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Estimating a War of Attrition: The Case of the US Movie Theater Industry†

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This paper empirically studies firm's strategic exit decisions in an environment where demand is declining. Specifically, I quantify the extent to which the exit process generated by firms' strategic interactions deviates from the outcome that maximizes industry profits. I develop and estimate a dynamic exit game using data from the US movie theater industry in the 1950s, when the industry faced demand declines. Using the estimated model, I quantify the magnitude of strategic delays and find that strategic interactions cause an average delay of exit of 2.7 years. I calculate the relative importance of several components of these strategic delays. (*JEL* D92, L11, L82, N72)

In their life cycle, industries experience both numerous entries and exits of firms. While there is a vast literature on strategic entry (Bresnahan and Reiss 1991; Berry 1992; Berry and Waldfogel 1999; Mazzeo 2002; Seim 2006; and Ciliberto and Tamer 2009), firm exits have not been well studied empirically.[1] Exit is a particularly relevant decision of firms and observed frequently in declining industries. Given that declining industries are very common in the economy,[2] it is important to fill the gap in the literature.

Exit in nonstationary environments, such as declining industries, is an important decision that could significantly affect market outcomes and efficiency. The importance of analyzing exit appears clearly in an environment where a concentrated industry faces a long-run decline in demand. In such a situation, the industry

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[1] In dynamic frameworks, most papers consider entry and exit as the two sides of the same coin in a stationary/constant environment (see Collard-Wexler 2013, Dunne et al. 2013, and Ryan 2012).

[2] Industries whose real output had shrunk more than 10 percent from 2000 to 2010 accounted for approximately 27 percent of US manufacturing output in 2010 (Employment Projections Program by US Bureau of Labor Statistics, calculated based on the 2007 NAICS 3 digit-level).

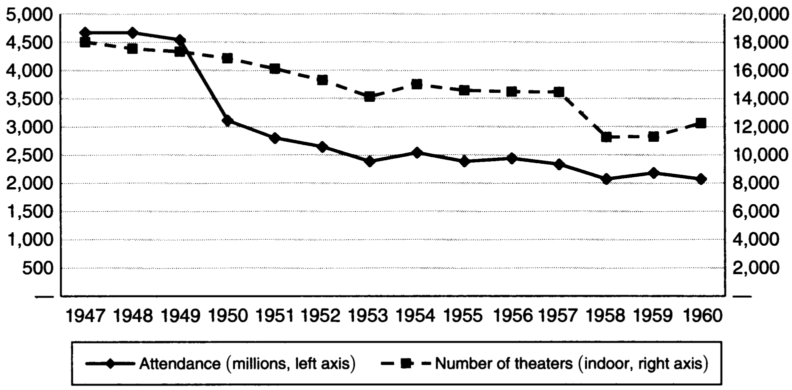

Figure 1. Movie Attendance and Number of Movie Theaters

Note: Movie theater yearly attendance and the total number of indoor movie theaters.

Source: The Film Daily Yearbook of Motion Pictures.

capacity must be reduced over time. However, capacity reduction is a public good that should be provided privately, so firms have an incentive to free-ride on competitors' divestment (or exit). In addition, because firms do not have exact information about competitors' profitability or about the future demand process, they have an incentive to wait to acquire more information before they act. Furthermore, noncooperative natures of firms' interaction may lead to coordination failure, delaying the industry-level divestment process. These factors can create an inefficiently slow divestment process.

This paper empirically studies firm's strategic exit decisions in a declining environment and evaluates the economic costs that arise due to strategic interactions during the exit process. Specifically, I quantify the extent to which the exit process generated by firms' strategic interactions deviates from the outcome that maximizes industry profits. As an example, I study the US movie theater industry in the 1950s, which is an ideal case to study strategic exits for several reasons. First, the industry faced a long-run decline in demand. Figure 1 shows the total yearly theater attendance and the total number of indoor theaters from 1947 to 1960. The average attendance for the average theater declined severely during the period. This decline in demand was mostly due to exogenous forces, such as the nationwide penetration of TVs (Lev 2003; Stuart 1976). Figure 2 shows growth in TV penetration in the United States. Second, firm's decisions were close to a simple binary exit-stay decision. In those days, costs were mostly fixed and capacity adjustments were usually infeasible. Hence, theaters responded to declining demand by leaving the market. Third, given localized demand and a small number of movie theaters in each market, it is reasonable to assume that theaters considered their opponents' behavior when choosing an optimal exit time.

Since each theater does not internalize increased profits received by its competitors when exiting the market, oligopolistic competition can lead to slower sequential exits when compared to coordinated exits that would maximize the industry's profit. In addition, theaters were unlikely to have exact information about competitors'

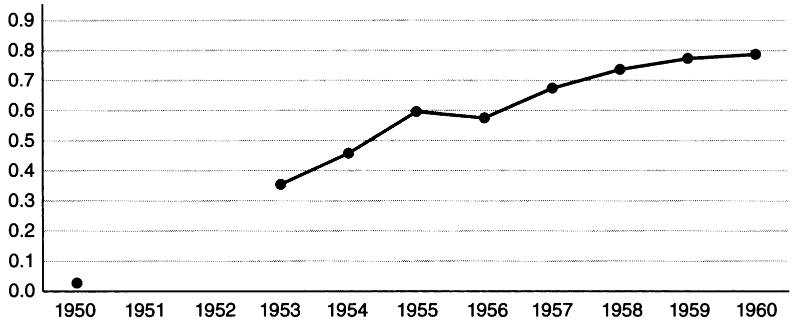

Figure 2. Average of Market-Level TV Penetration Rates

Note: These rates are not reported in 1951 and 1952.

Source: Gentzkow and Shapiro (2008a).

profitability, because a major part of a theater's profit depends on sales/costs from concession stands and rent payments, which are private information. Since these variables tend to be correlated over time and differ widely and in idiosyncratic ways across theaters, theaters learn about their competitors' profitability over time, and may remain open while incurring a loss in the hopes of outlasting their competitors. Thus, strategic interactions could generate a significant delay in the exit process.[3]

To analyze such behaviors, I modify Fudenberg and Tirole's (1986) model of exit in duopoly with incomplete information to one that can be used in an oligopoly setting. At each instant, theaters choose whether to exit or stay in the market. I assume each theater knows its own time-invariant fixed cost but not that of its competitors. Thus, from a theater's perspective, there is a benefit to not exiting the market, as there is some chance their competitors will exit instead, which would increase their profit. They compare this benefit of waiting with the cost of waiting, which increases over time because of declining demand. In equilibrium, theaters exit sequentially, with the theater with the highest fixed cost leaving first.

One major advantage of this framework is that the uniqueness result in Fudenberg and Tirole (1986) is preserved in the N-player game. Thus, for any set of parameters of the model, there is a unique distribution of equilibrium exit times. Furthermore, as demonstrated in Section II, the cost of computing the equilibrium is low. As a consequence, I can take the full-solution approach, which allows me to explicitly take theaters' expectations and unobservable market-level heterogeneity into account.

I apply the proposed framework to theater-level panel data from the US movie theater industry, estimating theaters' payoff functions and the distribution of fixed costs. I use TV penetration rates, which vary across locations and time, to measure changes in demand. By imposing the equilibrium condition, the model predicts the distribution of theaters' exit times for a given set of parameters and unobservables. I estimate the parameters by matching the distribution predicted by the model with the observed distribution of exit times.

[3] There is another dimension in which strategic interaction could have nontrivial impacts on the consolidation process. The noncooperative nature of the game could result in an inefficient order of exits; less efficient firms outlast more efficient competitors. Ghemawat and Nalebuff (1985) demonstrate such a possibility theoretically.

In addition, I exploit the fact that, in the analysis of exit, there are more data on exiting firms, as opposed to potential entrants in the analysis of entry. Specifically, I utilize the information on the observed market structure before the exit game started to estimate a hypothetical entry game jointly with the exit game. This allows me to address the initial conditions problem caused by the selection on unobservables; i.e., unobservable variables that affect initial market structures also affect the behavior of firms in the following periods.

Identification of the model is possible because, in equilibrium, exit times are determined by theaters' expectations about their competitors' behavior as well as demand decline and product market competition. Therefore, exit times are informative about all these factors. In addition, I observe the number of theaters in each market before the war of attrition started. Intuitively, the strategic delay is measured as follows. The market structure before the decline in demand helps me to infer how theaters interact in the product market. Using exit behavior in monopoly markets, I can infer how demand declines with TV penetration. With these components, exit behaviors in a strategic environment (markets with more than one theater) are implied from the model without strategic delays. Then, the difference between these implied exit behaviors and data is attributed to the strategic delay in exit.

Using the estimated model, I quantify the effect of strategic interaction on the consolidation process. To do so, I define two benchmarks. First, I consider a coordinated solution where each theater exits the market at the exact time that its operating profit becomes lower than its fixed costs. This is called the coordination benchmark. Under this scenario, there is no ex post regret nor delays in exit due to learning. The difference in cumulative market profits between the war of attrition and the coordination benchmark is defined as the cost of strategic behavior. Second, I shut down the incentive to free-ride on competitors' exit and calculate the path of theater exits that maximizes the industry's profit. I call this the regulator benchmark, and the difference in cumulative industry profits under the coordination benchmark and the regulator benchmark is defined as the cost of oligopolistic competition.

The delay in exit that arises from strategic interactions is 2.676 years on average. From these years, 3.7 percent of this delay is accounted for by strategic behavior, while the remaining 96.3 percent is explained by oligopolistic competition. The resulting cost, measured by the percentage difference in cumulative market profits, is 4.9 percent in the median market. The cost of oligopolistic competition accounts for 95.5 percent of this total cost, while the cost of strategic behavior accounts for 4.5 percent.

The cost of strategic interaction differs across different market structures. Specifically, the loss of industry profit is larger in markets with fewer competitors. For example, the cost of oligopolistic competition in the median duopoly market, measured by the percentage difference in cumulative market profits, is 7.22 percent, while the cost in the median market with four initial competitors is 4.56 percent. Intuitively, business stealing effects are weaker in markets with more competitors. As the initial number of competitors gets large, competition becomes closer to perfect competition, and the cost of oligopolistic competition tends to vanish.

The cost of strategic behavior is larger in markets with a slow decline in demand. Splitting the sample into markets with slow and fast decline based on the speed of

TV diffusion, the median cost in slowly declining markets, measured by the percentage difference in cumulative market profits, is 0.83 percent, while the corresponding number for markets with fast decline is 0.57 percent. The intuition is as follows. In markets with slow decline, the cost of waiting increases slowly. On the other hand, the benefit of waiting is still large because a winner of the game can enjoy a higher profit over a longer period of time. These two factors prolong the war of attrition. For example, in a counterfactual scenario in which demand is fixed over time, the average delay in exit due to strategic behavior becomes 1.059 years, which is more than ten times as long as the original case. An example of such a situation would be battles to control new technologies discussed by Bulow and Klemperer (1999), as demand in those industries is not declining. Consequently, large losses accumulate over time.

Related Literature.—I use a full-solution approach to estimate the dynamic game with learning, exploiting the uniqueness property of the game and simplicity of computation. In contrast, most papers estimate a dynamic game using a two-step estimation method. Early papers that proposed two-step estimation methods for dynamic Markov games include Jofre-Bonet and Pesendorfer (2003); Aguirregabiria and Mira (2007); Bajari, Benkard, and Levin (2007); Pakes, Ostrovsky, and Berry (2007); and Pesendorfer and Schmidt-Dengler (2008). Recent empirical applications using a two-step method include Ryan (2012), Collard-Wexler (2013), and Sweeting (2013). In the first stage of the two-step method, a policy function is calculated for every possible state, which is difficult in a nonstationary environment. Moreover, unobservable variables (market-level heterogeneity and theaters' profitability) play an important role in my model, so the first-stage estimation in the two-step method would not be consistent.

Schmidt-Dengler (2006) analyzes the timing of new technology adoption, separately estimating how it is affected by business stealing and preemption. In the environment he considers, the cost of adopting a new technology declines over time, as opposed to the current study where the cost of waiting increases over time because of declining demand. In his model, players can delay competitors' adoption times by adopting before they do, even though such an adoption time is earlier than the stand-alone incentive would suggest as optimal. Thus, this preemption motive hastens the industry's adoption of new technology. On the other hand, in the current study, there is asymmetric information that persists over time, so players have an incentive to delay their exit, hoping that they can outlast their competitors, even if they are currently making a negative profit.

Klepper and Simons (2000) and Jovanovic and MacDonald (1994) investigate the US tire industry, in which a large number of firms exited within a relatively short period of time. They assume this market is competitive. In their model, innovation opportunities encourage entry in the early stage of the industry's development. As the price decreases due to the new technology, firms that fail to innovate exit. Competition affects the devolution of the industry through the market price. In comparison, in the movie theater industry during the relevant period, competition was local, and hence strategic interactions among theaters should be taken into account. Another important difference is that the shakeout in the US tire industry was not due to declining demand.

