Preemptive Entry and Technology Diffusion in the Market for Drive-in Theaters*

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Abstract

This paper provides an empirical test for entry preemption, and quantify its impact on the dynamics of new industries. The case-study is the evolution of the U.S. drive-in theater market between 1945 and 1955. We exploit a robust prediction of dynamic entry games to test for preemption incentives: the deterrence effect of entering early is only relevant for firms in markets of intermediate size. Potential entrants in small and large markets face little uncertainty about the actual number of firms that will eventually enter. This leads to a non-monotonic relationship between market size and the probability of observing an early entrant. We find robust empirical support for this prediction using a large cross-section of markets. We then estimate the parameters of dynamic entry game that matches this reduced-form prediction, and quantify the strength of the preemption incentive.

Preliminary and Incomplete. Comments welcome.

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1 Introduction

In strategic environments, firm's behavior often deviates from what the stand-alone incentive suggests as optimal, if it can affect rivals' behavior. Entry deterrence is one example. A monopolist who faces a threat of entry may expand its capacity beyond the level of monopolist's optimum. As another example, in a newly created market where only several potential entrants exist, those entrants may enter as soon as possible, if their entry is able to preempt rivals' entry later on. These behaviors are an important activity and have been well studied theoretically. However, it is difficult to find it empirically for several reasons. Most importantly, economists would not observe firms' costs nor profits, so wouldn't the optimal behavior that would be taken if such deterrence/preemptive incentives were absent. Furthermore, in the example of entry deterrence, we may not even observe entry because of entry deterrence. When entry is not observed, we do not know if it is indeed because of deterrence or not.

This paper provides evidence for preemptive entry, building on the insight of Ellison and Ellison (2011); when an incumbent faces a threat of entry, the likelihood of further capacity investment depends non-monotonically on market size. If the market is too small, entry is not attractive for potential entrants, so the incumbent does not need to invest further. When the market is too large, the incumbent would not be able to block entry. In "intermediate" markets, the incumbent can deter entry by expanding capacity. Thus, investment capacity by the incumbent is non-monotonic in market size.

We apply this insight to the U.S. drive-in theater industry. Drive-in theaters were a newly commercialized technology in the early 1940s and diffused broadly and rapidly in the U.S. over the following 10 years. Anticipating this rapid growth, forward-looking firms can deter the entry of future competitors by entering the market at an early date. The deterrence effect of entering early is only relevant for firms in markets of intermediate size. Potential entrants in small and large markets face little uncertainty about the actual number of firms that will eventually enter. This leads to a non-monotonic relationship between market size (measured by the number of days of summer), and the probability of observing an early entrant, as in Ellison and Ellison (2011). We find robust empirical support for this prediction using data on entry of drive-in theaters in the U.S. between 1945 and 1955.

We then develop a simple two-period entry model that captures several relevant incentives in the dynamics of new industries and estimate the parameters such that the model's prediction matches the reduced-form prediction in the data. Using the estimated parameters, we quantify the magnitude of the preemption incentive.

The rest of the paper is organized as follows. In Section 2, we first describe the background of the U.S. drive-in theater industry and explain the data for our empirical analysis. Then, we show evidence of preemptive entry. Section 3 develops a simple entry game and shows by simulation that the simple model can generate the non-monotonicity observed in the data. We estimate the structural parameters of the model and perform several counterfactual analyses. Section 4 concludes.

2 Institutional Detail and Data Description

2.1 The Industry

A drive-in theater differs from a regular theater in that it consists of a large outdoor movie screen, a projection booth, a concession stand and a large parking area for automobiles and in that customers can view films from the privacy and comfort of their cars within an enclosed area. The screen can be as simple as a white wall or as complex as a steel truss structure. While sound was originally provided by speakers on the screen, this system was overtaken by the cheaper and higher quality technology of broadcasting the soundtrack through individual speakers for each car in the 1940s and 1950s and ultimately in the 1960s and 1970s to be picked up by a AM or FM radio in stereo on an often high fidelity stereo installed in the car.

