ | 1.05 | 7.48 | | | 1000 | 1000 | | |
| $J=3,\ N=1$ | | | | | | | | |
| $\theta=1$ | 1.32 | 5.44 | 12.73 | | 1000 | 1000 | 995 | |
| $J=4,\ N=1$ | | | | | | | | |
| $\theta=1$ | 1.52 | 4.62 | 9.53 | 17.12 | 1000 | 1000 | 1000 | 965 |
| $J=1,\ N=2$ | | | | | | | | |
| $\theta=1$ | 1.90 | | | | 966 | | | |
| $\theta=2$ | 7.43 | | | | 1000 | | | |
| $J=2,\ N=2$ | | | | | | | | |
| $\theta=1$ | 1.52 | 3.28 | | | 997 | 268 | | |
| $\theta=2$ | 8.00 | 11.13 | | | 999 | 999 | | |
| $J=3,\ N=2$ | | | | | | | | |
| $\theta=1$ | 1.72 | 3.22 | 3.69 | | 995 | 418 | 35 | |
| $\theta=2$ | 9.85 | 10.10 | 15.27 | | 999 | 998 | 998 | |
| $J=4,\ N=2$ | | | | | | | | |
| $\theta=1$ | 1.85 | 3.20 | 3.72 | — | 985 | 477 | 53 | 0 |
| $\theta=2$ | 10.36 | 10.62 | 12.23 | 20.39 | 996 | 997 | 1000 | 979 |
| $J=1,\ N=3$ | | | | | | | | |
| $\theta=1$ | 1.88 | | | | 965 | | | |
| $\theta=2$ | 7.51 | | | | 832 | | | |
| $\theta=3$ | 12.85 | | | | 1000 | | | |
| $J=2,\ N=3$ | | | | | | | | |
| $\theta=1$ | 1.40 | 3.25 | | | 996 | 257 | | |
| $\theta=2$ | 6.96 | 7.39 | | | 726 | 507 | | |
| $\theta=3$ | 13.85 | 17.50 | | | 1000 | 998 | | |
| $J=3,\ N=3$ | | | | | | | | |
| $\theta=1$ | 1.62 | 3.22 | 3.79 | | 993 | 406 | 33 | |
| $\theta=2$ | 7.20 | 7.29 | 7.90 | | 580 | 548 | 242 | |
| $\theta=3$ | 14.54 | 17.81 | 20.01 | | 999 | 994 | 993 | |
| $J=4,\ N=3$ | | | | | | | | |
| $\theta=1$ | 1.82 | 3.27 | 3.75 | 3.67 | 993 | 469 | 51 | 3 |
| $\theta=2$ | 7.36 | 7.28 | 7.77 | 8.18 | 507 | 566 | 358 | 44 |
| $\theta=3$ | 15.65 | 18.25 | 18.20 | 24.20 | 999 | 998 | 996 | 980 |

*Parameterization:* $\xi_j \sim N(0,1)$, $\phi_2 = \omega_{jt} = 0$, $\phi_0 = \phi_1 = \alpha = \tau = x_{jt} = 1$, $\gamma = 6$, $\rho = 0.2$, $\beta = 0.95$, $C(t) = 10/\sqrt{(1+t)}$, *RD*$(\theta=2)$=5, *and RD*$(\theta=3)$=10

Table B.9: 1,000 Simulations with Heterogeneous Firms (*by order of* ***adoption***)

| | *Average Adoption Date* | | *Total Number of Adoptions* | |
|---|---|---|---|---|
| | $j = 1$ | $j = 2$ | $j = 1$ | $j = 2$ |
| $J = 2,\ N = 1$ | | | | |
| $\theta = 1$ | 1.30 | 7.17 | 1000 | 1000 |
| $J = 2,\ N = 2$ | | | | |
| $\theta = 1$ | 1.55 | 5.10 | 994 | 791 |
| $\theta = 2$ | 12.75 | 18.96 | 1000 | 998 |
| $J = 2,\ N = 3$ | | | | |
| $\theta = 1$ | 1.56 | 5.04 | 1000 | 778 |
| $\theta = 2$ | 13.15 | 15.10 | 965 | 698 |
| $\theta = 3$ | 24.26 | 29.71 | 1000 | 998 |

*Parameterization:* $\phi_2 = \xi_2 = \omega_{jt} = 0$, $\xi_1 = \phi_0 = \phi_1 = \alpha = \tau = x_{jt} = 1$, $\gamma = 6$, $\rho = 0.1$, $\beta = 0.95$, $C(t) = 10/\sqrt{(1+t)}$, *RD*($\theta = 2$)*=10, and RD*($\theta = 3$)*=20*

Table B.10: 1,000 Simulations with Asymmetric Firms (*by order of* ***moves***)

## B.2 Data Collection

### Michigan

As previously mentioned, the data collected by the MDCH are incredibly well-organized. I started with the entire CON history in the state from 1980 to the present and extracted all of the projects related to MRI. Cleaning the data was relatively straightforward except for some isolated instances where it was difficult to determine if a hospital had an affiliation with a local university. I remedied the issue by calling these facilities and conducting additional research on the facilities' websites.

### Mississippi

Through conversations with the MSDH I was informed that I would be able to track all MRI purchases in the state via documentation in the CON program. However, the vast majority of the documentation was only available in hard copies. As a result, I traveled to Jackson, MS and collected data over a four-day span. The MSDH publishes an almost-yearly State Health Plan that lists all of the facilities in the state providing MRI service along with number and type (fixed/mobile) of their scanners. I used these health plans as the basis for my search through the myriad of CON applications and listings and declaratory rulings. I was able to locate the documentation for all but fifteen of the fixed MRI scanners owned by hospitals since the inception of MRI. Since I was instructed to consider the annual health plans as "absolute fact," in these instances I used the year of the annual survey as a hospital's adoption date.[1]

### Tennessee

The Tennessee Health Services and Development Agency (HSDA) originally provided me with a "Medical Equipment Registry" that lists both active and inactive MRI scanners in the state. The registry was initially claimed to be comprehensive, including all scanners that were ever

[1]Since it is impossible to identify replacement scanners in the State Health Plans it is possible that I missed some replacement purchases in the data. However, I slowly and systematically read through binders of CON applications and declaratory rulings to minimize these occurrences.

utilized in the state. However, an initial data analysis suggested that some facilities claiming to operate with fixed MRI scanners in the 1980s and early 1990s (according to the AHA dataset) were missing from the TN Medical Equipment Registry. I reached out to the HSDA and was informed that the Medical Equipment Registry contains "as much of the equipment history as could be identified." In an attempt to rectify this issue I searched through the entire CON history in the state and identified each instance of a CON relating to the purchase of MRI equipment.[2] I merged the data from the CON listings with the Medical Equipment Registry to form the final dataset.

### Virginia

The Virginia Certificate of Public Need program provided me with a listing of nearly the entire CON program and equipment registration program histories in the state. While each entry in the data included the hospital's name it did not include the hospital's location. I managed to identify the location for each facility through a combination of manually searching through the AHA data, calling facilities using the telephone number provided in the AHA data, and using information on Google maps. The process was complicated by the fact that many facilities changed names during my panel due to mergers or acquisitions.