A number of papers analyze firm exit (Fudenberg and Tirole 1986; Ghemawat and Nalebuff 1985, 1990).[4] I estimate a modified version of Fudenberg and Tirole (1986), which has asymmetric information between players that delays their exits. Ghemawat and Nalebuff (1985) construct a game of exit and obtain a unique equilibrium where firms exit sequentially, with the largest firm exiting first. In their environment, every firm will eventually exit by a finite date, so this may not fit my application. Ghemawat and Nalebuff (1990) consider a case in which firms can continuously divest their capacity in a declining industry. While such a case is more sensible in many settings, as Section I will discuss, the current application fits better into a case of binary exit/stay decisions.

Several recent papers analyze consolidation processes using a dynamic structural model. Stahl (2011) uses the deregulation in the US broadcast TV industry as an exogenous event that led to significant consolidation to estimate firms' benefits (increased revenue) and costs of purchasing competitors' stations. Jeziorski (2014) develops a dynamic model of endogenous mergers to estimate fixed-cost efficiencies of mergers in the US radio industry. These two papers quantify the cost reduction the merging firm achieves. On the other hand, Nishiwaki (2010) develops and estimates an oligopolistic model of divestment using data from the Japanese cement industry. With the estimated demand and cost parameters, he asks the hypothetical question of what would have happened to social welfare if a merger in the data had not been approved. An important difference from the current study is that he considers a case in which the number of firms is fixed over time and focuses on firms' divestment.

This paper is related to the literature on all-pay auctions with incomplete information. Krishna and Morgan (1997) analyze auction settings in which losing bidders also have to pay positive amounts and examine the performance of these settings in terms of expected revenues. Moldovanu and Sela (2001) study a contest with multiple unequal prizes with asymmetric bidding costs. Bulow and Klemperer (1999) analyze a general game in which there are $N + K$ players competing for N prizes. My model can be considered as one variant of this class of models with heterogeneous costs/prizes of bidders, but it is different because the value of the prize (operating profits) changes over time and is affected by the number of surviving players, which is endogenous. In addition, this paper is one of few empirical applications of such models.

To the best of my knowledge, almost no paper in the literature estimates a dynamic game with serially-correlated private values (a notable exception is Fershtman and Pakes 2012). Two difficulties arise in estimating such models. First, to account for theaters' expectations, the entire history of the game should be included in the state space. It is difficult to do so in the framework of Ericson and Pakes (1995), which is commonly used in the literature. Second, the initial conditions problem is more significant with serially-correlated private values, as players at the beginning of the sample period are selected samples. Because I account for these factors, I can estimate a game with serially-correlated private values, in comparison to much of the literature.

[4] Several papers, including Baden-Fuller (1989), Deily (1991), and Lieberman (1990) analyze empirically the relationship between a firm's characteristics and its exit (plant closing) behavior.

The remainder of the paper is organized as follows. Section I briefly summarizes the US movie theater industry in the 1940s and 1950s. Section II modifies the model of Fudenberg and Tirole (1986) to be used in an oligopoly. Section III describes the data. Section IV discusses my estimation strategy. Section V presents estimation results and simulation analysis. Section VI concludes. All proofs are shown in the appendices.

I. Case Study: The US Movie Theater Industry

The US movie theater industry in the late 1940s and 1950s is a relevant case study for the economic costs of consolidation. This section discusses the industry background and underlying factors behind its declining demand. I focus on demand and exit behavior in the classic single-screen movie theater industry.

After a big boom starting in the 1920s, the US movie theater industry faced a severe decrease in demand in the 1950s and the 1960s, primarily due to the growth of TV broadcasting. In 1950, fewer than one out of ten households in the United States owned a TV set. By 1960, however, almost 90 percent of households had a TV. In response, demand for theaters decreased. Movie attendance declined most quickly in places where TVs were first available, implying that TV penetration caused a decline in demand. According to Stuart (1976), the addition of a broadcast channel in the market caused an acceleration in the decline in movie theater attendance. There were other factors that contributed to the decline in demand. Suburb growth and motorization facilitated the growth of drive-in theaters, which in turn further decreased demand for classic single-screen movie theaters.

Changes in government policy at the end of the 1940s also contributed to the downturn in demand.[5] Vertical integration among producers, distributors, and exhibitors had been widespread until the late 1940s. The major movie producers (called the "Hollywood majors" [6]) formed an oligopoly, and they had control over theaters through exclusive contracts and explicit price management. They owned 3,137 of 18,076 movie theaters (70 percent of the first-run theaters in the 92 largest cities). The Paramount Decree (1948), however, put an end to this vertical integration, resulting in the separation of those producers from their vertical chains of distributors and exhibitors.[7] For example, explicit price management by distributors was prohibited. The government also mandated that the spun-off theater chains would have to further divest themselves of between 25 and 50 percent of their theater holdings.

The Paramount Decree created a more unstable and risky business environment for movie theaters. For example, movie producers no longer had a strong incentive to produce movies year round. Furthermore, according to Lev (2003), the production companies started to regard TV as an important outlet for their movies. In the era of vertical integration, producers had an incentive to withhold their movies from TVs

[5] The figures and facts in this paragraph are from Chapter 6 of Melnick and Fuchs (2004).

[6] Majors in this era include the "Big Five" (Loew's/MGM, Paramount, 20th Century-Fox, Warner Bros., and RKO) and the "Little Three" (Universal, Columbia, and United Artists).

[7] *United States v. Paramount Pictures, Inc.*, 334 US 131 (1948).

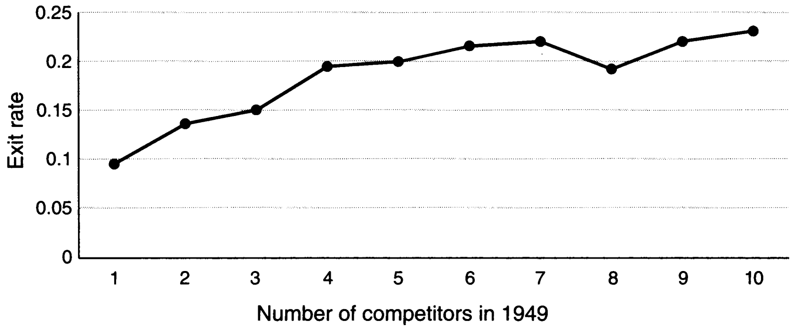

FIGURE 3. EXIT RATE BY NUMBER OF COMPETITORS IN 1949

Sources: The Film Daily Yearbook of Motion Pictures and author's calculation.

in the interests of their exhibitor-partners. After divestment, however, movie theaters became just one of the customers for producers, along with the TV companies.

Because of all of these factors, demand for incumbent movie theaters shrunk in an arguably exogenous way. As shown in Figure 1, theater attendance started to decrease in 1949, and kept declining mostly monotonically afterwards. Almost all theaters had only a single screen in those days (e.g., the first twin theater in the Chicago area opened in 1964), and their fixed investments were often heavily mortgaged. Therefore, they could not adjust capacity to deal with declining demand. They could only bear the loss and stay open or exit the market. Thus, the number of indoor movie theaters decreased with demand.

Figure 1 also shows that the decline in the number of indoor theaters was slower than the decline in theater attendance. This slow divestment process is consistent with the argument that capacity reduction is a public good so the industry tends to maintain excess capacity in a declining environment. One way to further explore this difference is to look at the relationship between exits of incumbent theaters and market structure. Figure 3 shows the exit rate during the sample period averaged by the initial number of competitors. As is clear from the figure, the exit rate increases with the number of competitors. One possible explanation is that theaters were trying to outlast their competitors in the declining environment. Since a few theaters could still operate profitably, each theater preferred to stay open as long as it expected some competitors to exit early enough. If there are many competitors, it is highly unlikely that a theater will be one of the few survivors at the end, so the theater may give up and exit early. This situation fits nicely into the framework of a war of attrition. Thus, in this paper, I use the framework of a war of attrition, exploiting the relationship between the number of competitors and exit probability to analyze the exit behavior of movie theaters.

The structure of the US movie theater industry changed significantly in the 1960s, when multiplex theaters emerged. This arguably changed the nature of competition. Once a theater has multiple screens, it can potentially respond to a change in demand by, for example, closing several screens. The structure of the industry became even more different and complicated after the 1980s because of the advent of home videos/DVD and horizontal integrations by big theater chains. Horizontal integration has become more prevalent over time. Nowadays, ten nationwide movie theater chains own 34 percent of indoor movie theaters and 58 percent of screens in the United States.[8] In the 1940s and 1950s, however, such horizontal integration was much less common.[9] Considering these changes in the industry structure since the 1960s, I focus on the late 1940s and 1950s.

It is difficult to evaluate how much of firms information is privately observed. Theater-specific demand is most likely common information between theaters, as the number of admissions is easily observed. Profits from concession sales, however, which account for an important part of total profit, are much harder to observe. Information about costs would also tend to be private. First, the outside option or opportunity cost of a theater's owner is difficult to observe. Second, the theater's fixed costs mainly come from rent payments, which vary widely across theaters and are not easily observed by competitors. In addition, these variables are likely correlated over time, so asymmetric information can persist. Therefore, in such an environment, theaters could keep updating their beliefs about competitors' profitability over time.

II. The Model

In this section, I modify Fudenberg and Tirole's (1986) model of exit in a duopoly with incomplete information to be used in an oligopoly. This section first describes the setup of the model and assumptions. Then, it provides the general solution followed by an example and intuition. The derivations of these results and all proofs are given in online Appendix A.

A. *Setup*

There are N theaters, $i = 1, \ldots, N$, which play a game of exit in a market. The game starts at $t = 0$ and time is continuous. At each instant, theaters decide whether to stay in or exit the market. Once a theater exits the market, it cannot reenter. While staying, theaters earn a common instantaneous profit of $\Pi_n(t)$, where $n \in \{1, \ldots, N\}$ is the number of currently active theaters in the market. When theater i exits, it receives an exit value (scrap value) of θ_i per unit time, which is privately observed by theater i at the beginning of the game. Note that θ_i incorporates both the value of exit (opportunity cost) that the theater would forgo by staying in and the fixed cost of production. The values θ_i are drawn independently from the common distribution $G : [\overline{\theta}, \underline{\theta}] \rightarrow [0, 1]$, where $0 < \underline{\theta} < \overline{\theta} < \infty$, with a density g everywhere positive and absolutely continuous. Theaters discount the future at a common rate of r. I use "theater θ_i" to denote a theater with exit value θ_i.

I use a notion of a Bayesian equilibrium. At each instant, the state variable of theater i consists of its private exit value θ_i and commonly observed state $\boldsymbol{\omega}_t = \{n, t, \mathbf{h}^t\}$, where n is the number of currently active theaters, t is the current time, and $\mathbf{h}^t$ is the history of the game up to time t. Given this information, theater i decides when to exit, conditional on none of the competitors having exited by then. In online Appendix A, I show that this decision is equivalent to choosing to exit or to remain

[8] See the website of the National Association of Theatre Owners at http://www.natoonline.org/ (accessed September 25, 2013).

[9] Online Appendix D analyzes how important movie theater chains are in determining the exit process.

open at every instant, and therefore, I work with this decision problem. A strategy T_i is a mapping from the state space to the planned exit time, $T_i : \mathcal{S} \times [\bar{\theta}, \underline{\theta}] \to \mathbb{R}_+$, where $\mathcal{S}$ denotes the space of commonly observed states $\boldsymbol{\omega}$. When one theater exits, other surviving theaters revise their planned exit times based on the currently available information, since now the instantaneous profit is higher and there is one less active theater in the game.

I focus on an environment where the instantaneous profit satisfies the following conditions:

ASSUMPTION 1: *(i) $\Pi_n(t)$ decreases over time and converges to $\overline{\Pi}_n$ for all n. (ii) For each $n = 2, \ldots, N$, $\Pi_n(t) < \Pi_{n-1}(t)$ for all t. (iii) $\overline{\Pi}_N > \underline{\theta}$. (iv) $\Pi_1(0) < \bar{\theta}$.*

Assumption 1 (i) implies that theater's profit monotonically decreases over time, while Assumption 1 (ii) suggests that theater's profit is eroded by competition. Assumption 1 (iii) says that with some probability, all theaters may be able to stay in the market forever. Assumption 1 (iv) implies that some theater wants to exit the market as soon as the game starts.

Let $V_i(\tau, \mathbf{T}_{-i}, \boldsymbol{\omega}, \theta)$ be the present discounted value of i's expected payoff if theater i chooses stopping time τ when the state variables are given by $(\boldsymbol{\omega}, \theta)$ and the other theaters follow strategy $\mathbf{T}_{-i}$. Let $g(\theta_j | \mathbf{h}^t)$ be theater j's competitors' beliefs about theater j if theater j has survived until time t. Using these, I use the following equilibrium concept.

DEFINITION 1: *A set of strategies $\{\hat{T}_i(\boldsymbol{\omega}, \theta)\}_{i=1}^N$ with posterior beliefs $g(\theta | \mathbf{h}^t)$ is a perfect Bayesian equilibrium if for all $\boldsymbol{\omega} \in \mathcal{S}$ and $\theta \in [\bar{\theta}, \underline{\theta}]$,*

(i) For all i and any strategy T_i,

$$V_i(\hat{T}_i, \hat{\mathbf{T}}_{-i}, \boldsymbol{\omega}, \theta) \geq V_i(T_i, \hat{\mathbf{T}}_{-i}, \boldsymbol{\omega}, \theta),$$

and

(ii) For any opponent j, $g(\theta_j | \mathbf{h}^t)$ is given by Bayes' rule when possible.