The first ever known drive-in took place in 1921 in Comanche, Texas, when Claude Caver obtained a public permit to project silent films downtown to be viewed from cars parked bumper to bumper. Following these experiments in Texas, it was Richard Hollingshead from Camden, New Jersey, who applied August 6, 1932, for a patent of his invention, and consequently given U.S. Patent 1,909,537 on May 16, 1933. Hollingshead's drive-in opened in New Jersey June 6, 1933, on Admiral Wilson Boulevard in Pennsauken, offering 400 slots and a 40 by 50 ft (12 by 15 m) screen. The facility only operated three years, but during that time the concept caught on in other states. The opening of this theater was followed by many others in other states such as Pennsylvania, California, Massachusetts, Ohio, Rhode Island, Florida, Maine, Maryland, Michigan, New York, Texas and Virginia.

The drive-in's peak popularity came in the late 1950s and early 1960s, particularly in rural areas, with some 4,000 drive-ins spread across the United States. Among its advantages was the fact that a family with a baby could take care of their child while watching a movie, while teenagers with access to autos found drive-ins ideal for dates. Revenue is more limited than regular theaters since showings can only begin at twilight. While part of the increase in number of drive-in theaters is explained by this increase in popularity from the demand side, it is also true that fixed costs of entry steadily decreased over time between 1933 to its demise in the 1970s. From the invalidation of the patent in 1950 by the Delaware District Court (by the end of its life) to the appearance of better and cheaper technology over time together with constant learning by doing of industry practitioners that was easily transmittable across current and future exhibitors, it is easy to see that entry costs went down over time in the drive-in theatrical industry.

Finally, the shift in content of drive-ins was less of a problem than competition from home entertainment, from color television to VCRs and video rentals. This, along with the 1970s oil crisis and wide adoption of daylight saving time as well as the 1980s real estate interest rate hikes led to a sharp decline of attendance and made it harder for drive-ins to operate profitably. Although less than two hundred drive-ins were in operation in the U.S. and Canada by the late 1980s, since the 1990s they have lapsed into a quasi-novelty status and by 2013 drive-ins comprised only 1.5 percent of movie screens in the United States, with 389 theaters in operation. At the industry's height, about 25 percent of the nation's movie screens had been in a drive-in.

2.2 Data

Our data come from the yearly issues of the Movie Yearbook between 1945 and 1955. This Yearbook published annually a de facto census of theaters in the US as well as a directory of US theatrical firms with 4 or more theaters. Importantly for our purposes, the Movie Yearbook also contained a listing of all drive-in theaters by city and state under a separate cover. Because most of the theaters from the data no longer exist, or were located in cities or towns that are no longer independent municipalities, we complemented the data with information from www.cinematreasures.com when necessary. The information on this site allowed us to find the approximate location of theaters and check whether changes in theater name that may have occurred during the sample period.

We complemented these data with county level data from the "County and City Data Book" from 1947 to 1960, and county level weather data from NOAA Satellite and Information Service.[1] The resulting data consists of 2112 county data points per year from 1945 to 1955. These are all counties that observe any entry during our sample period. 1030 counties out of a total of 3142 never observe entry of drive-in theaters and therefore do not contribute to explain the observed variation in number of drive-in theaters, entry and exit rates.

In our reduced-form analysis we reduce even further the scope of our data to those counties that only observe entry of one or two drive-in theaters during the period 1945-1955. That restriction leaves us with a total of 1393 theaters for which we describe the variables that we will use in the next section where we conduct our reduced-form empirical analysis. Limiting our sample in the reduced-form analysis is important because we want to capture the strategic

[1] http://www.ncdc.noaa.gov/oa/climate/ghcn-daily/

interaction and corresponding non-monotonicity of those markets that are bounded to have a maximum of two drive-in theaters given their market and potential profitability characteristics. Note that in our structural estimation we will not need to restrict the sample as both empty and more competitive markets will contribute to the estimation of the level of monopoly profits and to the identification of the effect of competition on those profits. Having said this, we focus on our sample of 1393 counties from this point forward in this section.