### ARF

While the current release of the ARF is publicly available, I was granted access to older versions through UNC's Cecil G. Sheps Center for Health Services Research. I merged data from several editions of the ARF to generate county-level variables spanning the entire length of my panel.[3] The FIPS codes utilized for Virginia's independent cities changed in 1992 so I adjusted all of

[2]It is somewhat unclear what actions related to MRI required a CON in Tennessee in the 1980s. I was initially told that only the initiation of MRI services or the addition of MRI equipment required a CON (so that replacement MRI scanners would not be captured in the CON process). However, there are several instances in the CON data where a replacement scanner is documented. I recognize that the potential omission of replacement scanners in the early years of this dataset is a limitation.

[3]I collected an assortment of variables in addition to population and per capita income. However, similarly to Schmidt-Dengler (2006), I find that the vast majority of the variables are insignificant when included in my empirical model.

the codes accordingly. To construct the per capita income variable I started with data from 1983 to 2008. Next, I extrapolated the 2008 data to 2009 and 2010 using national percent changes in per capita income from the Bureau of Economic Analysis (per capita income fell 5.64% from 2008 to 2009 and then increased 2.99% from 2009 to 2010). Finally, I converted nominal per capita income to real per capita income using 2000 as the base year. The ARF included a county-level population measure for every year in my panel except for 1989. I interpolated the 1989 population by taking the average of the 1988 and 1990 populations. For both variables I aggregated counties into HSACs and then averaged the variables across all years to generate a single income and population measure in each market. After dropping HSACs that were not included in my sample, I formed z-scores for both variables.

### AHA

In addition to the ARF data, I was also granted access to the AHA's annual survey data for 1987 to 2009 through the Sheps Center. I first merged all of the individual surveys, correcting numerous discrepancies between variable names and codes across years. Additionally, I corrected several errors in variables across time. For instance, a number of hospitals were reported as having different FIPS county codes over time even though their physical addresses remained unchanged.[4] I utilized the (corrected) FIPS codes to link the AHA data with the ARF data. In each survey every hospital is labeled by a seven-digit identification number that allows me to track the hospitals through time. I use the annual "summary of changes" to account for differences in these identification numbers across years resulting from mergers, demergers, entry/exit, etc. Next, I extrapolated all of the 1987 data to years 1983–1986 and the 2009 data to 2010. I generated time-invariant values for the "control" of each hospital (i.e. for-profit, not-for-profit, government-federal, government-nonfederal) and whether or not the hospital is affiliated with a medical school. If a hospital's control or medical school affiliation changes over time I set it equal to the mode of variable during my panel. Finally, to calculate a time-invariant value for each hospital's bed size I average its bed sizes across all years in the

[4]In these instances I made sure that the FIPS county codes themselves were not revised during the years in question.

panel and subsequently calculate the hospital-level z-score.

The AHA collects data on whether a hospital offers MRI as a service but the information is summarized in a single variable that is not very informative for my empirical analysis. While there are slight differences in the survey question across years, in general the survey asks whether or not a hospital is a "provider" of MRI (and only distinguishes between fixed and mobile MRI from 1990–1993). In comparing the AHA data with the state CON data I find that there are significant reporting discrepancies, especially for hospitals with mobile MRI service. For instance, assuming that the Michigan data is "fact," some hospitals with mobile MRI are reported as "providers" in the AHA data and some are reported as non-providers. Thus, in the context of my analysis, the accuracy and consistency of this variable is questionable at best.[5]

[5]Schmidt-Dengler (2006) uses the AHA dataset in his empirical analysis. For the years in his sample (1986–1993), each hospital is asked whether MRI is "a hospital-based service," "provided by another hospital or provider," or "not an available service." He assumes that if a hospital responds that it has MRI as "a hospital-based service" then the hospital has adopted an MRI scanner. However, in comparing my state CON data with the AHA data, there is little consistency in the responses to this question by hospitals with a mobile MRI scanner (some report a mobile MRI as a hospital-based service and others do not). Since I focus attention on hospitals with *fixed* MRI scanners, my dataset likely suggests that there are fewer adopters of MRI scanners (in the early years of the panel) relative to his dataset.