I focus on symmetric perfect Bayesian equilibria, so the player subscript is omitted from here on. In addition, I assume that if more than one theater chooses to exit at $t = 0$, one of these theaters is randomly chosen with equal probability and exits, and then the remaining $N - 1$ theaters restart the game at $t = 0$.[10]

B. *The General Solution*

This subsection characterizes the perfect Bayesian equilibrium in an N-player game. The major difference between this game and Fudenberg and Tirole's (1986)

[10] This assumption is imposed to avoid the problem of the nonexistence of a pure strategy equilibrium. It is possible in the case of N-player games that exiting immediately given opponents not doing so is optimal for more than one player. In this case, a symmetric equilibrium does not exit. For the necessity of this randomization device in N-player games and discussion, see Haigh and Cannings (1989), footnote 31 of Bulow and Klemperer (1999), and Argenziano and Schmidt-Dengler (2014).

duopoly game is that when one player drops out, the game still continues. The following lemmas fully characterize the necessary conditions of the perfect Bayesian equilibrium in an N-player game.

LEMMA 1: *If $T(\cdot)$ is the equilibrium strategy in a Bayesian equilibrium, then (i) For all $\theta \in \left[\Pi_{N-1}(0), \bar{\theta}\right]$, $T(\boldsymbol{\omega}, \theta) = 0$. (ii) $T(\boldsymbol{\omega}, \theta)$ is continuous and strictly decreasing in θ on $\left(\underline{\theta}, \Pi_{N-1}(0)\right)$. (iii) The inverse function of strategy in terms of θ, denoted as $\Phi(t; \boldsymbol{\omega}) \equiv T^{-1}(t; \boldsymbol{\omega})$, is differentiable on $(0, \infty)$, and its derivative is given by*

$$(1) \qquad \Phi'(t; \boldsymbol{\omega}) = -\frac{G(\Phi(t; \boldsymbol{\omega}))}{(N-1)\, g(\Phi(t; \boldsymbol{\omega}))} \left[\frac{\Phi(t; \boldsymbol{\omega}) - \Pi_N(t)}{V(T, \boldsymbol{\omega}', \Phi(t; \boldsymbol{\omega})) - \Phi(t; \boldsymbol{\omega})/r}\right],$$

where $\boldsymbol{\omega}' = \left(N-1, t, \mathbf{h}^t\right)$, with the boundary conditions

$$(2) \qquad \Phi(0; \boldsymbol{\omega}) = \Pi_{N-1}(0)$$

$$(3) \qquad \lim_{t \to \infty} \Phi(t; \boldsymbol{\omega}) = \overline{\Pi}_N.$$

This lemma provides a policy function when $t = 0$. That is, this gives a planned exit time for each type before any selection takes place.

LEMMA 2: *Suppose that one theater drops out at $t' > 0$ and $n > 1$. Let $\boldsymbol{\omega}' = \left(n, t', \mathbf{h}^{t'}\right)$. Then, (i′) There is no exit at $t \in (t', t^*]$ where $t^* = \Pi_n^{-1}(\theta^*)$ and $\theta^* = \Phi(t'; \boldsymbol{\omega})$. From t^* on, given that $T(\cdot)$ is the equilibrium strategy, (ii′) $T(\boldsymbol{\omega}', \theta)$ is continuous and strictly decreasing in θ on $\left(\underline{\theta}, \theta^*\right)$. (iii′) The inverse function of strategy in terms of θ, denoted as $\Phi(t; \boldsymbol{\omega}') \equiv T^{-1}(t; \boldsymbol{\omega}')$, is differentiable on (t^*, ∞), and its derivative is given by (1) with N being replaced by n, and the boundary conditions are*

$$(4) \qquad \Phi(t^*; \boldsymbol{\omega}') = \theta^*$$

$$(5) \qquad \lim_{t \to \infty} \Phi(t; \boldsymbol{\omega}') = \overline{\Pi}_n.$$

Finally, suppose the last competitor drops out at $t' > 0$ and $n = 1$. The exit time of the surviving theater is given by the solution to the following single-agent problem.

$$(6) \qquad T(\boldsymbol{\omega}', \theta) \in \underset{\tau \in [t', \infty]}{\arg\max} \left[\int_{t'}^{\tau} \Pi_1(t)\, e^{-r(t-t')}\, dt + \frac{\theta}{r} e^{-r(\tau - t')}\right].$$

This lemma characterizes the equilibrium strategy for $n < N$ and $t > 0$. That is, this gives a planned exit time for each type after some (or all) competitors have dropped out.

Finally, Lemma 1 (ii) and Lemma 2 (ii′) allow me to describe $g(\theta_j | \mathbf{h}^t)$ explicitly:

$$g(\theta_j | \mathbf{h}^t) = \begin{cases} \dfrac{g(\theta_j)}{\Pr(T(\omega, \theta_j) \geq t)} & T(\omega, \theta_j) \geq t, \\ 0 & T(\omega, \theta_j) < t. \end{cases} \tag{7}$$

PROPOSITION 1: *Equations* (1)–(7) *constitute a symmetric perfect Bayesian equilibrium of the entire game.*

The existence of equilibrium is not proved in a general case. In the estimation, however, for any set of parameters including estimated parameter values, I could numerically find the $\Phi(t; \omega)$ that satisfies equations (1), (2), and (3).[11] Moreover, as Proposition 2 shows, if I find a symmetric equilibrium, it is the unique symmetric equilibrium.

PROPOSITION 2: *The symmetric equilibrium, if it exists, is unique.*

The logic behind this result is the same as that of Fudenberg and Tirole (1986). Introducing a positive probability that no theater has to exit brings the uniqueness. This is an attractive feature of the model and is extremely important for the full-solution approach in estimation. Finally, the following proposition bounds the policy function from below and above.

PROPOSITION 3: $0 < \Pi_n(t) < \Phi(t; \omega) < \Pi_{n-1}(t)$ *for all* $n > 1$.

C. *Intuition and Example*

The basic intuition behind the solution is simple. In each instant, theaters compare the benefit of staying with the cost of staying. The benefit is the product of the conditional (on survival) probability that one of the competitors drops out in the next instant and the value of the game after the competitor drops out. The cost of waiting equals the foregoing exit value less the instantaneous profit. Theaters exit as soon as the cost of waiting exceeds the benefit of waiting. With these concepts, consider the *marginal* player. For the marginal player i, at time t, the benefit of staying until time $(t + dt)$ and then dropping out should be equal to the cost of doing so:

$$\underbrace{\left(-(N-1)\frac{g(\Phi(t;\omega))}{G(\Phi(t;\omega))}\Phi'(t;\omega)\right)}_{\substack{\text{probability that one of } N-1 \text{ competitors} \\ \text{drops in } [t, t+dt] \text{conditional on survival until } t}} \cdot \underbrace{\left[V(T, \omega', \tilde{\theta}') - \frac{\tilde{\theta}'}{r}\right]}_{\substack{i\text{'s payoff when one of} \\ \text{competitors drops}}} dt = \underbrace{\left[\tilde{\theta}' - \Pi_N(t)\right]}_{i\text{'s cost of staying in}} dt, \tag{8}$$

where $\omega' = (N - 1, t, \mathbf{h}^t)$ and $\tilde{\theta}' = \Phi(t; \omega)$. Rearranging (8) gives the differential equation (1).

[11] Online Appendix E provides the details for computing the solution to the differential equation.

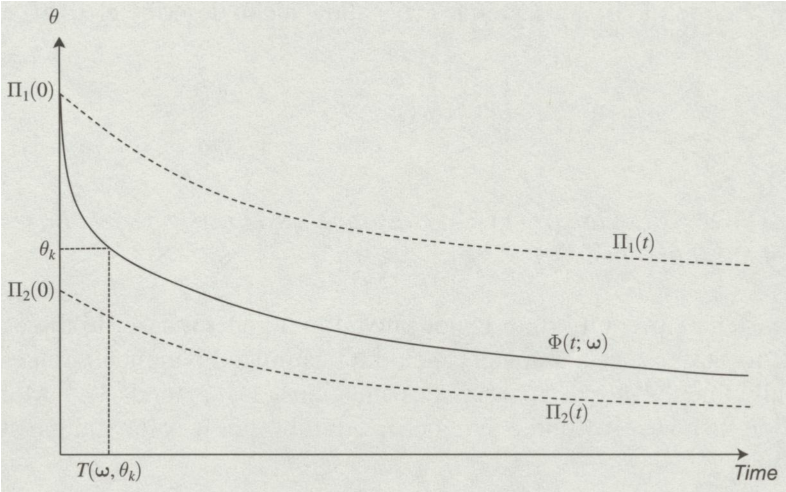

Figure 4. Policy Function in the Case of Duopoly

Notes: The policy function in the two-player game is given by $\Phi(t;\omega)$. Following this, theater θ_k waits until $T(\omega, \theta_k)$, and in case nobody has dropped out, exits.

Thus, the differential equation with boundary conditions fully characterizes the time path of the marginal type and serves as a policy function. Figure 4 shows a typical duopoly case. The policy function $\Phi(t;\omega)$ gives a one-to-one mapping between the type space $[\underline{\theta}, \overline{\theta}]$ and the space of exit time $[0, \infty]$. For example, starting the game from $t = 0$, a theater with θ_k makes a negative profit (or equivalently, the value of exit is higher than the operating profit) from the beginning, which is represented by the vertical distance between $\Pi_2(0)$ and θ_k. Despite this being the case, theater θ_k chooses to remain in the market in the hope that its competitor will exit soon, because at that point the theater would earn $\Pi_1(t)$. If the competitor has not dropped out by $T(\omega, \theta_k)$, however, then theater θ_k gives up competing and exits.

To see how the game transitions from an n player to an $n - 1$-player game, consider the case of triopoly. Figure 5 shows a typical example. When no competitors have dropped out, theaters follow the policy function $\Phi(t;\omega)$. Assume that three theaters have $(\theta_i, \theta_j, \theta_k)$ and that $\theta_k = \max\{\theta_i, \theta_j, \theta_k\}$. Following the policy function, theater θ_k waits until $T(\omega, \theta_k)$ and then drops out. At this moment, the highest possible exit value in the two-player game, denoted by $\tilde{\theta}$, is equal to θ_k. Any theaters with a higher exit value should have exited earlier in equilibrium. Now that there is one less competitor, the instantaneous payoff jumps from $\Pi_3(t)$ to $\Pi_2(t)$, so any surviving theaters are not making a negative profit. Thus, there will be no selection until the marginal player $\tilde{\theta}$ gets hit by $\Pi_2(t)$; i.e., until $t = \Pi_2^{-1}(\tilde{\theta})$, when the marginal player just breaks even. Then, selection restarts again. The time path of the marginal player in the two-player game is given by $\Phi(t;\omega')$ and serves as a policy function.

D. *Computing the Equilibrium of the Model*

For a given payoff function and exit values of theaters, I can simulate the game and compute the equilibrium exit times. As the three-player example above illustrates, a

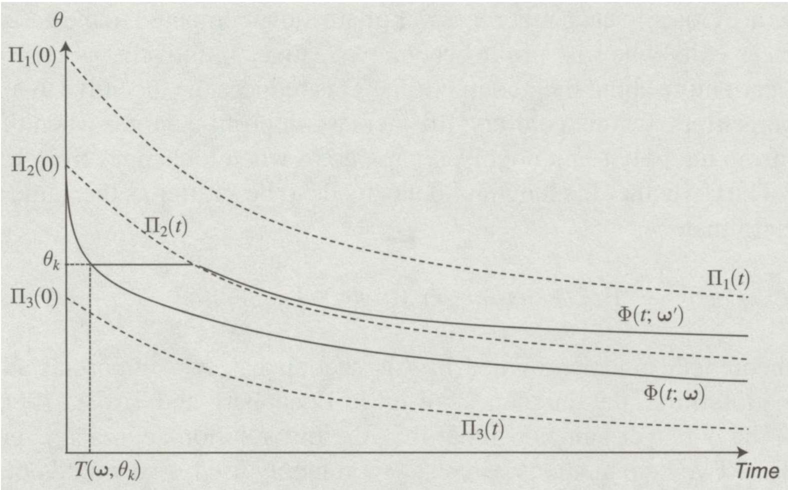

FIGURE 5. POLICY FUNCTION IN THE CASE OF OLIGOPOLY

Notes: The policy function in the three-player game is given by $\Phi(t;\, \omega)$. After theater θ_k drops out at time $T(\omega, \theta_k)$, the policy function in the two-player subgame is given by $\Phi(t;\, \omega')$.

general N-player game can also be solved sequentially, starting from solving $\Phi(t;\boldsymbol{\omega})$ with $\boldsymbol{\omega} = (N, 0, \mathbf{h}^0)$. The key to the tractability is that the evaluation of $V(T, \boldsymbol{\omega}', \tilde{\theta}')$ with $\boldsymbol{\omega}' = (N-1, t, \mathbf{h}^t)$ and $\tilde{\theta}' = \Phi(t;\boldsymbol{\omega})$ in equation (1) is computationally simple. Since this is the value of entering the $N-1$ player subgame for the "worst" type implied by the equilibrium, it can be written as

$$V(T, \boldsymbol{\omega}', \tilde{\theta}') = \int_t^{\Pi_{N-1}^{-1}(\tilde{\theta}')} \Pi_{N-1}(t') e^{-r(t'-t)}\, dt' + \frac{\tilde{\theta}'}{r} e^{-r(\Pi_{N-1}^{-1}(\tilde{\theta}')-t)}.$$

That is, if a player is the worst type at the moment, then the value of entering the subgame is simply the sum of the following two terms: the discounted sum of profits earned until $\Pi_{N-1}(t)$ declines down to $\tilde{\theta}'$ and the discounted sum of exit values from time $\Pi_{N-1}^{-1}(\tilde{\theta}')$ on. Note that these terms consist of the model's primitives only. Thus, computing an equilibrium repeatedly is feasible in my framework.[12]

Finally, I investigate the model's predictions about exit times. In a duopoly, as demonstrated in Figure 4, the first exit is delayed while the second exit is not, compared to the case in which theaters exit as soon as their profits become negative. Thus, exit times tend to cluster in the war of attrition. This holds for a general N-player game when it comes to the interval between the Nth and $(N-1)$th exit, since the last firm simply solves the monopoly problem and never delays its exit.