Table 1 provides summary statistics for the cross-section of 1393 theaters that comprise our final sample. Our dependent variables are dummy variables for whether a county experienced entry before 1950, or after 1950, and the number of years within our sample that the county lasts to experience entry (a combination of the information of the former two dummies). As we show in Table 1, 12.3% of counties experience entry prior to 1950 and almost 73% of counties experience entry between 1950 and 1955. Consistently with the information in these two dummies, the average county in our final sample experiences entry between 6 and 7 years after 1945 (more likely to see entry after 1950).

Table 1 also shows summary statistics of our measures of county "market" size, mainly weather variables. While population is widely used to measure market size, in our context does not provide a complete picture of the potential number of clients per year. Population affects economic activities in many different ways; it will affect the number of customers, which is directly related to market size; however, it could also affect entry and labor costs. Therefore, population is something that we need to control for. On the other hand, weather variables may be a more direct and transparent measure of market size. Because drive-in theaters were set outdoors, weather affected its actual appeal to consumers. Even if a county has large population, if it has a long and severe winter, the effective market size would be small. For that reason, we bring into our analysis the frequency of warm days (above 25 degree Celsius), the average temperature and the average precipitation at the county level. Table 1 shows that the average county in our sample had 40% warm days, 20 degree Celsius and an average precipitation of 2.3 millimeters.

Finally, we use as controls median family income, urban population share, employment share, college share, share of adults, share of black population, population density, and farm value as provided by the county and city data set.[2] We include these variables to control for

[2] Median Family Income is a categorical variable and group averages within categories. It is divided in 10 groups (coded 0 to 9) and has an average of 5. Urban Population Share is defined as the number of people living in urban areas devided by the total population. Employment Share is the share of employed people out of the total population in labor force above 14 years old. College share is the share of people who have at least college education. Share of Adults is the share of people who are over 21 years old. Share of Black Population is the share of black people. Population Density is the number of people (thousand) divided by the area of the county (in square miles). Finally, Farm Value is the value of all farm products ($ million).

differences across cities that may not be captured by our measures of market size but may be driving the potential profitability of entry of a drive-in theater during our sample period. For example, because of the existing correlation in the US between temperature and poverty, not controlling for income in our regressions would definitely bias our results.

Our Table 2 describes entry and exit patterns between 1945 and 1955. Because we do not observe data prior to 1945, we take as departure point 1945 and show number of counties experiencing entry and exit in the US conditional on never having more than two drive-in theaters during our sample period. On the one hand, Table 2 shows how exit is rather rare for all years except for 1953 and 1954 when 106 and 274 counties observed exit respectively. On the other hand, entry was sparse during the first years of our sample (1946 to 1948) and speeded up between 1949 and 1954. Entry rates seem to have rather slowed down in 1955 relative to previous years but we cannot be too certain of that because our data ends that year and we cannot tell what happened from 1955 onwards. These data are consistent in any case with our anecdotal evidence in that drive-in theaters spread quite rapidly between the 1940s and 1950s, and slowed down in the 1960s. We want to note that we do not entirely trust exit information because it is usually followed by entry and therefore it may be disguised by changes in ownership, renaming or rebranding of existing drive-in theaters.

3 A Simple Entry Game

In this section, we provide a simple model of entry with preemption gains that builds on work by Ellison and Ellison (2011) and Yang (2014). The goal of this simple game is then to gain intuition on why the probability of entry in the first period is non-monotonic on the market size. In a world with uncertain but decreasing fixed costs of entry, firms benefit from delaying entry all else equal. Yet, in markets where duopoly profits may not cover entry costs, strategic entry in the first period may decrease the expected gains of entry in the second period. However, the probability of late entry does not depend on whether early entry occurred for very small markets (zero anyway) or large markets (very likely). Thus, the likelihood of entry in a given market must be non-monotonic in market size. Because in mid-size markets the likelihood of late entry decreases with early entry, gains of early entry increase faster than market size in this intermediate range of market size because it directly preempts late entry.