## B.3 Sample Statistics

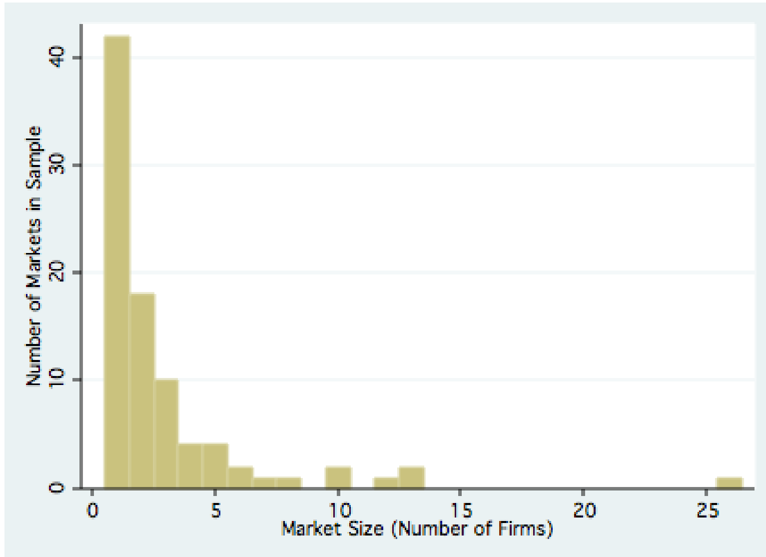



Figure B.4: Sample Market Size Distribution

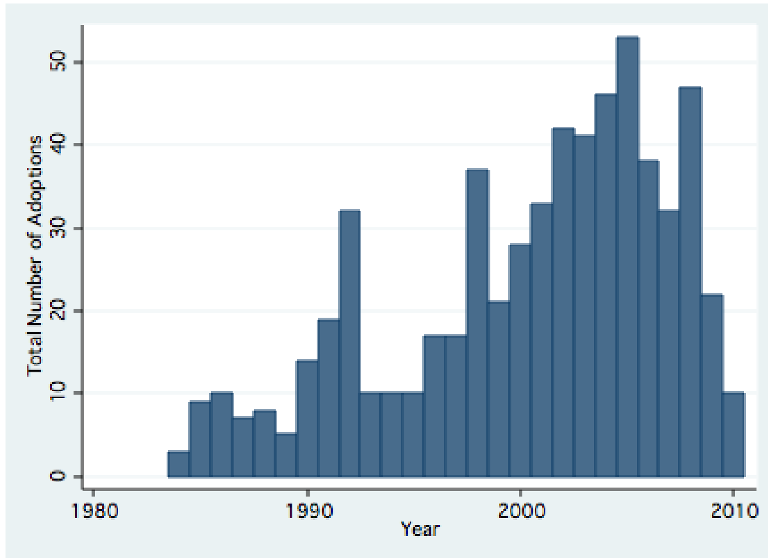



Figure B.5: Total Number of MRI Scanners Purchased in Each Year

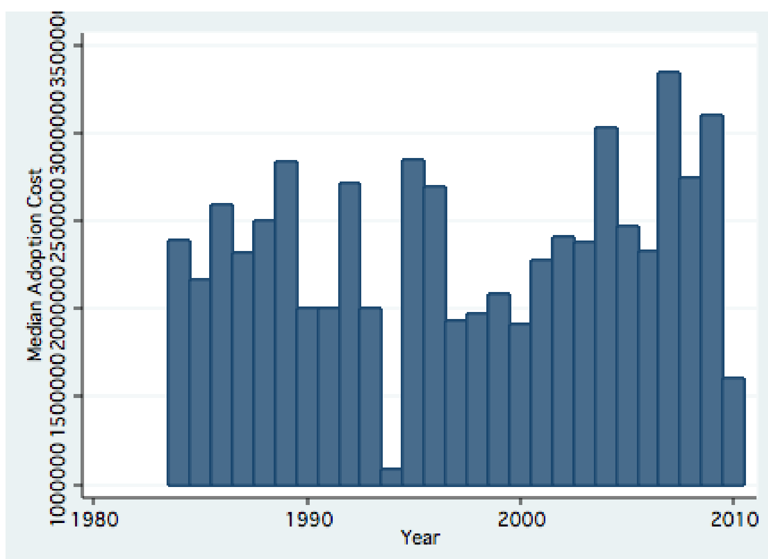



Figure B.6: Median Adoption Cost in Each Year

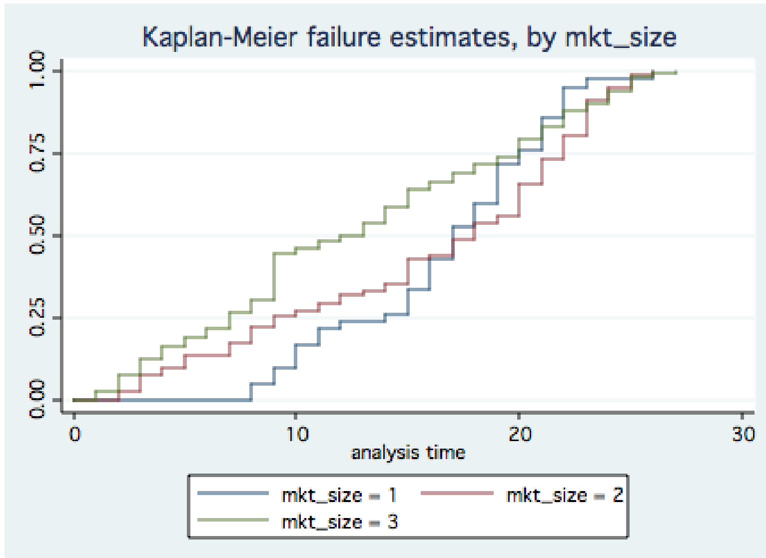



Figure B.7: Kaplan-Meier Failure Function By Market Size

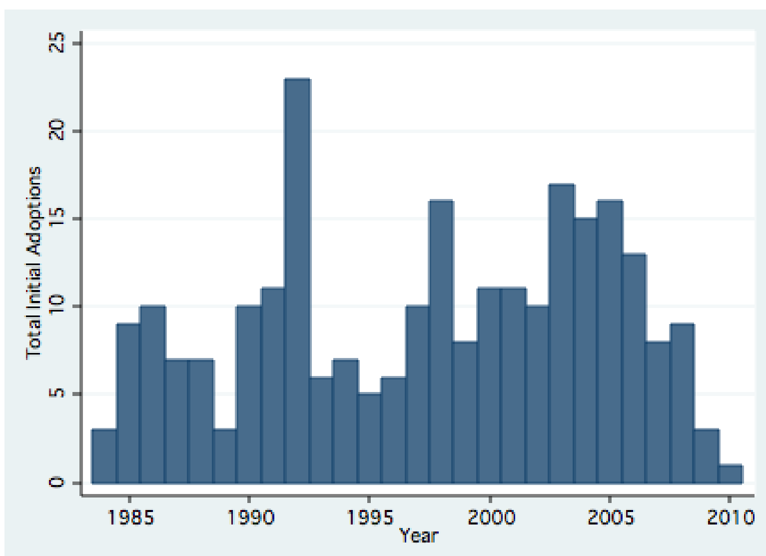



Figure B.8: Total Number of Initial Adoptions by Year

| | *Sample* | | | | | *Contiguous US* | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Obs. | Mean | S.D. | Min. | Max. | Obs. | Mean | S.D. | Min. | Max. |
| **Market-Level** | | | | | | | | | | |
| *population* | 88 | 293,636 | 517,555 | 20,551 | 4,416,580 | 802 | 334,176 | 723,615 | 3,181 | 1.18e+07 |
| *real income (2000 Dollars)* | 88 | 21,249 | 3,965 | 15,007 | 43,872 | 802 | 22,555 | 4,504 | 12,430 | 50,583 |
| **Hospital-Level** | | | | | | | | | | |
| *beds* | 255 | 246.5 | 198.2 | 6 | 1,180 | 8745 | 157.7 | 178.4 | 5 | 2,219 |
| *med. school affiliation* | 255 | 0.23 | 0.42 | 0 | 1 | 8745 | 0.20 | 0.40 | 0 | 1 |
| *prev. had mobile?* | 255 | 0.51 | 0.50 | 0 | 1 | — | — | — | — | — |
| *Control Code...* | | | | | | | | | | |
| *for-profit* | 255 | 0.18 | 0.38 | 0 | 1 | 8745 | 0.20 | 0.40 | 0 | 1 |
| *non-profit* | 255 | 0.60 | 0.49 | 0 | 1 | 8745 | 0.51 | 0.50 | 0 | 1 |
| *gov. (federal)* | 255 | 0.0 | 0.0 | 0 | 0 | 8745 | 0.04 | 0.20 | 0 | 1 |
| *gov. (non-federal)* | 255 | 0.22 | 0.42 | 0 | 1 | 8745 | 0.25 | 0.43 | 0 | 1 |

Table B.11: Hospital- and Market-Level Sample Statistics (with corresponding values for the contiguous US)

| **Mkt. Size** | Obs. | Mean | S.D. | Min. | Max. |
|---|---|---|---|---|---|
| $J = 1$ | 42 | 16.64 | 4.62 | 8 | 26 |
| $2 \leq J \leq 4$ | 82 | 15.83 | 7.04 | 2 | 26 |
| $J \geq 5$ | 131 | 12.87 | 7.33 | 1 | 27 |

*Values measured relative to 1983*

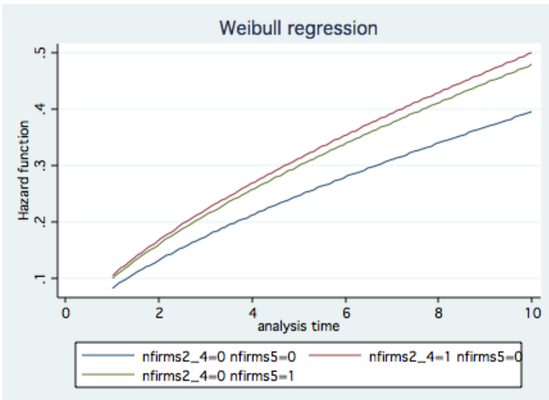
Table B.12: Years Until First Adoption for Each Hospital By Market Size

| **Mkt. Size** | Obs. | Mean | S.D. | Min. | Max. |
|---|---|---|---|---|---|
| ***Second Adoption*** | | | | | |
| $J = 1$ | 21 | 19.71 | 4.62 | 13 | 27 |
| $2 \leq J \leq 4$ | 41 | 17.88 | 7.04 | 7 | 26 |
| $J \geq 5$ | 90 | 17.49 | 7.33 | 5 | 27 |
| ***Third Adoption*** | | | | | |
| $J = 1$ | 9 | 22.11 | 4.62 | 16 | 25 |
| $2 \leq J \leq 4$ | 27 | 20.96 | 7.04 | 8 | 27 |
| $J \geq 5$ | 59 | 19.29 | 7.33 | 8 | 26 |