What is less clear is about other intervals. In a triopoly, for example, consider the first and second exit times. In Figure 5, the delay of theater θ_k is given by $T(\boldsymbol{\omega}, \theta_k)$. On the other hand, assuming that theater θ_j is the next one to exit, its delay is measured by $T(\boldsymbol{\omega}', \theta_j) - \Pi_2^{-1}(\theta_j)$. If this is smaller than $T(\boldsymbol{\omega}, \theta_k)$, then the two

[12] The standard Ericson-Pakes model may be difficult to compute. For example, the iterative method proposed by Pakes and McGuire (1994) may not converge to symmetric equilibria of the standard model. For an extensive discussion, see Besanko et al. (2010).

exit times are closer to each other in a war of attrition, compared to the case in which each theater exits when its profit becomes negative. Intuitively, as time goes on, theaters learn more about their competitors. This reduces the incentive to learn more about competitors. On the contrary, the increase in profit is larger when the market changes from duopoly to monopoly, compared to when it changes from triopoly to duopoly. Thus, whether the length of delay tends to be shorter as the game proceeds is not determinate.

E. *Discussion on Model's Assumptions*

The theoretical model provided in this section has two important advantages for estimation. First, the uniqueness result in Fudenberg and Tirole (1986) is preserved in the N-player game. Without this, the full-solution approach is practically infeasible.[13] Two-step methods, which are commonly used, also would not be feasible.[14] Second, the model is numerically tractable and easy to compute, as discussed above. These features allow me to use the full-solution approach (nested fixed-point approach), where the model is fully solved many times in the estimation algorithm.

It is important to emphasize that several assumptions in the model are useful for obtaining these tractable features. First, asymmetric information, coupled with the assumption that with some probability the market can accommodate existing players, results in a unique equilibrium as in Fudenberg and Tirole (1986). A possible alternative is a model with complete information. Such a model often has only mixed strategy equilibria. In such equilibria, some firms may earn a negative profit due to a coordination failure. This is comparable to the negative profit earned due to asymmetric information in my model. On the other hand, there is a strictly positive probability that more profitable firms will exit before less profitable firms, which does not arise in my model. Thus, an equilibrium in a game with asymmetric information and a mixed-strategy equilibrium in the game when information is symmetric may have different implications.[15] However, testing one model against the other is not feasible, as firms' profitability is not observed. Which framework is more suitable depends on the model at hand. In the current context, given that finding a mixed-strategy equilibrium can be computationally demanding, and that the value of exit is likely private information as is discussed in Section I, I assume the presence of asymmetric information in the model. Note that private information assumptions are

[13] See Aguirregabiria and Mira (2010) for a discussion of the difficulty.

[14] Since the number of time periods in the data is small, one would have to pool different markets to calculate the conditional choice probabilities. With multiple equilibria, the estimate of conditional choice probabilities would be inconsistent. Another problem is that the industry is still in a transition process during the sample period (i.e., observed states are in the transient class). Therefore, we cannot form the conditional choice probability for some state that the game has not reached yet but could visit at some point in the future. Furthermore, unobservable variables seem to be important in the current application, which is difficult to deal with in two-step methods.

[15] This depends on the model at hand. For example, Bulow and Levin (2006) provide a case in which firms' behavior in the pure strategy equilibrium under asymmetric information is very similar to firms' behavior in the mixed strategy equilibrium of their model with complete information. On the other hand, for comparisons, I compute a mixed-strategy equilibrium in a special case of my model assuming that information is symmetric. Specifically, I focus on the case with two theaters in which the duopoly profit is negative from the start, while the monopoly profit is positive. I compute a mixed strategy equilibrium in which at every instant each theater exits with a constant probability and compare it with the war-of-attrition equilibrium in the original model. The simulated distribution of exit times is different between these two equilibria. Some results of this exercise are available from the author upon request.

also introduced to guarantee the existence of pure-strategy equilibria in empirical work; e.g., private shocks in the Ericson-Pakes type model (see Doraszelski and Satterthwaite 2010).

While there are several possible information structures, it is difficult to test to distinguish alternative models. In theory, one could possibly check if there is any history dependence after controlling for current state variables. In standard dynamic oligopoly models used for empirical work (e.g., Ericson and Pakes 1995), there is no learning, and thus the current market structure is sufficient to predict players' decisions. Therefore, any history dependence would suggest a deviation from such standard settings. However, one major difficulty for performing such a test is the existence of unobservable market-level heterogeneity that persists over time. Even if private shocks do not persist and thus there is no learning, conditional choice probabilities depend on past state variables after controlling for current state variables. In this paper, I am not able to test for the existence of asymmetric information.

Second, the value of exit is assumed time invariant, so asymmetric information persists over time. If it is not correlated over time, theaters do not learn about their rivals and there is no delay in exit due to asymmetric information. In addition, the value of exit is assumed perfectly correlated over time, as opposed to imperfectly-correlated shocks. This is assumed for the tractability of the theoretical model. It is not straightforward to evaluate how the degree of persistence of asymmetric information affects the exit process, since nonpersistent random shocks and imperfectly-correlated shocks are difficult to handle in continuous time.

Third, although I add asymmetric information to the value of exit only, other types of uncertainty and private information could exist in the market so that a different type of learning takes place. For example, we could consider a case in which theaters are uncertain about the process of demand decline in the market but they privately observe a signal about the true demand process. In such an environment, theaters update their beliefs about the demand decline not only by observing their own signal, but also by observing the rivals' exit behavior. In the current application, however, I assume that the demand process was known to the theaters.

Which model is more appropriate depends on the application at hand. In principle, we can potentially estimate various models using data on market structure and firms' exits.[16] It should be emphasized, however, that the result of the analysis depends on these modeling assumptions.

III. Data

A. *Data Source and Selection Criteria*

The main data for this study come from *The Film Daily Yearbook of Motion Pictures* (1949–1952, 1954, and 1955), which contains information on every theater

[16] Data on firm-level sales or profits would aid the identification of models of demand learning. For example, using data on sales histories, Abbring and Campbell (2004) estimate a model of demand learning in an environment where strategic interactions are absent. How to estimate a model in which both demand learning and strategic interactions are present is an open question in the literature.

that has ever existed in the United States.[17] The dataset includes the name, location, number of seats, and type (indoor, drive-in, etc.) of each theater.[18] The data do not show the exact date of exit, so I constructed the exit year in the following way. If a theater was observed in year t but not year $t + 1$, I assume that the theater exited sometime between years t and $t + 1$.[19]

I assume that wars of attrition started in 1949, when demand started to shrink rapidly in an exogenous way. I define all the indoor movie theaters that were open in 1949 as players in the exit game. Theaters that entered after 1949 are treated as exogenous demand shifters. While the focus of this analysis is on single screen theaters, theaters that entered after 1949 were brand-new, and sometimes equipped with luxurious concession stands and nicer seats. There was certainly competition between classic single-screen theaters and these new theaters. It is not unreasonable, however, to assume that the game I developed was played among old theaters, and the entry/exit of new theaters was exogenous from the viewpoint of the old theaters.

Movie theaters compete in local markets (Davis 2005). In this paper, I define a market as a county. One big advantage of doing this is that data on demand shifters, such as TV penetration and demographics, are at the county-level. One drawback of this market definition is that the geographical area of some markets may be too large, because customers would not drive for long distances to go to a movie theater. Another problem is that some counties extend over many cities and contain hundreds of theaters (e.g., San Francisco county). To alleviate these problems, I focus on markets (counties) with fewer than or equal to ten theaters in 1949. Because of this selection, 313 markets out of 3,020 markets were dropped.

I assume that the diffusion of TVs was the main driving force behind the decline in demand for classic single-screen movie theaters. Gentzkow and Shapiro (2008a) provide TV penetration rates by county and year. The TV penetration rate is defined as the share of households which have at least one TV set. These data are available for 1950, 1953, 1954, and 1955. To interpolate and extrapolate TV diffusion rates, for each market, I fit the cumulative distribution function (CDF) of the Weibull distribution to finite data points and minimize the distance between these points and the interpolated series by choosing two parameters. Thus, the TV penetration rates are obtained for all $t \in [1949, \infty)$, and they are smooth and monotonically increasing everywhere. Since I specify the theater's profit as a decreasing function of TV penetration, this approach guarantees that the profit function satisfies Assumption 1-(i). Online Appendix C provides the details of the interpolation method. Fifty-seven markets are dropped from the sample because TV penetration rates are not observed in multiple years.

[17]The *Yearbook* in 1953, unlike other years, does not provide a list of all movie theaters. Movie theaters in Alaska are listed only in the 1949 *Yearbook*, so I exclude Alaska from the analysis.

[18]For location variables, the exact address is often missing. We do, however, know the name of the city where the theater is/was located. The number of seats is often missing, too.

[19]Occasionally, a theater is observed in t, not observed in $t + 1$, and observed again in $t + 2$. In this example, it could be the case that the theater did not exit between years t and $t + 1$, but it was simply missed in the *Yearbook* for year $t + 1$. To deal with such spurious exits, I use the following criterion. If a theater is observed in year t but not in year $t + 1$, I also check whether the theater is observed in years $t + 2$ or $t + 3$. If the theater is not observed in both years, the theater is considered to have exited the market. If the theater is observed again in either year $t + 2$ or $t + 3$ with exactly the same name and location as in year t, then it is considered not to have exited in year t. Note that I also augment the data using the *Yearbooks* of 1956 and 1957 to deal with spurious exits between 1954 and 1955.

TABLE 1—NUMBER OF COMPETITORS

Number of theaters in 1949	Frequency	Percent
1	451	17.31
2	520	19.95
3	445	17.08
4	369	14.16
5	245	9.40
6	209	8.02
7	143	5.49
8	87	3.34
9	80	3.07
10	57	2.19
Total	2,606	100.00

Basic demographic/market variables, obtained from the US census, also provide across-market variations that will help to identify the theaters' payoff functions. Population determines the potential market size of a county. I assume that the median age, family income, urban share, and employment share also shift demand. Counties are substantially different in terms of geographic sizes, which may affect the profitability of theaters. To account for this, I also include land area in the theater's payoff function. As I discuss in the next section, I assume that these variables determine the base demand for theaters, which is market-specific and constant over time.[20] I also discard markets with missing covariates. Because of this, 44 markets were dropped from the sample.

Thus, for estimation, I am left with 2,606 markets, which have a total of 9,768 theaters in 1949.

B. *Data Description*

Market-Level State Variables.—Table 1 shows the frequency of markets according to the initial number of competitors. There are a lot of monopoly markets, which helps identify the theater's payoff function, as decisions in such markets are a single-agent optimal stopping problem. The majority of markets have few competitors in 1949, there are many duopoly and triopoly markets, and almost 80 percent of all markets have five competitors or fewer. Table 2 shows summary statistics for the market-level variables that determine the base demand for theaters.

While these demographic variables shift the base demand, I assume that TV diffusion, population changes, and the entry of theaters affect how demand for incumbent theaters declines over time. The diffusion process of TVs varies across markets. In 1950, in 87 percent of the markets, TV penetration rates were lower than 10 percent. In 1955, however, the fifth and ninety-fifth percentiles of the TV penetration rate across markets were 14 percent and 86 percent, respectively, indicating a wide variation in the diffusion process across counties. This rich cross-section and time-series variation in the TV penetration rate is the main source of identification of theaters'

[20] A regression analysis shows that these demographic variables can explain a substantial portion of the cross-sectional variation in the number of theaters in 1949.