3.1 Setup

Consider a game of entry with two potential entrants. Time is discrete; $t = 1, 2, ...$ For simplicity, we assume that players can make an entry decision only in the first two periods,

$t \in \{1, 2\}$. Entry is a terminating action so there is no exit. Initially, no player has entered the market. At the beginning of the first period, two players simultaneously decide whether to enter the market or not. Based on players' decisions, period 1 payoffs realize. In the second period, players who have not entered the market in the previous period decide whether to enter or not. Based on players' decisions, period 2 payoffs realize. From the third period on, no decision is made and both players receive the same payoff forever.

The per-period payoff is common across players and time period; the monopoly profit is M, while the duopoly profit D with $D < M$. In addition, upon entry, a player incurs one-shot entry cost of $\varphi_t + \varepsilon_t$. φ_t is a common (across players) and deterministic entry cost that satisfies $\varphi_1 > \varphi_2$. ε_t is a stochastic and privately observed entry cost that follows some continuous distribution F. We assume that ε is iid across players and time periods. Players maximize the expected discounted sum of payoffs. They discount future with a common discount factor δ.

The timing of the game is as follows. At the beginning of period 1, each player draws ε from F and simultaneously decides whether to enter or not. At the end of period 1, both players observe the decisions made in this period, and the period payoff realizes accordingly. At the beginning of period 2, each player who has not entered draws new ε from F and simultaneously decides whether to enter or not.

We analyze symmetric Markov Perfect Equilibria. An MPE is a set of beliefs and strategies such that (i) given beliefs, the strategies are optimal; and (ii) those beliefs are consistent with the strategies. Since the deterministic cost of entry declines over time, there is a benefit of waiting in the first period. This tends to delay entry. On the other hand, to secure higher profits from period 2 on, a firm may want to enter the market at a loss in the first period but thereby reduce the probability of competitor's entry in the second period (preemption incentive). This tends to hasten entry. We expect that these two effects are at work in equilibrium.

We solve the model backward, since the game is essentially over at the end of period 2. Let $V_t^{in}(n)$ and $V_t^{out}(n)$ denote the value of a firm at the end of period t of staying in and out of the market, respectively, when the state of the opponent is given by $n \in \{0, 1\}$ where 0 means "out" and 1 means "in". After decisions are made in the second period, the values are simply $V_2^{in}(1) = \frac{D}{1-\delta}$, $V_2^{in}(0) = \frac{M}{1-\delta}$, and $V_2^{out}(n) = 0$ for $n = 0, 1$.

Let $\sigma_t(n)$ denote a belief about a firm's entry probability at period t where n is the state of the opponent. Suppose both firms have not entered the market in the first period. At the beginning of period 2, the expected value of entering is

$$\begin{aligned} E_{n_2}\left[V_2^{in}(n_2)|n_1=0\right] &= \sigma_2\left(0\right)\frac{D}{1-\delta}+\left(1-\sigma_2\left(0\right)\right)\frac{M}{1-\delta}-\varphi_2-\varepsilon \\ &= \frac{D-M}{1-\delta}\sigma_2\left(0\right)+\frac{M}{1-\delta}-\varphi_2-\varepsilon. \end{aligned}$$

Since the expected value of not entering at this stage is zero, the optimal choice $a_t(n,\varepsilon)$ is given by

$$a_2(0,\varepsilon)=\mathbf{1}\left(\frac{D-M}{1-\delta}\sigma_2\left(0\right)+\frac{M}{1-\delta}-\varphi_2-\varepsilon>0\right).$$

In an MPE, beliefs should be consistent with strategies. Thus, the symmetric assumption implies that a solution to the following equation

$$\sigma_2\left(0\right)=F\left(\frac{D-M}{1-\delta}\sigma_2\left(0\right)+\frac{M}{1-\delta}-\varphi_2\right)$$

gives the equilibrium belief $\sigma_2^*\left(0\right)$. It is easy to show that a fixed-point exists and is unique.