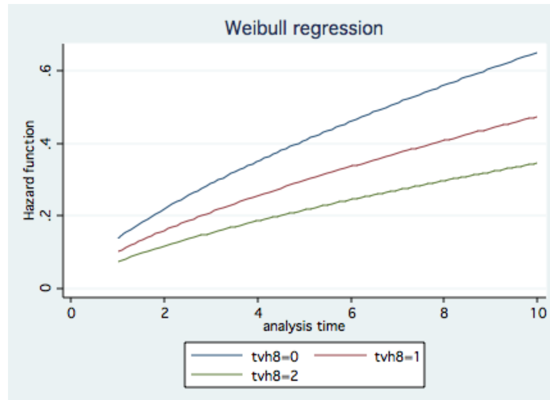
*Values measured relative to 1983*

Table B.13: Years Until Second and Third Adoptions for Each Hospital By Market Size

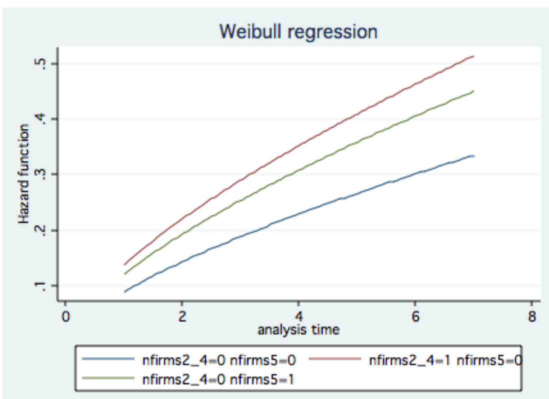
## B.4 Descriptive Results



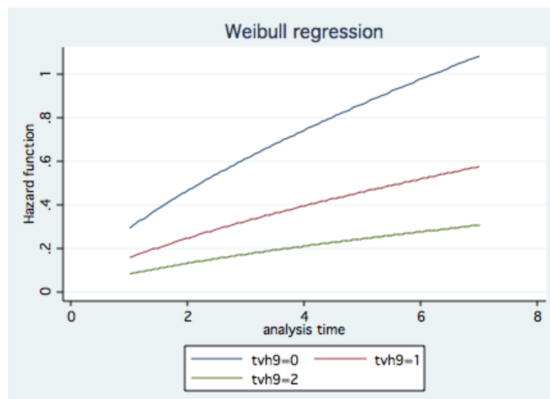

(a) Diff. Mkt. Size (**8**)




(b) Diff. Tech. Entering (**8**)




(c) Diff. Mkt. Size (**9**)




(d) Diff. Tech. Entering (**9**)

Figure B.9: Hazard Rates for Specifications (**8**) and (**9**) in Table B.19 for Different Market Sizes and Technologies Entering Period $T_N$

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| ***Outcome 2 (1993–2001)*** | | | | |
| *constant* | 0.50 | -0.01 | 1.42* | 0.73 |
| | (0.37) | (0.41) | (0.64) | (0.65) |
| *for-profit* | 0.55 | 0.49 | 0.62 | 0.57 |
| | (0.63) | (0.65) | (0.63) | (0.66) |
| *non-profit* | 0.09 | 0.07 | 0.08 | 0.07 |
| | (0.46) | (0.49) | (0.47) | (0.49) |
| *medical school?* | -0.32 | -0.23 | -0.22 | -0.14 |
| | (0.52) | (0.53) | (0.53) | (0.55) |
| *z-beds* | -1.11* | -1.08* | -1.09* | -1.07* |
| | (0.29) | (0.30) | (0.29) | (0.30) |
| *z-pop.* | 0.43 | 0.31 | 0.20 | 0.16 |
| | (0.24) | (0.26) | (0.12) | (0.13) |
| *z-real-inc.* | -0.59 | -0.48 | -0.49 | -0.42 |
| | (0.31) | (0.31) | (0.31) | (0.31) |
| *z-num-firms* | -0.31 | -0.22 | — | — |
| | (0.30) | (0.31) | | |
| $2 \leq J \leq 4$ | — | — | -1.36* | -1.04 |
| | | | (0.66) | (0.66) |
| $J > 4$ | — | — | -1.39* | -1.06 |
| | | | (0.70) | (0.74) |
| *had mobile?* | — | 1.21* | — | 1.11* |
| | | (0.40) | | (0.40) |
| ***Outcome 3 (2002–2010)*** | | | | |
| *constant* | -0.63 | -2.10* | 0.25 | -1.48 |
| | (0.46) | (0.60) | (0.67) | (0.80) |
| *for-profit* | 0.75 | 0.87 | 0.81 | 0.93 |
| | (0.68) | (0.73) | (0.68) | (0.74) |
| *non-profit* | 1.05* | 1.15* | 1.02 | 1.11* |
| | (0.50) | (0.58) | (0.50) | (0.57) |
| *medical school?* | -0.52 | -0.36 | -0.43 | -0.27 |
| | (0.65) | (0.62) | (0.65) | (0.64) |
| *z-beds* | -2.78* | -2.77* | -2.62* | -2.64* |
| | (0.58) | (0.58) | (0.55) | (0.55) |
| *z-pop.* | 1.14* | 0.88* | 0.52* | 0.42* |
| | (0.30) | (0.32) | (0.14) | (0.13) |
| *z-real-inc.* | -0.68* | -0.45* | -0.51* | -0.32 |
| | (0.17) | (0.17) | (0.20) | (0.21) |
| *z-num-firms* | -0.89* | -0.67* | — | — |
| | (0.30) | (0.33) | | |
| $2 \leq J \leq 4$ | — | — | -0.97 | -0.59 |
| | | | (0.69) | (0.75) |
| $J > 4$ | — | — | -2.04* | -1.56 |
| | | | (0.77) | (0.89) |
| *had mobile?* | — | 2.39* | — | 2.37* |
| | | (0.48) | | (0.46) |

** denotes significance at the 5% level with robust standard errors*

Table B.14: Multinomial Logit Regression Results of Initial Adoption Date Versus Hospital- and Market-Level Covariates (Base Outcome: Initial Adoption in 1983–1992)

| | (**1**) | (**2**) | (**3**) | (**4**) | (**5**) | (**6**) |
|---|---|---|---|---|---|---|
| *constant* | -6.63** | -6.45** | -5.49** | -5.18** | -5.54** | -5.02** |
| | (0.39) | (0.39) | (0.40) | (0.40) | (0.55) | (0.56) |
| *for-profit* | -0.18 | -0.22 | -0.35 | -0.30 | -0.84 | -0.52 |
| | (0.63) | (0.22) | (0.27) | (0.27) | (0.57) | (0.57) |
| *non-profit* | -0.52** | -0.54** | -0.68** | -0.66** | -0.56 | -0.40 |
| | (0.18) | (0.18) | (0.22) | (0.22) | (0.36) | (0.36) |
| *medical school?* | 0.14 | 0.00 | 0.24 | 0.11 | 1.01** | 0.86** |
| | (0.20) | (0.20) | (0.24) | (0.25) | (0.38) | (0.38) |
| *z-beds* | 0.77** | 0.76** | 0.80** | 0.77** | 0.71** | 0.61** |
| | (0.08) | (0.09) | (0.09) | (0.09) | (0.12) | (0.12) |
| *z-pop.* | -0.24** | -0.13* | -0.27** | -0.11 | -0.18 | -0.04 |
| | (0.08) | (0.08) | (0.10) | (0.10) | 0.16 | (0.15) |
| *z-real-inc.* | 0.14* | 0.07 | 0.15* | 0.04 | -0.21 | -0.30** |
| | (0.07) | (0.07) | (0.08) | (0.08) | 0.16 | (0.15) |
| *z-num-firms* | 0.18* | 0.09 | 0.22* | 0.08 | 0.23 | 0.07 |
| | (0.10) | (0.09) | (0.11) | 0.11 | 0.20 | (0.19) |
| *had mobile?* | — | -0.81** | — | -1.13** | — | -1.93** |
| | | (0.14) | | (0.18) | | (0.42) |
| $p$ | 2.54 | 2.68 | 2.07 | 2.21 | 2.03 | 2.11 |
| *Adoptions Censored After...* | — | — | 2001 | 2001 | 1991 | 1991 |