Table 2—Summary Statistics of Demographic Variables in 1950

Variable	Obs.	Mean	SD	Min.	Max.
Population	2,606	22,791	19,627	1,870	194,182
Median age	2,606	4.09	1.03	1.00	7.00
Median family income	2,606	4.91	1.57	0.00	9.00
Urban share	2,606	0.24	0.23	0.00	0.95
Employment share	2,606	0.96	0.02	0.81	1.00
Land area (square miles)	2,606	967	1,289	25	18,573

Note: Median age and median family income are categorical variables.

Sources: Hanes, Michael R., and Inter-university Consortium for Political and Social Research. "Historical, Demographic, Economic, and Social Data: The United States, 1790–2002."

payoff functions.[21] In the estimation, I specify the decline in demand as a function of the TV penetration rates.

The change in population during the sample period may affect the decline in demand. The fifth, twenty-fifth, seventy-fifth, and ninety-fifth percentiles of the population change are −23.7, −11.2, 10.0, and 40.7 percent, respectively. Because of these large population changes, it is important to control for population growth when measuring declines in demand.

New theater entry is also assumed to affect the decline in demand for incumbent theaters. In 1,611 markets (61.8 percent), there was no entry in any year studied. In 641 markets (24.6 percent), there was one entry. In the remaining 354 markets (13.6 percent), there was more than one entry in the sample period. If I focus on markets with four competitors or fewer, in 90 percent of the markets, the number of entries is one or fewer.

Exit Behavior.—As shown in Figure 1, the number of indoor movie theaters decreased from 17,367 in 1949 to 11,335 in 1959 (a 34.7 percent decrease). During the sample period, 1,836 theaters (18.8 percent of the sample) exited the market. In 1949, there were 3.75 theaters in the average market. Out of these theaters, 3.66 theaters survived in 1950, 3.64 in 1951, 3.58 in 1952, 3.24 in 1954, and 3.04 in 1955. The standard deviation across counties decreased gradually and monotonically from 2.34 in 1949 to 1.95 in 1955. This implies that markets with more competitors have higher exit rates. Demand for movie theaters declined significantly during this time period. Looking at the aggregate statistics in Figure 1, attendance in the average movie theater per year was 261,991 in 1949. This figure dropped to 184,571 in 1950, and it gradually decreased to 163,689 in 1955.

Exit behaviors appear to be correlated with the initial market structure. Figure 3 plots the exit rate in the sample period against the initial number of theaters. The exit rate increases with the initial number of theaters, and is concave. About 9.5 percent of the sample exited in monopoly markets, 13.7 percent in duopoly markets, and 15.1 percent in triopoly markets.

[21] I assume the diffusion of TVs across households is exogenous. Alternatively, Gentzkow and Shapiro (2008b) use the year in which each geographical market began receiving TV broadcasts as an instrument for TV diffusion across households.

Table 3—Preliminary Evidence

	OLS		OLS		IV Regression	
Parameters	Estimate	SE	Estimate	SE	Estimate	SE
Constant	0.0845	0.0114	0.0200	0.0163	−0.2272	0.0541
n_m in 1949	—	—	0.0365	0.0071	0.1907	0.0323
$(n_m \text{ in } 1949)^2$	—	—	−0.0025	0.0007	−0.0193	0.0033
Change in TV rate	0.1229	0.0216	0.0813	0.0222	0.0729	0.0262
Change in population	−0.0229	0.0227	−0.0382	0.0226	−0.0369	0.0251
New entrants	0.0706	0.0088	0.0604	0.0089	0.0612	0.0100
Adjusted R^2	0.0350		0.0533		0.0598	

Notes: The dependent variable is the share of theaters in each market that exit during the sample period. For the IV regression, I use demographic variables in Table 2 as instruments for the initial number of competitors and its squared term. The p-value for the F-statistic in the first stage is 0.0000 for both regressions.

To further investigate the determinants of theaters' exits, I regress the market-level exit share (the share of theaters in each market that exited during the sample period) on the change in the TV rate, the change in population, and the number of new entrants in the market. The first two columns of Table 3 show the result. The coefficient of TV penetration is positive, implying that the faster is the TV diffusion in a county, the higher is the exit rate. The negative coefficient of change in population means that the inflow of population slows down the decline in demand, although it is not statistically significant. The result also shows that new entrants hasten theaters' exits.

Strategic elements appear to be important in theaters' exits. The second regression includes the number of theaters in 1949. To capture the nonlinear effect of market structure, I also add its squared term. The linear term is positive, while the quadratic term is negative. This implies that a market with more competitors has a higher exit rate, and that the increment in the exit rate becomes smaller as the number of theaters increases. This is consistent with what I found in Figure 3.

One potential problem of this regression analysis is that the market structure may be endogenous. If unobservable demand shifters that affect the initial number of competitors are correlated with unobservable declines in demand, then the coefficients of the number of competitors and its squared term would be inconsistent. To alleviate the endogeneity problem, I run an instrumental variable (IV) regression. I use the demographic variables reported in Table 2 as instruments for the number of competitors and its squared term, assuming that these demographic variables are uncorrelated with unobservable decline in demand. The results are reported in the last column of Table 3. Importantly, the signs of the number of competitors and its squared term remain the same and statistically significant. To conclude, the market structure seems to have an important impact on theaters' exit behaviors.

Theaters' exits tend to be clustered within a market. Focusing on markets that experienced at least two exits during the sample period, I calculated the interval between the first and second exit. In approximately 74 percent of these markets, the interval is shorter than two years. On the contrary, only in 16 percent of these markets was the interval longer than three years. Such clusters are observed even after controlling for observable variables.[22] This observation points to two things. First,

[22] For a simple check, I divide these markets into four groups based on the change in the TV penetration rate. The share of markets within each group in which the interval between the first and second exit is shorter than two years ranges between 69 and 75 percent.

there could be unobservable heterogeneity in the decline in demand. In a market with severe decline in demand, theaters could exit shortly one after another. Second, in a duopoly with asymmetric information, the first exit is delayed while the second exit is not, implying shorter intervals on average. In an N-player game, this corresponds to the case in which the learning process is not fast, as discussed in Section IID. Thus, clustered exits in the data are consistent with the theoretical model.

In the empirical analysis below, I assume that theaters have symmetric instantaneous profits and focus on the symmetric equilibrium; i.e., theaters are different from one another only in terms of unobserved (to the econometrician) and privately known exit values. There are several reasons for this assumption. First, the data are not rich enough to capture theater level heterogeneity. The capacity variable (the number of seats) and the name of the street where a theater is located are frequently missing in my dataset. In addition, information on chain stores is only partially observed. Second, the differential equation (1) that I use for estimation will be very complicated once I abandon the symmetry assumption. This would make computation highly demanding. Thus, rather than a firm-level analysis, this study may also be considered as a market-level analysis; e.g., how the initial market structure and the exit process in the market are related.

IV. Estimation Strategy

I observe M independent markets and from this section on, I use a market subscript $m \in \{1, \ldots, M\}$ for all variables that differ across markets. For each market, I observe the initial number of theaters n_m, their exit times $\{t_1, \ldots, t_{n_m}\}$ with right censoring, the TV penetration rate over time, and the set of market-level time-invariant variables that affect market profitability and decline in demand. Note that, because of relatively short time periods in the data, many independent repetitions of the game (markets) with the uniqueness property are essential for inference.

A. *Specification*

To solve the model numerically, I parameterize the payoff function. The specification and selection of variables are guided by the data analysis in Section III and theoretical requirements. Let $\Pi_n(t,m)$ be a theater's instantaneous profit in market m at time t, when n theaters stay in the market. I assume that

$$\Pi_n(t,m) = \pi_n(m) \cdot d(t,m),$$

where $\pi_n(m)$ is the base demand and $d(t,m)$ is a function showing the decline in demand (called "decay function" hereafter).

The base demand is specified as

$$\pi_n(m) = \frac{\alpha_m + \boldsymbol{\beta}'\mathbf{X}_m}{n_m^{\delta}}, \tag{9}$$

where α_m is unobservable (to the econometrician) market-level heterogeneity, and $\mathbf{X}_m$ is a vector of observable demographic variables, including a constant, population

TABLE 4—SUMMARY STATISTICS OF NUMBER OF THEATERS IN 1949 BY POPULATION SIZE

Population of counties	Observations	Mean	SD	Minimum	Maximum
0–10,000	648	2.0	1.1	1	7
10,000–20,000	863	3.0	1.6	1	9
20,000–30,000	473	4.2	1.9	1	10
30,000–40,000	258	5.4	2.2	1	10
40,000–50,000	161	6.2	2.1	1	10
50,000–75,000	129	7.2	1.8	2	10
75,000–100,000	49	8.0	1.7	5	10
100,000–150,000	23	8.3	1.2	6	10
150,000+	2	8.0	1.4	7	9

Sources: Author's calculation based on the population data used in Table 2 and theaters' data from *The Film Daily Yearbook of Motion Pictures*.

size, the median age of the population, the median income, the share of the population living in urban areas, the employment share of the population, and land size. $\delta > 0$ is a parameter that captures the effect of competition and guarantees that $\pi_n(m)$ decreases in n.[23] This specification captures the idea that the change in profit when an additional theater is added depends on the original size of demand. Since the market size differs significantly across markets, this dependence is reasonable.[24]

Note that α_m plays an important role in theaters' profit. Not all the determinants of movie demand are likely observed by the econometrician. To see this, Table 4 splits markets into several groups according to population size in 1950 and calculates the summary statistics of the number of theaters in 1949. There is wide variation in the initial number of theaters among similarly sized markets. Furthermore, even when I control for other observable covariates, there still is variation in the initial number of theaters. Thus, it is important to account for unobservable market-level heterogeneity.

I assume that $d(t,m)$ decreases over time to satisfy Assumption 1 in Section II and is specified as

$$d(t,m) = \{1 - \lambda_1 TV_{tm}\}^{\exp(\lambda_m + \lambda_2 \Delta POP_m + \lambda_3 NEW_m)},$$

where TV_{tm} is the TV penetration rate in market m at time t, ΔPOP_m is the growth rate of the population in market m from 1950 to 1960,[25] and NEW_m is the total number of new entrants in market m during the sample period. I restrict $0 \leq \lambda_1 \leq 1$. Note that $d(t,m)$ is between zero and one, and decreases over time as long as TV_{tm} is increasing in time. To rationalize the observation that exit times are sometimes clustered, unobservable heterogeneity λ_m is introduced in the decay function. This

[23] I use a reduced-form profit function instead of fully specifying demand and cost functions. Demand for differentiated products is implicitly considered.

[24] Another possible specification would be

$$\pi_n(m) = \alpha_m + \beta' \mathbf{X}_m + \delta \log(n_m),$$

where δ is negative and the logarithm generates a decreasing effect of competition. One problem for this specification is that the amount of profit eroded by additional competitors is independent of market size.

[25] I use demographic data from 1950 and 1960 because census data are available only every ten years.

specification is flexible and potentially captures various types of declines in demand. In later sections, the set of λ is denoted by $\boldsymbol{\lambda} = (\lambda_1, \lambda_2, \lambda_3)$.

I assume that theaters' exit values identically and independently follow a truncated normal distribution with mean μ_θ, variance σ_θ^2, and lower and upper bounds of l_θ and h_θ, respectively. I also assume that $\alpha_m(\lambda_m)$ follows a normal distribution with mean $\mu_\alpha(\mu_\lambda)$ and variance $\sigma_\alpha^2(\sigma_\lambda^2)$. To allow for the possibility that a market with high unobservable demand shrinks more slowly or quickly due to unobservable factors, α_m and λ_m may be correlated with the correlation coefficient $\rho_{\alpha\lambda}$. For tractability, (α_m, λ_m) are assumed to be ex ante independent of θ, and all unobservable variables are ex ante independent of $\mathbf{X}_m$.

B. *An Auxiliary Entry Model*

I construct an auxiliary entry model and assume that potential entrants make their entry decisions right before the war of attrition starts. I jointly estimate the entry model and the exit game. There are two main advantages of doing so. First, as Table 1 shows, there are substantial variations in the number of theaters in 1949. Since firm entry reveals profitability, I utilize the variation in the initial number of theaters to infer the parameters in the base demand function (9).

Second, the entry model helps solve the initial conditions problem. If unobservable market heterogeneity α_m affected theaters' profit before 1949, the number of theaters in 1949 and market heterogeneity would be correlated through selection. Furthermore, firm-level unobservables, if they are serially correlated, introduce an additional source of endogeneity. In other words, the initial competitors (incumbent firms in 1949) are a selected sample so the distribution of exit values of incumbents is different from the population distribution. To solve this initial conditions problem, I approximate the joint distribution of α_m and $\boldsymbol{\theta}$ conditional on n_m using the restrictions implied by the entry model. Then, I use this joint distribution to solve the dynamic exit game. Online Appendix B provides a detailed discussion and procedure of the proposed method.