Next, suppose a firm did not enter but the opponent entered the market in the first period. Then, the firm's optimal choice in the second period is given by

$$a_2(1,\varepsilon)=\mathbf{1}\left(\frac{D}{1-\delta}-\varphi_2-\varepsilon>0\right),$$

and thus the ex-ante entry probability (before ε realizes) is

$$\sigma_2^*\left(1\right)=F\left(\frac{D}{1-\delta}-\varphi_2\right).$$

Using these, we can define the value of a firm at the end of period 1 (after first period decisions are made):

$$\begin{aligned} V_1^{in}\left(1\right) &= D+\delta V_2^{in}\left(1\right) \\ V_1^{in}\left(0\right) &= M+\delta\left[\sigma_2^*\left(1\right)V_2^{in}\left(1\right)+\left(1-\sigma_2^*\left(1\right)\right)V_2^{in}\left(0\right)\right] \end{aligned}$$

and

$$\begin{aligned} V_1^{out}\left(1\right) &= \delta\sigma_2^*\left(1\right)\left[V_2^{in}\left(1\right)-\varphi_2-e^{\sigma_2^*(1)}\left(a_2(1,\varepsilon)=1\right)\right] \\ V_1^{out}\left(0\right) &= \delta\sigma_2^*\left(0\right)\sigma_2^*\left(0\right)\left(V_2^{in}\left(1\right)-\varphi_2-e^{\sigma_2^*(0)}\left(a_2(0,\varepsilon)=1\right)\right)+ \\ & \quad \delta\sigma_2^*\left(0\right)\left(1-\sigma_2^*\left(0\right)\right)\left(V_2^{in}\left(0\right)-\varphi_2-e^{\sigma_2^*(0)}\left(a_2(0,\varepsilon)=1\right)\right) \\ &= \delta\sigma_2^*\left(0\right)\left(V_2^{in}\left(0\right)+\sigma_2^*\left(0\right)\left[V_2^{in}\left(1\right)-V_2^{in}\left(0\right)\right]-\varphi_2-e^{\sigma_2^*(0)}\left(a_2(0,\varepsilon)=1\right)\right), \end{aligned}$$

where

$$\begin{aligned} e^{\sigma_2^*(1)}\left(a_2(1,\varepsilon)=1\right) &= E\left(\varepsilon|a_2(1,\varepsilon)=1,\sigma_2^*\left(1\right)\right) \\ e^{\sigma_2^*(0)}\left(a_2(0,\varepsilon)=1\right) &= E\left(\varepsilon|a_2(0,\varepsilon)=1,\sigma_2^*\left(0\right)\right). \end{aligned}$$

Finally, the decision in period 1 is written as

$$a_1(0,\varepsilon) = 1\left(E_n\left[V_1^{in}(n)\,|\sigma_1(0)\right] - \varphi_1 - \varepsilon \geq E_n\left[V_1^{out}(n)\,|\sigma_1(0)\right]\right),$$

where

$$\begin{aligned} E_n\left[V_1^{in}(n)\,|\sigma_1(0)\right] &= \sigma_1(0)\,V_1^{in}(1) + (1-\sigma_1(0))\,V_1^{in}(0) \\ E_n\left[V_1^{out}(n)\,|\sigma_1(0)\right] &= \sigma_1(0)\,V_1^{out}(1) + (1-\sigma_1(0))\,V_1^{out}(0). \end{aligned}$$

Thus, the equilibrium entry probability in the first period is given by a fixed point of the following system:

$$\sigma_1(0) = F\left(E_n\left[V_1^{in}(n)\,|\sigma_1(0)\right] - E_n\left[V_1^{out}(n)\,|\sigma_1(0)\right] - \varphi_1\right).$$

Let $\sigma_1^*(0)$ denote the fixed-point of this system. Thus, a triple $(\sigma_1^*(0), \sigma_2^*(0), \sigma_2^*(1))$ as well as corresponding value functions fully characterize an MPE.