*** and * denote significance at the 5% and 10% levels, respectively*

Table B.15: Proportional Hazard Model of Initial Adoption Date with Hospital- and Market-Level Covariates (Using a Weibull Distribution)

| | (**1**) | (**2**) | (**3**) | (**4**) | (**5**) | (**6**) |
|---|---|---|---|---|---|---|
| *for-profit* | -0.18 | -0.10 | -0.04 | -0.17 | -0.09 | -0.04 |
| | (0.34) | (0.28) | (0.25) | (0.35) | (0.28) | (0.25) |
| *non-profit* | 0.09 | 0.29 | 0.19 | 0.08 | 0.26 | 0.16 |
| | (0.29) | (0.24) | (0.20) | (0.29) | (0.24) | (0.20) |
| *medical school?* | -0.37 | -0.20 | -0.08 | -0.38 | -0.21 | -0.10 |
| | (0.34) | (0.30) | (0.26) | (0.34) | (0.30) | (0.26) |
| *z-beds* | 0.46** | 0.38** | 0.47** | 0.48** | 0.40** | 0.49** |
| | (0.18) | (0.15) | (0.13) | (0.18) | (0.15) | (0.13) |
| *z-pop.* | -0.11** | -0.09* | -0.07 | -0.11** | -0.09* | -0.06 |
| | (0.05) | (0.05) | (0.04) | (0.05) | (0.05) | (0.04) |
| *z-real-inc.* | 0.02 | -0.06 | -0.07 | 0.02 | -0.06 | -0.07 |
| | (0.12) | (0.10) | (0.09) | (0.12) | (0.10) | (0.08) |
| $2 \leq J \leq 4$ | -0.09 | 0.43 | 0.47** | -0.10 | 0.40 | 0.44* |
| | (0.36) | (0.27) | (0.23) | (0.37) | (0.27) | (0.23) |
| $J \geq 5$ | -0.18 | 0.43 | 0.42 | -0.21 | 0.37 | 0.35 |
| | (0.41) | (0.31) | (0.27) | (0.41) | (0.31) | (0.26) |
| *had mobile?* | -0.02 | -0.08 | -0.01 | -0.02 | -0.08 | 0.00 |
| | (0.23) | (0.20) | (0.17) | (0.23) | (0.20) | (0.17) |
| *Cut 1* | -2.08 | -1.47 | -1.45 | -2.11 | -1.52 | -1.51 |
| | (0.39) | (0.29) | (0.27) | (0.39) | (0.30) | (0.27) |
| *Cut 2* | -1.59 | -0.61 | 0.11 | -1.93 | -1.34 | -1.33 |
| | (0.37) | (0.27) | (0.24) | (0.38) | (0.29) | (0.26) |
| *Cut 3* | — | — | — | -1.62 | -0.65 | 0.04 |
| | | | | (0.37) | (0.27) | (0.24) |
| *Release Dates...* | | | | | | |
| $\theta = 2$ | 1989 | 1989 | 1989 | 1992 | 1992 | 1992 |
| $\theta = 3$ | 1998 | 2001 | 2004 | 1998 | 2001 | 2004 |

*** and * denote significance at the 5% and 10% levels, respectively*

Table B.16: Ordered Probit Regressions of Hospital-Level Technology Entering 2008 Versus Hospital- and Market-Level Covariates (For Different Release Dates of the New Technologies)

| | **(7)** | **(8)** | **(9)** | **(10)** | **(11)** | **(12)** |
|---|---|---|---|---|---|---|
| *for-profit* | -0.18 | -0.11 | -0.08 | 0.76 | 0.02 | -0.09 |
| | (0.35) | (0.28) | (0.25) | (0.61) | (0.41) | (0.30) |
| *non-profit* | 0.07 | 0.23 | 0.13 | 0.28 | -0.11 | 0.24 |
| | (0.29) | (0.23) | (0.20) | (0.40) | (0.33) | (0.25) |
| *medical school?* | -0.37 | -0.21 | -0.09 | -0.58 | -0.39 | -0.35 |
| | (0.34) | (0.29) | (0.25) | (0.53) | (0.36) | (0.31) |
| *z-beds* | 0.47** | 0.38** | 0.46** | 1.06** | 0.57** | 0.45** |
| | (0.18) | (0.15) | (0.12) | (0.40) | (0.21) | (0.16) |
| *z-pop.* | -0.11** | -0.09* | -0.06 | -0.20** | -0.11** | -0.09* |
| | (0.05) | (0.05) | (0.04) | (0.08) | (0.05) | (0.05) |
| *z-real-inc.* | 0.01 | -0.06 | -0.08 | 0.02 | -0.07 | -0.02 |
| | (0.12) | (0.10) | (0.08) | (0.23) | (0.12) | (0.11) |
| $2 \leq J \leq 4$ | -0.09 | 0.40 | 0.44* | -0.30 | -0.13 | 0.26 |
| | (0.36) | (0.27) | (0.23) | (0.56) | (0.41) | (0.29) |
| $J \geq 5$ | -0.18 | 0.38 | 0.37 | -0.10 | -0.15 | 0.27 |
| | (0.40) | (0.31) | (0.26) | (0.68) | (0.45) | (0.33) |
| *had mobile?* | -0.03 | -0.07 | 0.00 | -0.43 | -0.18 | 0.05 |
| | (0.23) | (0.20) | (0.17) | (0.36) | (0.25) | (0.20) |
| *Cut 1* | -2.10 | -1.53 | -1.51 | -2.60 | -2.37 | -1.57 |
| | (0.39) | (0.30) | (0.27) | (0.59) | (0.44) | (0.31) |
| *Cut 2* | -1.75 | -1.18 | -1.17 | — | -2.01 | -0.83 |
| | (0.38) | (0.28) | (0.25) | | (0.43) | (0.29) |
| *Cut 3* | -1.61 | -0.67 | 0.03 | — | — | — |
| | (0.37) | (0.27) | (0.24) | | | |
| *Release Dates...* | | | | | | |
| $\theta = 2$ | 1995 | 1995 | 1995 | 1990 | 1995 | 2000 |
| $\theta = 3$ | 1998 | 2001 | 2004 | — | — | — |