The auxiliary entry model is based on Seim (2006). Specifically, I assume that $\bar{N}$ potential theaters decide simultaneously whether or not to enter the market at the beginning of 1949, right before the war of attrition starts. Before making a decision, each player draws and privately observes its own value of exit, θ_i. If n theaters enter the market as a result of their decisions, each entrant earns

$$\pi_n^e(m) = \frac{\alpha_m + \boldsymbol{\beta}'\mathbf{X}_m}{n_m^{\delta_e}}.$$

On the other hand, if theater i does not enter, it earns θ_i. Although I use the same form of base demand as in (9), I allow the effect of competition, δ_e, to be different from δ in the base demand of the exit stage to capture the effect of the Paramount Decree on competition.

Let $D_i = 1$ if theater i enters the market and zero otherwise. Theater i enters if the expected profit $E[\pi_n^e(m)]$ is higher than θ_i, so its optimal choice D_i^* is given by

$$D_i^* = \mathbf{1}\left\{ (\alpha_m + \boldsymbol{\beta}'\mathbf{X}_m) E\left[n_m^{-\delta_e}\right] \geq \theta_i \right\}.$$

Letting P denote a theater's belief about the probability that an opponent enters the market, it can be shown easily that $E\left[n_m^{-\delta_e}\right]$ is simply a decreasing function of P, which is denoted by $K(P)$. The symmetric equilibrium belief $P^*(\mathbf{X}_m, \alpha_m)$ is thus given by a unique fixed point of the following equation:

$$P = G\big((\alpha_m + \boldsymbol{\beta}'\mathbf{X}_m)\, K(P)\big), \tag{10}$$

where G is the CDF of θ_i.

The number of entrants predicted by this entry model equals the number of $\theta_i s$ in $\{\theta_1, \ldots, \theta_{\bar{N}}\}$ that satisfy

$$(\alpha_m + \boldsymbol{\beta}'\mathbf{X}_m)\, K\big(P^*(\mathbf{X}_m, \alpha_m)\big) - \theta_i \geq 0. \tag{11}$$

Thus, for any pair $(\alpha_m, \mathbf{X}_m)$ and realization of $\boldsymbol{\theta} = \{\theta_1, \ldots, \theta_{\bar{N}}\}$, I can compute the equilibrium number of entrants. Arguing backwards, for any pair of $(\mathbf{X}_m, n_m)$, the entry model implies the set of $(\alpha_m, \boldsymbol{\theta})$ that is consistent with the pair. I use simulation to approximate the joint distribution of $(\alpha_m, \boldsymbol{\theta})$ conditional on $(\mathbf{X}_m, n_m)$.

C. *Identification and Estimator*

The theoretical model was constructed in continuous time in order to exploit several convenient properties of the model for estimation (uniqueness and ease of computation). On the other hand, the data are discrete. Therefore, when aggregating over time, one wants to keep as much of the power of the model's identifying restrictions as possible.[26]

The intuition behind the identification of strategic delay is given by the following argument. First, for the sake of argument, suppose that the effect of competition is the same between the exit and entry game; i.e., $\delta = \delta_e$. The market structure before the war of attrition helps me to infer how theaters interact in the product market. That is, the base demand is identified from the entry stage. Next, using information on exits in monopoly markets in which strategic interactions are absent, the decay function is identified. Then, with these components, exit behaviors in markets with more than one theater are implied from the model without strategic delays. In theory, any difference between these implied exit behaviors and their empirical counterparts is attributed to the strategic delay of exit. Next, assume that $\delta \neq \delta_e$. In this case, I need another source of information, as the difference between the implied exit and data mentioned above could also come from a different value of δ. Note that for a given rate of decline in demand and exit rate during the entire sample period, how many exits took place in the first several years would be informative about the extent of strategic delay. Therefore, by adding such information, I can separate the strategic delay in exit from the effect of competition (δ).

For estimation, I use indirect inference. I choose several moments that seemingly capture the relevant features of the data. I simulate moments from the model and minimize the distance between the simulated moments and data moments. I use moments jointly from the dynamic exit game and from the entry game.

[26] For a discussion of several estimation issues in continuous-time models, see Arcidiacono et al. (2015). See also Doraszelski and Judd (2012) for a discussion of tractability of continuous time models.

Let $\boldsymbol{\gamma}$ be a set of structural parameters and $\boldsymbol{\rho}$ be a set of auxiliary parameters (moments) that summarize certain features of the data. For any arbitrary moment x, I use x and $\hat{x}$ to denote the empirical and computed (from the model) moments, respectively. Thus, $\hat{\boldsymbol{\rho}}(\boldsymbol{\gamma})$ denotes the set of auxiliary parameters estimated from the simulated data. Note that I keep the dependence of $\hat{\boldsymbol{\rho}}$ on $\boldsymbol{\gamma}$ explicit.

Several normalizations are necessary to identify the parameters of the model. First, location normalization for profit is achieved by setting the means of unobservable market heterogeneity and exit values to zero, $\mu_\alpha = \mu_\theta = 0$. The constant in $\boldsymbol{\beta}$ pins down the mean profit. Next, I normalize the mean of unobservable heterogeneity in the decay function to zero, $\mu_\lambda = 0$, because in practice it is difficult to identify it separately from the coefficient of the TV penetration rate λ_1. Finally, I set the variance of unobservable heterogeneity in the decay function to one, $\sigma_\lambda^2 = 1$, since it is not well identified empirically given that there are a number of markets with no exit during the sample period. In sum, the set of structural parameters to be estimated is $\boldsymbol{\gamma} = (\delta, \delta_e, \boldsymbol{\beta}, \boldsymbol{\lambda}, \sigma_\theta, \sigma_\alpha, \rho_{\alpha\lambda})$.

Moment selection is guided by the theoretical model and data analysis in Section IIIB. The restrictions implied by the entry model identify δ_e, $\boldsymbol{\beta}$, and σ_α. I use the average number of entrants $E(n_m)$ and the average of interactions between n_m and each of the demographic variables and its squared term in $\mathbf{X}$. As was discussed above, there is additional variation in the number of entrants after controlling for demographic variables. To capture this, $\mathrm{var}(n_m)$ is also added. The parameters in the decay function, $\boldsymbol{\lambda}$, are identified mainly by the average of market-level exit rates interacted with the TV penetration rate in 1955, the growth rate of the population during the sample period, and the total number of new entrants.

The relationship between exit and the market structure at the beginning of the exit game is informative about δ and $\rho_{\alpha\lambda}$. The effect of competition δ determines how quickly profits decrease in the number of active theaters, and hence affects theaters' exit. As is seen in Figure 3, the market-level exit rate and the initial number of theaters are positively correlated. This aids identification of δ. On the other hand, a large market (which typically has large α_m and n_m) may have a different rate of decline in demand, which could slow down or speed up theaters' exit. This is captured by $\rho_{\alpha\lambda}$. Intuitively, δ affects the slope of the line in Figure 3, while $\rho_{\alpha\lambda}$ affects the curvature of the line. I add the following ten moments: the average of market-level exit rates in monopoly markets, in duopoly markets, and in markets with $n_m = 3$, etc.

To capture the magnitude of asymmetric information, which is mainly given by the variance σ_θ, I use one additional moment. The rate of exit in the first three years of the sample period is calculated for each market and is denoted as the rate of *early* exit. This variable, for given values of total exit rates and the decay function, is expected to capture the magnitude of strategic waiting. I use the average of the rate of *early* exit as an additional moment.

I have 28 moments to estimate 15 parameters. The elements in $\hat{\boldsymbol{\rho}}(\boldsymbol{\gamma})$ consist of the same 28 moments with the exit rates and the number of entrants being replaced by their simulated counterparts. The indirect inference estimator $\hat{\boldsymbol{\gamma}}$ is given by

$$\hat{\boldsymbol{\gamma}} = \arg\min_{\boldsymbol{\gamma}} (\boldsymbol{\rho} - \hat{\boldsymbol{\rho}}(\boldsymbol{\gamma}))' \boldsymbol{\Omega} (\boldsymbol{\rho} - \hat{\boldsymbol{\rho}}(\boldsymbol{\gamma})), \tag{12}$$

where $\boldsymbol{\Omega}$ is a positive definite weighting matrix.

The procedure to calculate the value of the objective function is as follows:

Step 1: Take a guess of structural parameters γ.

Step 2: Draw $\{\theta^{ns}\}_{ns=1}^{NS}$ and $\{\alpha^{ns}\}_{ns=1}^{NS}$ independently from their distributions. Use (10) and (11) to solve the entry game to calculate $\hat{n}_m^{ns}$ for $ns = 1, \ldots, NS$ and form $\hat{n}_m = \frac{1}{NS}\sum_{ns=1}^{NS} \hat{n}_m^{ns}$. To solve the entry game, I set $\bar{N} = 11$.[27]

Step 3: For $\mathbf{X}_m$ and n_m, simulate $\hat{F}_{\theta,\alpha|\mathbf{X}_m,n_m}$, following the procedure in online Appendix B.

Step 4: Draw $(\theta^{ns}, \alpha^{ns})_{ns=1}^{NS}$ randomly from $\hat{F}_{\theta,\alpha|\mathbf{X}_m,n_m}$. For each simulation draw, calculate the equilibrium of the dynamic game of exit: $\left\{\left(t_1^{ns}, \ldots, t_{n_m}^{ns}\right)\right\}_{ns=1}^{NS}$.

Step 5: Calculate the rate of theaters' exit for each market, denoted by $\hat{e}_m^{ns}$, and form $\hat{e}_m = \frac{1}{NS}\sum_{ns=1}^{NS} \hat{e}_m^{ns}$.

Step 6: Calculate moments $\hat{\rho}(\gamma)$ and obtain the value of the criterion function

$$J(\gamma) = (\rho - \hat{\rho}(\gamma))'\Omega(\rho - \hat{\rho}(\gamma)).$$

Then, repeat Steps 1–6 to minimize $J(\gamma)$.

The estimator $\hat{\gamma}$ is consistent and the asymptotic distribution is

$$\sqrt{M}(\hat{\gamma}-\gamma) \xrightarrow{d} \mathcal{N}(0, \mathbf{W}), \tag{13}$$

where $\mathbf{W}$ is given by

$$\mathbf{W} = \left(1 + \frac{1}{NS}\right)[\mathbf{H}'\Omega\mathbf{H}]^{-1}\mathbf{H}'\Omega(E\rho\rho')\Omega\mathbf{H}[\mathbf{H}'\Omega\mathbf{H}]^{-1},$$

with $\mathbf{H} = \partial\hat{\rho}(\gamma)/\partial\gamma'$. An optimal weight matrix $\Omega = (E\rho\rho')^{-1}$ is used so I have $\mathbf{W} = \left(1 + \frac{1}{NS}\right)\left[\mathbf{H}'(E\rho\rho')^{-1}\mathbf{H}\right]^{-1}$. For implementation, I bootstrap the data 1,000 times to get $\{\rho_b\}_{b=1}^{1,000}$, and then calculate its variance-covariance matrix Σ_M. Then, I replace $(E\rho\rho')^{-1}$ and $\mathbf{H}$ with Σ_M^{-1} and $\mathbf{H}_M$, respectively.

V. Estimation Results

This section first presents parameter estimates. Using these estimated parameters, I then perform several counterfactual analyses.

[27] I set $\bar{N}$ at 11 arbitrarily, since the maximum number of actual entrants is 10 in my sample.

Table 5—Estimates of Structural Parameters

Parameters	Estimate	SE
δ (competition in dynamic game)	0.2416	0.0362
δ_e (competition in entry game)	0.3121	0.0167
β_0 (constant)	0.8744	0.0221
β_1 (population)	7.4122	0.2179
β_2 (median age)	1.9634	0.0997
β_3 (median income)	0.8300	0.0186
β_4 (urban share)	−0.3939	0.0118
β_5 (employment share)	−3.4959	0.0282
β_6 (log of land area)	2.4158	0.1060
λ_1 (TV rate)	0.3715	0.0175
λ_2 (change in population)	−0.2220	0.7917
λ_3 (new entrants)	0.5137	0.0945
σ_θ (std. of exit value)	2.4130	0.0901
σ_α (std. of demand shifter)	0.0354	0.0049
$\rho_{\alpha\lambda}$ (corr. coefficient b/w α_m and λ_m)	−0.1892	0.1323

A. *Parameter Estimates*

Base Demand.—Table 5 presents estimates of the structural parameters. The coefficient of population (β_1) implies that theaters earn higher profits in bigger markets. The coefficients of median age (β_2), income (β_3), and land area (β_6) are all positive and significant. One possible interpretation for the coefficient of urban share (β_4) is that once I control for other observable and unobservable (to the econometrician) market characteristics, people living in urban areas are exposed to various types of other entertainment. An interpretation of the coefficient of employment share (β_5) could be that employed people have less time to watch movies. The parameters that capture competition (δ and δ_e) suggest that a theater's profit is eroded by competition. To see the relative sizes of these estimates, I calculate the value of base demand (9) at the sample mean of $\mathbf{X}$. Then, $\hat{\boldsymbol{\beta}}'\bar{\mathbf{X}} = 1.89$. Duopoly and triopoly profits are 1.59 and 1.45, which are about 15 percent and 23 percent lower than monopoly profits, respectively. In the entry stage, using the same mean $\hat{\boldsymbol{\beta}}'\bar{\mathbf{X}}$ and a different competition effect $\hat{\delta}_e$, duopoly and triopoly profits are 19 percent and 29 percent lower than monopoly profits, respectively.