3.2 Measure of Preemption

To quantify the magnitude of the preemption incentive, we also consider the following commitment equilibrium: at the beginning of the game (even before ε in the first period realizes), each firm chooses a single entry probability for each time period, which cannot be conditioned on rival's state. Since firms cannot affect rival's behavior by their actions, there is no preemption by assumption (see Fudenberg and Tirole, 1985).

To be more specific, at the beginning of the first period, each firm chooses a pair of entry probabilities (σ_1, σ_2). Let (σ_1', σ_2') denote the rival's choice probabilities. In period 1, the value of entering when the random part of entry cost is ε_1 equals

$$\sigma_1' \frac{D}{1-\delta} + (1-\sigma_1')\left[M + \delta\left[\sigma_2' \frac{D}{1-\delta} + (1-\sigma_2')\frac{M}{1-\delta}\right]\right] - \varphi_1 - \varepsilon_1.$$

On the other hand, the value of not entering is

$$\sigma_1'\delta\sigma_2\left[\frac{D}{1-\delta} - \varphi_2 - e^{\sigma_2}\right] + (1-\sigma_1')\,\delta\sigma_2\left[\left[\sigma_2'\frac{D}{1-\delta} + (1-\sigma_2')\frac{M}{1-\delta}\right] - \varphi_2 - e^{\sigma_2}\right],$$

where $e^{\sigma_2} \equiv E(\varepsilon_2 | a_2(1,\varepsilon_2) = 1, \sigma_2)$. Note that the entry probability σ_2 does not depend on rival's state because firms cannot condition on it in a commitment equilibrium. We define the *indifferent type* in period 1 $\bar{\varepsilon}_1$ such that entering and not entering is indifferent. The indifference condition is given by

$$\begin{aligned} & \sigma_1' \frac{D}{1-\delta} + (1-\sigma_1')\left[M + \delta\left[\sigma_2' \frac{D}{1-\delta} + (1-\sigma_2')\frac{M}{1-\delta}\right]\right] - \varphi_1 - \bar{\varepsilon}_1 \\ = \; & \sigma_1'\delta\sigma_2\left[\frac{D}{1-\delta} - \varphi_2 - e^{\sigma_2}\right] + (1-\sigma_1')\,\delta\sigma_2\left[\left[\sigma_2'\frac{D}{1-\delta} + (1-\sigma_2')\frac{M}{1-\delta}\right] - \varphi_2 - e^{\sigma_2}\right]. \end{aligned} \tag{1}$$

In period 2, the value of entering when the random part of entry cost is ε_2 equals

$$\sigma_1' \frac{D}{1-\delta} + (1-\sigma_1') \left[\sigma_2' \frac{D}{1-\delta} + (1-\sigma_2') \frac{M}{1-\delta} \right] - \varphi_2 - \varepsilon_2.$$

Likewise, we define the indifferent type in period 2 $\bar{\varepsilon}_2$ such that entering and not entering is indifferent:

$$\sigma_1' \frac{D}{1-\delta} + (1-\sigma_1') \left[\sigma_2' \frac{D}{1-\delta} + (1-\sigma_2') \frac{M}{1-\delta} \right] - \varphi_2 - \bar{\varepsilon}_2 = 0. \tag{2}$$

The optimality condition imposes that whenever $\varepsilon_1 \leq \bar{\varepsilon}_1$, the firm should enter in period 1. Therefore, before ε_1 realizes, we should have $\sigma_1 = F(\bar{\varepsilon}_1)$ where F is the CDF of ε. Similarly, $\sigma_2 = F(\bar{\varepsilon}_2)$. In a symmetric commitment equilibrium, we impose $\sigma_1 = \sigma_1'$ and $\sigma_2 = \sigma_2'$. Thus, we have a system of two equations ((1) and (2)) and two unknowns (σ_1, σ_2). We use $(\sigma_1^{**}, \sigma_2^{**})$ to denote entry probabilities in the commitment equilibrium.