*** and * denote significance at the 5% and 10% levels, respectively*

Table B.17: Ordered Probit Regressions of Hospital-Level Technology Entering 2008 Versus Hospital- and Market-Level Covariates (For Different Release Dates of the New Technologies)

| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
|---|---|---|---|---|---|---|
| *for-profit* | -0.16 | -0.17 | -0.14 | -0.17 | -0.18 | -0.16 |
| | (0.23) | (0.24) | (0.27) | (0.23) | (0.24) | (0.27) |
| *non-profit* | -0.04 | 0.02 | -0.02 | -0.04 | 0.02 | -0.04 |
| | (0.17) | (0.18) | (0.20) | (0.17) | (0.18) | (0.20) |
| *medical school?* | -0.09 | 0.05 | 0.27 | -0.12 | 0.02 | 0.24 |
| | (0.21) | (0.21) | (0.22) | (0.21) | (0.21) | (0.22) |
| *z-beds* | 0.54** | 0.49** | 0.50** | 0.53** | 0.48** | 0.52** |
| | (0.10) | (0.10) | (0.10) | (0.10) | (0.10) | (0.10) |
| *z-pop.* | -0.12** | -0.10** | -0.11** | -0.11** | -0.09** | -0.10** |
| | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) |
| *z-real-inc.* | 0.11 | 0.03 | 0.07 | 0.11 | 0.03 | 0.08 |
| | (0.07) | (0.07) | (0.08) | (0.07) | (0.07) | (0.08) |
| $2 \leq J \leq 4$ | -0.25 | 0.20 | 0.36 | -0.26 | 0.20 | 0.36 |
| | (0.20) | (0.22) | (0.26) | (0.20) | (0.22) | (0.26) |
| $J \geq 5$ | -0.25 | 0.22 | 0.30 | -0.29 | 0.18 | 0.25 |
| | (0.23) | (0.24) | (0.28) | (0.23) | (0.24) | (0.28) |
| *tech. entering* | -0.22** | -0.37** | -0.68** | -0.20** | -0.34** | -0.67** |
| | (0.08) | (0.08) | (0.09) | (0.09) | (0.09) | (0.09) |
| *constant* | -2.61** | -2.52** | -1.87** | -2.61** | -2.53** | -1.87** |
| | (0.25) | (0.28) | (0.31) | (0.25) | (0.28) | (0.31) |
| $p$ | 1.70 | 1.70 | 1.70 | 1.69 | 1.69 | 1.69 |
| | (0.09) | (0.09) | (0.10) | (0.09) | (0.09) | (0.10) |
| *Release Dates...* | | | | | | |
| $\theta = 2$ | 1989 | 1989 | 1989 | 1992 | 1992 | 1992 |
| $\theta = 3$ | 1998 | 2001 | 2004 | 1998 | 2001 | 2004 |

*** and * denote significance at the 5% and 10% levels, respectively*

Table B.18: Proportional Hazard Model of $\theta = N$ Adoption Date with Hospital- and Market-Level Covariates (Using a Weibull Distribution)

| | **(7)** | **(8)** | **(9)** | **(10)** | **(11)** | **(12)** |
|---|---|---|---|---|---|---|
| *for-profit* | -0.20 | -0.24 | -0.26 | 0.27 | 0.07 | -0.18 |
| | (0.23) | (0.24) | (0.27) | (0.21) | (0.22) | (0.24) |
| *non-profit* | -0.05 | 0.01 | -0.07 | -0.26 | -0.20 | -0.04 |
| | (0.17) | (0.18) | (0.20) | (0.17) | (0.17) | (0.17) |
| *medical school?* | -0.12 | 0.01 | 0.22 | 0.34 | 0.07 | -0.05 |
| | (0.21) | (0.20) | (0.22) | (0.21) | (0.21) | (0.20) |
| *z-beds* | 0.50** | 0.46** | 0.49** | 0.32** | 0.47** | 0.50** |
| | (0.10) | (0.10) | (0.10) | (0.09) | (0.10) | (0.09) |
| *z-pop.* | -0.10** | -0.08** | -0.10** | -0.15** | -0.09** | -0.10** |
| | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) |
| *z-real-inc.* | 0.09 | 0.01 | 0.05 | 0.24** | -0.02 | 0.13 |
| | (0.07) | (0.07) | (0.08) | (0.08) | (0.08) | (0.08) |
| $2 \leq J \leq 4$ | -0.23 | 0.23 | 0.43* | -0.25 | -0.19 | 0.00 |
| | (0.20) | (0.22) | (0.25) | (0.20) | (0.20) | (0.21) |
| $J \geq 5$ | -0.28 | 0.19 | 0.30 | -0.01 | -0.02 | 0.00 |
| | (0.23) | (0.24) | (0.28) | (0.23) | (0.23) | (0.23) |
| *tech. entering* | -0.18* | -0.32** | -0.63** | 0.16 | -0.33** | -0.62** |
| | (0.11) | (0.09) | (0.10) | (0.25) | (0.17) | (0.16) |
| *constant* | -2.64** | -2.56** | -1.93** | -4.49** | -4.06** | -2.64** |
| | (0.25) | (0.28) | (0.31) | (0.31) | (0.30) | (0.28) |
| $p$ | 1.68 | 1.68 | 1.68 | 1.95 | 2.08 | 1.75 |
| | (0.09) | (0.09) | (0.10) | (0.10) | (0.11) | (0.09) |
| *Release Dates...* | | | | | | |
| $\theta = 2$ | 1995 | 1995 | 1995 | 1990 | 1995 | 2000 |
| $\theta = 3$ | 1998 | 2001 | 2004 | — | — | — |

*** and * denote significance at the 5% and 10% levels, respectively*

Table B.19: Proportional Hazard Model of $\theta = N$ Adoption Date with Hospital- and Market-Level Covariates (Using a Weibull Distribution)

### B.5 Results

| | **(1)** | **(2)** | **(3)** |
|---|---|---|---|
| *constant* | -0.58 | 0.69 | 4.06** |
| | (1.13) | (1.37) | (1.90) |
| *had mobile?* | -2.71** | -4.13** | -7.01** |
| | (0.46) | (0.61) | (0.82) |
| *ln(1+z-beds)* | 8.94** | 11.56** | 18.00** |
| | (1.16) | (1.31) | (1.69) |
| *ln(1+z-pop)* | -1.04** | -1.57** | -2.23** |
| | (0.43) | (0.46) | (0.58) |
| *ln(1+comp-tech)* | — | — | — |
| *ln(1+extra-hosp.)* | — | — | — |
| $\eta$ | 6.87** | 7.26** | 9.89** |
| | (0.50) | (0.43) | (0.48) |
| *medical school?* | — | — | — |
| *Fixed Parameters...* | | | |
| $T_2$ | 1990 | 1995 | 2000 |
| *sample* | — | — | — |
| $\beta$ | 0.94 | 0.94 | 0.94 |
| $\rho$ | 0.10 | 0.10 | 0.10 |
| $\chi$ | 0.98 | 0.98 | 0.98 |
| *Total Adoptions* | | | |
| $\theta = 1$ | 39 | 96 | 141 |
| $\theta = 2$ | 255 | 246 | 230 |