Decay Function.—Table 5 reports the parameters in the decay function. The coefficient of the TV rate (λ_1) is significantly different from zero and is around 0.37. Since $1 - \lambda_1 TV_{tm}$ lies between 0 and 1, a larger value in the exponential function means that the rate of decline in demand is more severe. The coefficient of population growth (λ_2) is consistent with the intuition that in a county with an outflow of people, the decline in demand is faster. The coefficient is not, however, statistically significant. The coefficient of the number of theaters that entered after 1949 (λ_3) is positive, implying that entry of a new competitor hastens the decline in demand for incumbent theaters.

Estimates of Standard Deviations.—Estimates of σ_θ and σ_α are reported in Table 5. The standard deviation of exit values is 2.413 and is statistically significant. This implies that 95 percent of theaters have an exit value below 4.729. Meanwhile, the standard deviation of market-level heterogeneity is 0.035, which means that

95 percent of the value of unobservable market heterogeneity is between -0.071 and 0.071. Compared with the value of base demand (9) evaluated at the sample mean of $\mathbf{X}$ and the estimated parameters (i.e., $\hat{\beta}'\bar{\mathbf{X}} = 1.89$), this variation explains a relatively minor proportion of the variation in initial numbers of competitors among similarly sized markets.

The variance of exit values can be interpreted as the extent of asymmetric information. If the variance is small, a theater's assessment about its competitors' exit values is more precise. Hence, if a theater's value of exit is significantly higher than the mean, the theater would give up and exit relatively earlier. As the previous paragraph suggests, the value of exit varies widely, implying that theaters should stay in the market in the hope of outlasting their competitors.

The estimate of $\rho_{\alpha\lambda}$ is imprecisely estimated and not significantly different from zero. This implies that the base demand and rate of decline in demand may still be correlated, but the correlation can be captured by observable market-level variables. Indeed, the correlation between $\beta'\mathbf{X}_m$ and $\hat{\lambda}_2 \Delta POP_m + \hat{\lambda}_3 NEW_m$ is 0.15 and is statistically different from zero. That is, given the TV penetration rate, a larger market would have a faster rate of decline in demand on average.

B. *Model Fit*

To investigate the model fit, I simulate the model ten times and for each simulation calculate the rate of exit during the sample period. Then, I take average over simulation draws for different market structures. The rate of exit in monopoly markets is 9.5 percent in the data, while the prediction by the model is 9.9 percent. In duopoly or triopoly markets, the empirical and predicted exit rates are 14.4 percent and 13.0 percent, respectively. The corresponding numbers for markets with four or five theaters are 19.7 percent and 18.2 percent, respectively. Finally, in markets with more than five theaters, the rate of exit in the data is 21.6 percent, while the prediction of the model is 20.5 percent.

In addition, to investigate the model fit along the exit process, I randomly drew a set of structural parameters γ from the estimated asymptotic distribution $\mathcal{N}(0, \mathbf{W})$ given in (13) 200 times, and simulated the survival rate of theaters for each draw. Then, I calculated the 95 percent confidence interval (top 2.5 percent and bottom 2.5 percent of exit rates) for the exit rates for different market structures. Figure 6 shows four graphs. The model fits the data well, except for the survival rate in 1952 for markets with four or more theaters in 1949. For most of the other years for other markets, the model shows a good fit.

C. *Simulation Analysis*

Delay of Exit.—To quantify the effect of strategic interaction on the consolidation process, I define two benchmarks in relation to the war of attrition equilibrium. First, I consider a coordinated solution where no theater makes a negative flow profit.[28] That is, every theater exits the game at the exact moment when its profit becomes

[28] A loss or a negative profit in this context is in terms of economic profit. That is, if the profit of a theater is lower than its exit value (the value of the outside option), I call this "incur a loss" or "make a negative profit."

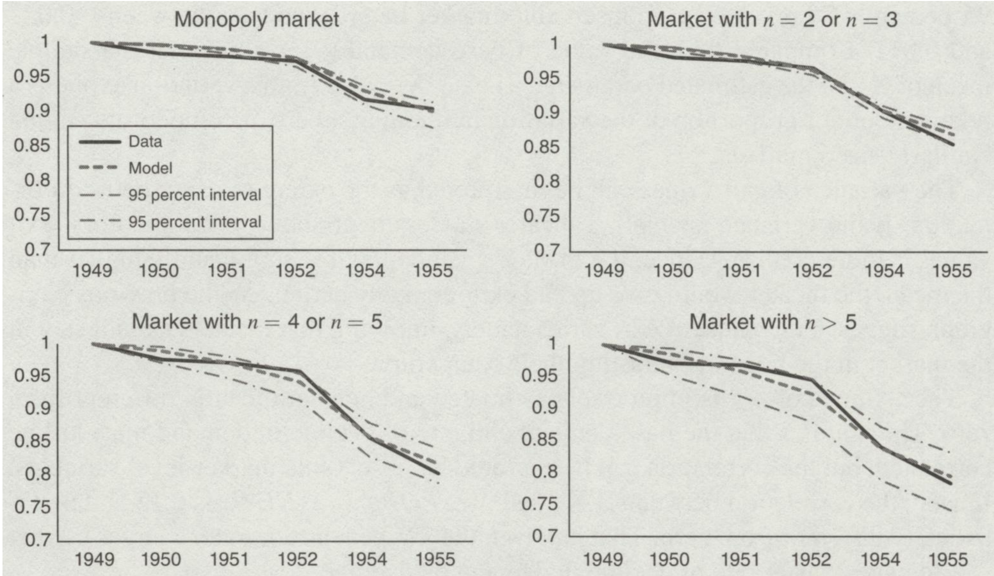

Figure 6. Model Fit

Notes: I randomly drew a set of structural parameters γ from the estimated asymptotic distribution $N(0,W)$ 200 times, and simulated the survival rate of theaters for each draw. Then, I calculated the 95 percent confidence interval (top 2.5 and bottom 2.5 percent of exit rates) for the exit rate for different market structures.

lower than its exit value. If more than one theater makes a negative profit at the same time, a theater with the highest exit value exits first. I call this the coordination benchmark. Under this scenario, there is no ex post regret nor delays in exit due to learning.

Second, since each theater does not internalize increased profits received by its competitors when exiting the market, the exit process in a noncooperative equilibrium in oligopolistic competition does not maximize the industry profit in general. I consider a hypothetical industry regulator that chooses a sequence of exit times to maximize the industry profit, in the same spirit as the counterfactual analysis of Schmidt-Dengler (2006). It would hasten the exit process in order to weaken business stealing effects and save fixed costs.[29] I call this the regulator benchmark. Note that this paper does not discuss social welfare, as the regulator solution ignores consumer surplus, which could increase due to more firms in the market.

Let $\mathbf{T}^* = \{t_1^*, \ldots, t_N^*\}$ and $\mathbf{T}^C = \left\{t_1^C, \ldots, t_N^C\right\}$ be the vector of exit times in a war of attrition equilibrium and in the coordination benchmark, respectively. The industry regulator chooses a vector of exit times $\mathbf{T} = \left\{t_1, \ldots, t_N\right\}$ to maximize the industry profit:

$$\int_{1949}^{1955} \sum_{k=1}^{n_t} \left[\Pi_{n_t}(t, m) - \theta_k\right] e^{-rt}\, dt,$$

[29]The logic behind this is similar to the argument of excess entry, where free entry can lead to social inefficiency. See Mankiw and Whinston (1986) for a theoretical argument, and see Berry and Waldfogel (1999) for an empirical work. Nishiwaki (2010) also considers the effect of a horizontal merger on the divestment process, where the externality that arises due to strategic interaction is internalized.

TABLE 6—DELAY IN EXIT IN YEARS

	$t^C - t^R$				$t^* - t^C$			
Market	Mean	1st	2nd	3rd	Mean	1st	2nd	3rd
$n_m = 2$	2.220	2.220	—	—	0.154	0.154	—	—
$n_m = 3$	2.587	2.967	1.265	—	0.120	0.126	0.102	—
$n_m = 4$	2.483	3.107	1.759	0.729	0.107	0.118	0.093	0.085
All markets	2.577	2.984	2.248	1.498	0.099	0.112	0.084	0.073

Notes: Let t^R, t^C, and t^* be the exit time in the regulator benchmark, in the coordination benchmark, and in a war of attrition equilibrium, respectively. The share of markets in which delays due to oligopolistic competition occur during the sample period is 0.39 for duopoly markets, 0.60 for triopoly markets, and 0.74 for markets with $n_m = 4$. The share of markets in which delays due to strategic behavior occur during the sample period is 0.20 in duopoly markets, 0.31 for triopoly markets, and 0.42 for markets with $n_m = 4$. I calculate the average delay of the first, second, and third exits, as well as the average of all delayed exits by the initial number of competitors.

where n_t is the number of theaters at time t implied by $\mathbf{T} = \{t_1, \ldots, t_N\}$. Denote the regulator's solution by $\mathbf{T}^R = \{t_1^R, \ldots, t_N^R\}$. In an oligopoly with declining demand, firms have an incentive to free-ride on competitors' exits/divestments, so the speed of capacity reduction is slower than what the profit-maximizing industry regulator would dictate. Therefore, for any n, $(t_n^C - t_n^R)$ measures the delay in exit that arises from oligopolistic competition. Meanwhile, $(t_n^* - t_n^C)$ measures the delay in exit due to strategic behavior.

I compute $(\mathbf{T}^*, \mathbf{T}^C, \mathbf{T}^R)$ for each market and calculate the average delay of the first, second, and third exits, as well as the average of all delayed exits. Table 6 summarizes the averages according to the initial number of competitors. Note that some markets do not have any delay during the sample period, so the averages are calculated only using markets in which delays occur by the end of the sample period. The footnote of the table also reports the share of such markets. Overall, a theater's exit is delayed by 2.577 years due to oligopolistic competition, while the delay in exit created by strategic behavior is 0.099 years. That is, 3.7 percent of the total delay is accounted for by strategic behavior. The delay in exit differs significantly across different market structures. In the case of duopoly, the exit is delayed by 2.22 years due to oligopolistic competition, while strategic behavior delays exit by 0.154 years, accounting for 6.5 percent of the total delay.

While the delay due to strategic behavior depends largely on the modeling choices, it is not entirely an artifact of the assumptions of the current model. For example, if information was symmetric, there would be mixed-strategy equilibria that lead to ex post regret with a strictly positive probability. Thus, the delay due to strategic behavior can arise under various sets of assumptions.[30] It is reassuring that most of the delay is due to oligopolistic competition, and thus the model's assumptions on the information structure are not the main driving force of the total delay in exit due to strategic interactions.

[30]On the other hand, there are cases in which such delays would not occur. For example, if private shocks are not correlated over time, learning would not occur. Another example is the subgame perfect equilibrium in Ghemawat and Nalebuff (1985), where ex post regret does not arise.

The delay in exit becomes shorter as the game proceeds. For example, in markets with four initial competitors, the first exit is delayed by 3.107 years due to oligopolistic competition, while the third exit is delayed by 0.729 years. One possible explanation is that the fixed cost that is saved is higher for the first exit than the third exit under the regulator's solution. The delay due to strategic behavior has the same features: the earlier exit is delayed more than later exits. Consistent with the argument in Section IID, as time goes on, theaters learn more about their competitors and the incentive to delay their exit becomes weaker.

Cost of Strategic Interaction.—Next, I compute the differences in industry profits and costs of strategic interaction. Let $\{n_t^C\}$, $\{n_t^*\}$, and $\{n_t^R\}$ be a sequence of the number of theaters in the market implied by $\mathbf{T}^C$, $\mathbf{T}^*$, and $\mathbf{T}^R$, respectively. Using these, define

$$Q_m^C = \int_{\underline{t}}^{1955} \sum_{k=1}^{n_t^C} \left[\Pi_{n_t^C}(t,m) - \theta_k\right] e^{-rt}\, dt \tag{14}$$

$$Q_m^* = \int_{\underline{t}}^{1955} \sum_{k=1}^{n_t^*} \left[\Pi_{n_t^*}(t,m) - \theta_k\right] e^{-rt}\, dt \tag{15}$$

$$Q_m^R = \int_{\underline{t}}^{1955} \sum_{k=1}^{n_t^R} \left[\Pi_{n_t^R}(t,m) - \theta_k\right] e^{-rt}\, dt, \tag{16}$$

where $\underline{t}$ denotes the moment when the first exit occurs under the regulator's solution. In other words, these variables measure the cumulative profits that all surviving theaters in market m earn in each scenario. The difference in cumulative industry profits under the coordination benchmark and the regulator benchmark can be regarded as the *cost of oligopolistic competition.* I use $(Q_m^R - Q_m^C)/Q_m^*$ to measure the cost. Meanwhile, the difference in cumulative industry profits under a war of attrition and the coordination benchmark can be regarded as the *cost of strategic behavior.* $(Q_m^C - Q_m^*)/Q_m^*$ measures such costs. Note that I use the same denominator to ease comparisons.