3.3 Simulation

3.3.1 MPE

Two different incentives exist in the firm's period 1 decision. The standalone incentive compares the cost and benefit of waiting. The cost of waiting is the forgone profit in period 1, while the benefit of waiting is the saved entry cost, as it decreases over time. Based on this incentive, the probability of entry in period 1 tends to increase as the market size increases. On the other hand, the strategic interaction creates the preemption incentive. By entering the market in period 1, firms can affect the probability of rival entry in the second period. In small markets, this incentive is not large as the competitors do not find entry profitable. In large markets, the competitors will enter the market no matter what firms do. Therefore, preemption is not feasible. On the other hand, in "intermediate" markets, strong preemption motives may exist.

We investigate how the period 1 entry probability $\sigma_1^*(0)$ changes as we increase (M, D). We assume that $D = M/3$, $\delta = 0.9$, and $(\varphi_1, \varphi_2) = (8, 4)$. We compute $(\sigma_1^*(0), \sigma_2^*(0), \sigma_2^*(1))$ for each of 200 equidistant grid points of $M \in [0, 3]$. Figure 1 plots $\sigma_1^*(0)$ and $\sigma_2^*(1) - \sigma_2^*(0)$ against M. Note that $\sigma_2^*(1) - \sigma_2^*(0)$ measures the difference in the probability of rival entry in period 2 and thus mainly determines the strength of preemption incentives. As is clear from the figure, $\sigma_1^*(0)$ exhibits non-monotonicity when $\sigma_2^*(1) - \sigma_2^*(0)$ is large.

To further investigate the sources of non-monotonicity, we change several parameters. Figure 2 plots $\sigma_1^*(0)$ against M in various scenarios. First, we assume $D = M/4$ while keeping other environments. That is, competition is more severe. The figure shows that the decrease in $\sigma_1^*(0)$ after it achieves the peak is slightly larger than the base case. This is intuitive because the first-mover advantage in this scenario is large. Second, we increase φ_2 to 6 and 10. If the cost of entry in period 2 is very large, we expect that a substitution between "enter in period 1" and "enter in period 2" becomes week and thus the entry probability and market size come to have a simple positive relationship. Figure 2 confirms this intuition. In particular, when $\varphi_2 = 10$, non-monotonicity almost vanishes.

3.3.2 Commitment Equilibrium

To see how the commitment equilibrium behaves, we use the same parametrization as in Figure 1, and compute the equilibrium entry probabilities $(\sigma_1^{**}, \sigma_2^{**})$. Figure 3 plots the entry probability in MPE ($\sigma_1^*(0)$ from Figure 1) and the entry probability in the commitment equilibrium σ_1^{**}. Since there is no preemption in the commitment equilibrium, we can interpret the difference in entry probability between the two solutions as the preemption incentive. As we can see, the preemption incentive is maximized in the intermediate range of market size.

4 Reduced-Form Evidence

4.1 Base Result

Let us now start our empirical exploration using reduced form specifications that will try to capture the non-monotonicity in the probability of entry with market size. We do this in two ways. First, we estimate the probability of entry in a given county prior to 1950 subject to market size measured by the frequency of warm days in that county and its square. We show results of this strategy running probit regressions in Table 3 below. This table reports marginal effects. In column 1 we control for market characteristics such as median family income and population density as well as market size measured with population and squared population and show frequency of warm days increases entry but frequency squared decreases entry. The predicted non-monotonicity of market size on the probability of entry is both present in the squared frequency of warm days.

To control for highly non-linear effects of population that cannot be captured by a linear and quadratic term, in columns 2 to 5 we divide our sample of counties by population quartiles and run probit regressions of the probability of entry prior to 1950 on frequency of warm days and its square, controlling for other differences across counties within population group. Our results show non-monotonicity in the first three quartiles of population but not on the fourth one (largest population within the sample).