*** and * denote significance at the 5% and 10% levels, respectively*

Table B.20: Parameter Estimates for the Model Assuming Every Hospital is a Monopolist

| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
|---|---|---|---|---|---|---|
| *constant* | -0.31 | -0.34 | 1.45 | 0.41 | 2.20 | 1.55 |
| | (2.07) | (2.14) | (2.45) | (2.48) | (3.31) | (3.34) |
| *had mobile?* | -2.43** | -2.50** | -3.96** | -3.93** | -5.25** | -5.19** |
| | (0.61) | (0.63) | (0.83) | (0.85) | (1.05) | (1.06) |
| *ln(1+z-beds)* | 9.35** | 9.45** | 12.87** | 13.08** | 20.68** | 19.91** |
| | (1.68) | (1.72) | (2.00) | (1.97) | (2.67) | (2.54) |
| *ln(1+z-pop)* | -3.41* | -2.84 | -5.51** | -4.18* | -7.26** | -5.39 |
| | (2.02) | (2.23) | (2.22) | (2.41) | (3.05) | (3.31) |
| *ln(1+comp-tech)* | 1.38** | 1.36** | 1.92** | 1.92** | 2.93** | 2.89** |
| | (0.40) | (0.41) | (0.44) | (0.45) | (0.60) | (0.62) |
| *ln(1+extra-hosp.)* | 0.92 | 2.45** | 1.07 | 2.06** | 0.94 | 2.27* |
| | (0.80) | (0.86) | (0.90) | (0.92) | (1.17) | (1.19) |
| $\eta$ | 6.30** | 6.79** | 6.89** | 7.10** | 9.23** | 9.35** |
| | (0.57) | (0.61) | (0.54) | (0.55) | (0.58) | (0.59) |
| *medical school?* | — | — | — | — | — | — |
| *Fixed Parameters...* | | | | | | |
| $T_2$ | 1990 | 1990 | 1995 | 1995 | 2000 | 2000 |
| *sample* | *beds* | *first4* | *beds* | *first4* | *beds* | *first4* |
| $\beta$ | 0.94 | 0.94 | 0.94 | 0.94 | 0.94 | 0.94 |
| $\rho$ | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 |
| $\chi$ | 0.98 | 0.98 | 0.98 | 0.98 | 0.98 | 0.98 |
| *Total Adoptions* | | | | | | |
| $\theta = 1$ | 34 | 36 | 74 | 77 | 104 | 106 |
| $\theta = 2$ | 180 | 180 | 174 | 174 | 159 | 159 |

*** and * denote significance at the 5% and 10% levels, respectively*

Table B.21: Parameter Estimates for the Two-Technology Model

| | **(7)** | **(8)** | **(9)** | **(10)** | **(11)** |
|---|---|---|---|---|---|
| *constant* | 1.83 | 0.64 | 0.77 | 2.75** | 1.13 |
| | (2.36) | (2.50) | (2.81) | (0.54) | (2.69) |
| *had mobile?* | -3.81** | -3.59** | -5.05** | — | -3.97** |
| | (0.80) | (0.81) | (0.99) | | (0.84) |
| *ln(1+z-beds)* | 12.51** | 12.18** | 18.06** | — | 13.13** |
| | (1.94) | (2.04) | (2.50) | | (2.26) |
| *ln(1+z-pop)* | -5.28** | -5.65** | -7.99** | — | -5.40** |
| | (2.11) | (2.30) | (2.61) | | (2.25) |
| *ln(1+comp-tech)* | 2.14** | 1.72** | 3.04** | 2.33** | 1.94** |
| | (0.43) | (0.45) | (0.52) | (0.35) | (0.44) |
| *ln(1+extra-hosp.)* | 0.79 | 1.17 | 1.22 | — | 1.06 |
| | (0.84) | (0.98) | (1.06) | | (0.90) |
| $\eta$ | 7.49** | 5.64** | 8.75** | 4.51** | 6.89** |
| | (0.68) | (0.31) | (0.71) | (0.33) | (0.54) |
| *medical school?* | | — | — | — | — |
| | -0.34 | | | | |
| | (1.33) | | | | |
| *Fixed Parameters...* | | | | | |
| $T_2$ | 1995 | 1995 | 1995 | 1995 | 1995 |
| *sample* | *beds* | *beds* | *beds* | *beds* | *beds* |
| $\beta$ | 0.94 | 0.94 | 0.94 | 0.94 | 0.94 |
| $\rho$ | **0.05** | **0.25** | 0.10 | 0.10 | 0.10 |
| $\chi$ | 0.98 | 0.98 | **0.94** | 0.98 | 0.98 |
| *Total Adoptions* | | | | | |
| $\theta = 1$ | 74 | 74 | 74 | 74 | 74 |
| $\theta = 2$ | 174 | 174 | 174 | 174 | 174 |

*** and * denote significance at the 5% and 10% levels, respectively*

Table B.22: Parameter Estimates for the Two-Technology Model

| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** | **(7)** | **(8)** |
|---|---|---|---|---|---|---|---|---|
| *constant* | -3.58* | -4.46** | -4.88** | -5.38** | -2.93 | -4.11** | -4.35** | -5.19** |
| | (1.83) | (1.84) | (1.85) | (1.88) | (1.91) | (1.92) | (1.96) | (1.99) |
| *had mobile?* | -2.77** | -2.84** | -2.83** | -3.01** | -2.94** | -2.90** | -3.16** | -3.18** |
| | (0.64) | (0.66) | (0.69) | (0.71) | (0.67) | (0.69) | (0.75) | (0.76) |
| *ln(1+z-beds)* | 14.14** | 14.48** | 15.75** | 16.23** | 14.42** | 14.89** | 16.16** | 16.73** |
| | (1.88) | (1.83) | (2.03) | (1.98) | (1.92) | (1.89) | (2.10) | (2.07) |
| *ln(1+z-pop)* | -5.98** | -4.83** | -6.00** | -5.16** | -6.48** | -5.23** | -6.40** | -5.40** |
| | (1.60) | (1.74) | (1.63) | (1.78) | (1.64) | (1.82) | (1.70) | (1.90) |
| *ln(1+comp-tech)* | 2.63** | 2.64** | 3.23** | 3.29** | 2.60** | 2.59** | 3.39** | 3.42** |
| | (0.31) | (0.32) | (0.35) | (0.37) | (0.32) | (0.33) | (0.37) | (0.39) |
| *ln(1+extra-hosp.)* | 0.10 | 0.77 | -0.21 | 0.74 | -0.22 | 0.67 | -0.60 | 0.46 |
| | (0.72) | (0.72) | (0.76) | (0.76) | (0.74) | (0.73) | (0.77) | (0.78) |
| $\eta$ | 4.99** | 5.21** | 5.16** | 5.51** | 4.92** | 5.14** | 5.02** | 5.33** |
| | (0.35) | (0.35) | (0.38) | (0.38) | (0.33) | (0.34) | (0.36) | (0.36) |
| *Fixed Parameters...* | | | | | | | | |
| $T_2$ | 1992 | 1992 | 1992 | 1992 | 1995 | 1995 | 1995 | 1995 |
| $T_3$ | 2001 | 2001 | 2004 | 2004 | 2001 | 2001 | 2004 | 2004 |
| *sample* | *beds* | *first4* | *beds* | *first4* | *beds* | *first4* | *beds* | *first4* |
| $\beta$ | 0.94 | 0.94 | 0.94 | 0.94 | 0.94 | 0.94 | 0.94 | 0.94 |
| $\rho$ | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 |
| $\chi$ | 0.98 | 0.98 | 0.98 | 0.98 | 0.98 | 0.98 | 0.98 | 0.98 |
| *Total Adoptions* | | | | | | | | |
| $\theta = 1$ | 48 | 55 | 48 | 55 | 74 | 77 | 74 | 77 |
| $\theta = 2$ | 102 | 100 | 136 | 135 | 85 | 85 | 128 | 128 |
| $\theta = 3$ | 154 | 154 | 127 | 126 | 154 | 154 | 127 | 126 |

*** and * denote significance at the 5% and 10% levels, respectively*

Table B.23: Parameter Estimates for the Three-Technology Model

## Bibliography


Aranibar, Roberto, 2013, Analysis of the u.s. magnetic resonance imaging (mri) systems market: An assessment and outlook through 2016, Discussion Paper, NC27-54 Frost & Sullivan.