Table 7 summarizes these two statistics according to the initial number of competitors. The cost of oligopolistic competition in the median market is 4.68 percent. Overall, the loss of industry profit due to oligopolistic competition is larger in markets with fewer competitors. For example, the cost in the median duopoly market is 7.22 percent, while the cost in the median market with four initial competitors is 4.56 percent. One explanation is that business stealing effects tend to be stronger in markets with fewer competitors, while fixed-cost savings are not. As the initial number of competitors gets large, competition becomes closer to perfect competition, and the cost of oligopolistic competition tends to vanish.

There may be systematically different market characteristics depending on the initial number of competitors. In such a case, the difference in the above results across different market structures may not necessarily be due to the difference in competition. To control for those observable differences, I choose Clay county in Alabama, as it is a median county among duopoly markets in terms of the size of population and TV penetration in 1955. Using this market, I simulate the game

Table 7—Cost of Oligopolistic Competition and Strategic Behavior (*In percentage difference*)

	$(Q_m^R - Q_m^C)/Q_m^*$				$(Q_m^C - Q_m^*)/Q_m^*$			
Market	Mean	5th	Median	95th	Mean	5th	Median	95th
$n_m = 2$	8.21	2.23	7.22	16.42	0.99	0.17	0.70	2.83
$n_m = 3$	5.67	2.57	5.34	10.18	0.37	0.07	0.30	0.91
$n_m = 4$	4.76	2.42	4.56	8.19	0.27	0.04	0.23	0.63
All markets	5.40	2.06	4.68	11.25	0.39	0.05	0.22	1.17

Notes: Let Q_m^R, Q_m^C, and Q_m^* be the total cumulative profit earned by all theaters in market m in the regulator benchmark, in the coordination benchmark, and in a war of attrition equilibrium, respectively. This table shows the summary statistics of these variables by the initial number of competitors.

1,000 times. To examine the effect of market structure on the cost of oligopolistic competition, I change the initial number of competitors and compare the results. The results are comparable to Table 7. In the median duopoly market, the cost is 6.78 percent, whereas it is 6.36 percent and 5.85 percent in the median market with three and four initial competitors, respectively. Thus, the cost of oligopolistic competition is larger in markets with fewer competitors, even after controlling for other observable differences. It is also interesting that, while the cost decreases in the initial number of competitors, its speed is slow.

The cost of strategic behavior has a similar variation across different market structures. The difference in the median duopoly market is 0.7 percent, which is more than three times as big as the median market of all samples (0.22 percent). For a given player, the probability of winning the war of attrition, i.e., the probability of being a monopolist, is highest in a duopoly, and therefore theaters have the greatest incentive to wait. Moreover, the increment of profit when one competitor exits is highest in duopoly, which also partly explains the big difference in the industry profit between the two cases. As the initial number of competitors gets large, competition becomes closer to perfect competition, and hence motives to outlast competitors become less significant.

The cost of strategic interaction also differs across markets with a different rate of decline in demand. To see this, I split the sample into two groups of markets with slow and fast rates of decline in demand according to the TV penetration rate in 1955. Table 8 summarizes the average of each group according to the initial number of competitors. The cost of strategic behavior is largest in markets with slow rates of decline in demand. For example, in duopoly markets, the median of the cost in the group of markets with slow declines in demand is 0.83 percent, while the corresponding number for markets with fast declines in demand is 0.57 percent. The intuition is as follows. In markets with slow declines in demand, the cost of waiting increases slowly. On the other hand, the benefit of waiting is still large because a winner of the game can enjoy a higher profit over a longer time period. These two factors prolong the war of attrition. On the contrary, interestingly, there is no clear pattern between markets in which demand declines quickly and markets in which demand declines slowly in terms of the cost of oligopolistic competition.

To further investigate the relationship between the decline in demand and the cost of strategic behavior, I separate the effect of the war of attrition from the effect of declining demand on the exit process. To do so, I fix the TV penetration rate at its initial level in each market so that the decay function is constant over time. As

TABLE 8—COST OF STRATEGIC INTERACTION AND DECLINE IN DEMAND
(*In percentage difference*)

	$(Q_m^R - Q_m^C)/Q_m^*$		$(Q_m^C - Q_m^*)/Q_m^*$	
Market	Slow	Fast	Slow	Fast
$n_m = 2$	7.25	7.21	0.83	0.57
$n_m = 3$	5.29	5.35	0.39	0.23
$n_m = 4$	4.61	4.46	0.27	0.17
All markets	4.44	5.09	0.24	0.20

Notes: Q_m^R, Q_m^C, and Q_m^* are defined in the same way as in Table 7. The table shows the value of the median market for each market structure and speed of decline in demand.

discussed in Section II, theaters expect a higher profit if they outlast their competitors and thus stay until the expected benefit of waiting becomes lower than the expected cost of waiting. As time goes on, theaters become discouraged and exit if their competitors remain in the market. Notice that this dynamic selection may occur even if demand is not declining.[31] There are three types of theaters in equilibrium. The first set of theaters does not exit. Since demand is constant, their instantaneous profits are forever higher than their values of exit. The second set of theaters exits as soon as a war of attrition starts. They chose to enter the market in the static entry game. Playing the exit game is, however, not profitable for them, so they exit immediately. The third set of theaters stays in the market for a while, in the hope that they will outlast their competitors.

Holding demand constant, I simulate the game 100 times for each market and focus on theaters that delay their exit. Table 9 averages the delay in exit due to strategic behavior according to the initial number of competitors. As above, the average delay is larger in markets with fewer competitors. In duopoly, the average delay is 1.841 years, which is significantly larger than the 0.154 years reported in Table 6. The constant demand prolongs the war of attrition the most. An example of such a situation would be battles to control new technologies discussed by Bulow and Klemperer (1999), as demand in those industries is not declining. Consequently, large losses accumulate over time.

Discussion.—My results show that most of delays and resulting costs stem from oligopolistic competition and the role played by strategic behavior is relatively minor. I investigate what in the data delivers this conclusion.

Three important factors determine the relative importance of strategic behavior in creating delays. First, as I already demonstrated in Table 8, the cost of strategic behavior is larger in markets with a slow decline in demand, whereas this pattern is not observed regarding the cost of oligopolistic competition. Therefore, the relative importance of strategic behavior is expected to be larger in markets with a slow decline in demand.

Second, the magnitude of the effect of competition, captured by δ in my model, also affects the relative importance of strategic behavior. If competition is more severe, the increment in the total industry profit when a theater exits becomes larger,

[31] For example, the original game in Fudenberg and Tirole (1986) is mainly for the case of a growing industry. The case of constant demand may be simply thought of as a special case of either a declining or growing market.

TABLE 9—DELAY IN EXIT IN YEARS WHEN DEMAND IS CONSTANT

	$t^* - t^C$			
Market	Mean	5th	Median	95th
$n_m = 2$	1.841	0.144	1.059	5.342
$n_m = 3$	1.593	0.002	0.908	5.412
$n_m = 4$	1.623	0.002	1.232	4.802
All markets	1.059	0.002	0.303	4.568

Notes: t^C and t^* are defined in the same way as in Table 6. I calculate the model 100 times in each market assuming demand is constant, and average the delay in exit due to strategic behavior by the initial number of competitors. Approximately one-third of the exits occur immediately.

implying a larger deviation of the coordination benchmark from the regulator benchmark. Therefore, the cost of oligopolistic competition is expected to be larger when competition is more fierce. On the other hand, the cost of strategic behavior tends to have the same pattern. If competition is severe, the increment of profit when one competitor exits is high. This implies that the "prize" of a war of attrition is large, and therefore, other things being equal, theaters tend to wait longer. Thus, which of these two costs becomes larger when competition becomes more severe cannot be determined a priori.

Third, the variance of exit values, which can be interpreted as the extent of asymmetric information, affects the relative importance of strategic behavior and oligopolistic competition. If the variance is large, a theater's assessment about its competitors' exit values is less precise, and so the delay in exit due to strategic behavior should be larger. On the other hand, there is no clear reason why a larger variance of exit values increases the delay due to oligopolistic competition. Hence, an increase in the variance of exit values is expected to increase the relative importance of strategic behavior.

To validate these arguments, I define and compute $Q_m^{rel} = \left(Q_m^C - Q_m^*\right)/\left(Q_m^R - Q_m^*\right)$ for each market, where Q_m^C, Q_m^*, and Q_m^R are defined in (14), (15), and (16), respectively. In words, Q_m^{rel} measures the relative importance of the cost of strategic behavior. Under the estimated parameters, this value is 4.6 percent in the median market and 8.6 percent in the median duopoly market. If I split the sample into two groups of markets with slow and fast rates of decline in demand as in Table 8, Q_m^{rel} in the median market with slow (fast) declines in demand is 5.1 percent (3.7 percent). Thus, the relative importance of strategic behavior is larger in markets with a slow decline in demand. Next, to investigate the relationship between the magnitude of the effect of competition (δ) and the relative importance of strategic behavior, I double the estimate of δ to be 0.483, simulate the model, and calculate the relative importance of strategic behavior. As a result, Q_m^{rel} in the median market and median duopoly market are 9.3 percent and 11.5 percent, respectively, implying that severe competition increases the cost of strategic behavior disproportionately. Finally, I double the estimated standard deviation of the exit values to be 4.826 and simulate the model.[32]

[32] Since the distribution of exit values is a truncated normal distribution, the increase in the variance does not imply a mean-preserving spread. Thus, I adjust μ_θ such that the mean exit value stays unchanged. In addition, to keep the initial condition fixed, I double σ_θ only in the dynamic exit game.

I find that 5.5 percent of the total cost is accounted for by strategic behavior in the median market, while it is 11.4 percent in the median duopoly market.

How would data look under these hypothetical scenarios? A higher magnitude of the effect of competition (δ) implies that the exit rate increases quickly in the initial number of competitors, following the argument in Section IVC. That is, the slope of the line in Figure 3 would be steeper. For the standard deviation of the exit values, our argument in Section IIIB is helpful. I argue that in a duopoly with asymmetric information, the first exit is delayed while the second exit is not, implying shorter intervals on average. If the standard deviation of the exit values is higher, intervals between two theaters' exits in a duopoly market will be shorter. To conclude, my finding about the relative importance of strategic behavior critically depends on the speed of decline in demand, the relationship between market structure and the exit rate, and intervals of adjacent exits in the data.

VI. Conclusion

Many industries face declining demand and consequently firms sequentially divest and exit from the market. In an oligopolistic environment, strategic interactions play an important role and have a nontrivial impact on the consolidation process. Despite their importance in the economy, economic costs of consolidation arising from strategic interactions have not been studied sufficiently well. This paper empirically studies the strategic exit decisions of firms in a declining environment and evaluates the economic costs that arise due to strategic interactions during the exit process.

Specifically, I modify Fudenberg and Tirole's (1986) model of exit in duopoly with incomplete information to work in an oligopoly. I use data on the US movie theater industry and rich cross-section and time-series variations of TV penetration rates to estimate theaters' payoff functions and the distribution of exit values. By imposing the equilibrium condition, the model predicts the distribution of theaters' exit times for a given set of parameters and unobservables. I use indirect inference and estimate the model parameters by matching the predicted distribution with the observed distribution of exit times.

Using the estimated model, I measure the delays in the exit process due to oligopolistic competition and strategic behavior. The delay in exit that arises from strategic interactions is 2.7 years on average. Out of these years, 3.7 percent is accounted for by strategic behavior, while the remaining 96.3 percent is explained by oligopolistic competition. I also find that the delay and its resulting cost are relatively large in markets with few competitors and in markets with slow rates of decline in demand.

The framework in this paper can be applied to analyze other industries in which exogenous decline in demand creates a nonstationary environment in an oligopoly. It should be emphasized that the profit lost in the war of attrition is not necessarily detrimental to society. Due to delays in exit, consumers have access to more varieties if movie theaters are differentiated products. If demand-side data (price and quantity of the product) are available, one could compare the increase in consumer surplus and decreased firms' profit due to the strategic delay in exit. Applying this method to a currently declining industry is a useful exercise.

An important topic for future research is the relationship between firm entry and the exit process. In an industry where both entry and exit are common phenomena, unlike my application, explicitly analyzing such a link is important to understand the industry dynamics. For example, inefficient exit processes can affect entry, as these two processes are related through firms' strategic and dynamic behavior. Suppose that firms do not know the value of exit when they make an entry decision. Since the industry profit in the war of attrition outcome is smaller than the one in the regulator solution, each entrant has a smaller expected profit, and thus entry is discouraged. If the entry process also suffers from excess entry, this implies that inefficient exits make entry less inefficient. How much of entry inefficiency is offset by inefficient exits is an important empirical question.

It is also worth mentioning that while this paper focuses on the case in which firms make a binary exit-stay decision, firms could also gradually divest or merge into a bigger entity in a declining process. Nishiwaki (2010) makes an important contribution toward one direction, estimating an oligopolistic model of gradual divestment with the fixed number of active firms. In reality, firms' behavior in a declining industry is perhaps a mixture of exit-stay decisions, divestment, and mergers and acquisitions. Analyzing these behaviors in a unified framework is important to better understand the economic costs of consolidation and is left for future research.

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