Baker, Laurence C., 2001, Managed care and technology adoption in health care: Evidence from magnetic resonance imaging, *Journal of Health Economics* 20, 395–421.

——— , and Ciaran S. Phibbs, 2002, Managed care, technology adoption, and health care: The adoption of neonatal intensive care, *RAND Journal of Economics* 33, 524–548.

Baker, Laurence C., and Susan K. Wheeler, 1998, Managed care and technology diffusion: The case of mri, *Health Affairs* 17, 195–207.

Bell, Robert A., 1996, Economics of mri technology, *Journal of Magnetic Resonance Imaging* 6, 10–25.

Berndt, Ernst, Bronwyn Hall, Robert Hall, and Jerry Hausman, 1974, Estimation and inference in nonlinear structural models, *Annals of Economic and Social Measurement* 3, 103–116.

Berry, Steven T., 1994, Estimating discrete-choice models of product differentiation, *RAND Journal of Economics* 25, 242–262.

Conover, Christopher J., and Frank A. Sloan, 1998, Does removing certificate-of-need regulations lead to a surge in health care spending?, *Journal of Health Politics, Policy and Law* 23, 455–481.

Doraszelski, Ulrich, and Ariel Pakes, 2007, A framework for applied dynamic analysis in io, in Mark Armstrong, and Robert Porter, ed.: *Handbook of Industrial Organization*vol. 3 . pp. 1887–1966 (North-Holland: Amsterdam).

Dranove, David, Mark Shanley, and Carol Simon, 1992, Is hospital competition wasteful?, *RAND Journal of Economics* 23, 247–262.

Dutta, Prajit K., Saul Lach, and Aldo Rustichini, 1995, Better late than early: Vertical differentiation in the adoption of a new technology, *Journal of Economics & Management Strategy* 4, 563–589.

Einav, Liran, 2010, Not all rivals look alike: Estimating an equilibrium model of the release date timing game, *Economic Inquiry* 48, 369–390.

Ericson, Richard, and Ariel Pakes, 1995, Markov-perfect industry dynamics: A framework for empirical work, *Review of Economic Studies* 62, 53–82.

Ford, Jon M., and David L. Kaserman, 1993, Certificate-of-need regulation and entry: Evidence from the dialysis industry, *Southern Economic Journal* 59, 783–791.

Frost, and Sullivan, 1998, World magnetic resonance imaging markets, Discussion Paper, 5824-01 Frost & Sullivan.

——— , 2000, United states magnetic resonance imaging (mri) equipment markets, Discussion Paper, 7282-01 Frost & Sullivan.

Fudenberg, Drew, and Jean Tirole, 1985, Preemption and rent equalization in the adoption of new technology, *The Review of Economic Studies* 52, 383–401.

Genesove, David, 1999, The adoption of offset presses in the daily newspaper industry in the united states, *NBER Working Paper 7076*.

Giovannetti, Emanuele, 2001, Perpetual leapfrogging in bertrand duopoly, *International Economic Review* 42, 671–696.

Goettler, Ronald L., and Brett Gordon, 2011, Does amd spur intel to innovate more?, *Journal of Political Economy* 119, 1141–1200.

Hamilton, Barton H., and Brian McManus, 2005, Technology diffusion and market structure: Evidence from infertility treatment markets, *mimeo* Washington University in St. Louis.

Harrington, Joseph E., Fyodor Iskhakov, John Rust, and Bertel Schjerning, 2010, A dynamic model of leap-frogging investments and bertrand price competition, *mimeo*.

Hoppe, Heidrun C., 2000, Second-mover advantages in the strategic adoption of new technology under uncertainty, *International Journal of Industrial Organization* 18, 315–338.

——— , 2002, The timing of new technology adoption: Theoretical models and empirical evidence, *The Manchester School* 70, 56–76.

——— , and Ulrich Lehmann-Grube, 2005, Innovation timing games: A general framework with applications, *Journal of Economic Theory* 121, 30–50.

Horner, Johannes, 2004, A perpetual race to stay ahead, *The Review of Economic Studies* 71, 1065–1088.

Huisman, Kuno, and Peter M. Kort, 1999, Strategic technology investment under uncertainty, *mimeo* Center for Economic Research, Tilburg University.

——— , 2000, Strategic technology adoption taking into account future technological improvements: A real options approach, *mimeo* Center for Economic Research, Tilburg University.

Iskhakov, Fyodor, John Rust, and Bertel Schjerning, 2013, The dynamics of bertrand price competition with cost-reducing investments, *mimeo*.

Jensen, Richard A., 1982, Adoption and diffusion of an innovation of uncertain profitability, *Journal of Economic Theory* 27, 182–193.

Kamien, Morton, and Nancy Schwartz, 1972, Some economic consequences of anticipating technical advance, *Economic Inquiry* 10, 123–138.

Katz, Michael L., and Carl Shapiro, 1987, R&d rivalry with licensing or imitation, *The American Economic Review* 77, 402–420.

Levin, Sharon, Stanford Levin, and John Meisel, 1987, A dynamic analysis of the adoption of a new technology: The case of optical scanners, *The Review of Economics and Statistics* pp. 12–17.

Makuc, Diane M., Bengt Haglund, Deborah D. Ingram, Joel C. Kleinman, and Jacob J. Feldman, 1991, Health service areas for the united states, Discussion Paper, 2 National Center for Health Statistics.

Pakes, Ariel, and Paul McGuire, 1994, Computing markov-perfect nash equilibria: Numerical implications of a dynamic differentiated product model, *RAND Journal of Economics* 25, 555–589.

Quirmbach, Herman, 1986, The diffusion of new technology and the market for an innovation, *RAND Journal of Economics* 17, 33–47.

Reinganum, Jennifer, 1981a, Market structure and the diffusion of new technology, *The Bell Journal of Economics* 12, 618–624.

———, 1981b, On the diffusion of new technology: A game theoretic approach, *The Review of Economic Studies* 48, 395–405.

Riordan, Michael, 1992, Regulation and preemptive technology adoption, *RAND Jouhornal of Economics* 23, 334–349.

———, and David Salant, 1994, Preemptive adoptions of an emerging technology, *The Journal of Industrial Economics* 42, 247–261.

Schmidt-Dengler, Philipp, 2006, The timing of new technology adoption: The case of mri, *mimeo* London School of Economics.

Sloan, Frank A., 1981, Regulation and the rising cost of hospital care, *The Review of Economics and Statistics* 63, 479–487.

Stenbacka, Rune, and Mihkel M. Tombak, 1994, Strategic timing of adoption of new technologies under uncertainty, *International Journal of Industrial Organization* 12, 387–411.

Sweeting, Andrew, 2009, The strategic timing of radio commercials: An empirical analysis using multiple equilibria, *RAND Journal of Economics* 40, 710–742.

Vickers, John, 1986, The evolution of market structure when there is a sequence of innovations, *The Journal of Industrial Economics* 35, 1–12.