A second way to estimate the non-monotonicity existing between market size and entry is to construct another dependent variable that measures the number of years observed before entry (since 1945, our first year of data). Once this variable is created, we follow the same strategy as in Table 3 and run OLS regressions that contain frequency of warm days, population and their squared variables as well as other demographic controls. We show our results in Table 4. Our results here are qualitatively the same as those in Table 3. Column 1 shows non-monotonicity in the frequency of warm days while controlling for county demographics. When we split the data according to population group (columns 2 to 5), we observe non-monotonicity in the first three quartiles of population but not in the fourth quartile (highest population), consistently with results in Table 3.

In a nutshell, we find robust evidence of a non-monotonic relationship between probability of entry and market size (measured with frequency of warm days) when measuring entry as rates prior to 1950 and number of years before observing entry. This is indicative that market size increases the probability of entry at low and high market size levels, yet it decreases entry at intermediate levels of market size.

4.2 Robustness

If similar non-monotonicity is observed in other entry variables such as late entry, the non-monotonicity we find above may not have been due to preemption incentives. To investigate this possibility, we create a dummy that takes value 1 if entry was observed in a county between 1950 and 1955. As shown in Table 1, 73% of counties experienced entry at least once after 1950 and therefore this is a more common event than entry prior to 1950 (12%). We run probit regressions of this dummy variable on frequency of warm days, population, their corresponding squared variables and county demographics and show results in column (1) of Table 5. We find no results when exploring entry after 1950. If anything, the patterns of entry (and non-monotonicity) are reverse from those patterns shown in Tables 3 and 4.

We repeat our analysis in columns 2 and 3 of Table 5 using different weather variables such as average temperature and average precipitation. We run probit regressions with these alternative measures of market size. Our findings show that while average temperature variables (not surprising correlated with frequency of warm days) are statistically significant and have expected signs, the entry probability does not achieve its maximum in the range of average temperature observed in the data. Therefore, we do not find non-monotonicity in the average temperature. One explanation is that temperature is not monotonically translated into market size or profitability, unlike the frequency of warm days. When using average precipitation we find no statistically significant relationship with entry rates.

Finally, we check the sensitivity of our results to the definition of early entry; we use "prior 1951" instead of "prior to 1950". This is to mitigate the concern that our results are produced by some factors specific to 1949. Column (4) in Table 5 shows the result. We still find non-monotonicity in the frequency of warm days as in Table 3, confirming robustness of our results.

5 Structural Analysis

5.1 Estimation

We develop an econometric model of the above entry game and take it to our data. Consider the following demand and marginal cost expressed in per-day basis:

$$\begin{aligned} P_t(Q) &= a_t - b_t Q \\ C_t(q) &= c_t q. \end{aligned}$$

Assuming Cournot competition, a symmetric equilibrium is given by

$$\begin{aligned} a_t - b_t q_t - b_t Q_t &= c_t \\ Q_t &= \frac{n(a_t - c_t)}{(n+1)\,b_t} \\ P_t^* &= \frac{a_t + c_t n}{n+1} \\ \pi_t^* &= \frac{(a_t - c_t)^2}{(n+1)^2\, b_t}, \end{aligned}$$

where n is the number of active firms in the market. The net annual variable profit is given by

$$\Pi_t(n) = W_t \frac{(a_t - c_t)^2}{(n+1)^2\, b_t},$$

where W_t is the number of days of operation in period t (i.e. fraction of warm days times 365). We parametrize

$$\frac{a_t - c_t}{\sqrt{b_t}} = X_t \beta$$

where X_t includes population size, income, urban share, employment share, education level, adult share, black share. This would turn the profit into the following reduced-form function:

$$\Pi_t(n) = W_t \left[\frac{X_t \beta}{n+1}\right]^2.$$

In addition, we assume that the entry cost is specified as

$$\varphi_t = \rho_t + Z_t \gamma,$$

where Z_t includes population density and the value of farm products, both of which measure the cost of land acquisition. Since weather variable W and demographic variables (X, Z) do not change significantly over several years, we assume they are constant over time and drop time subscript.

As in the data analysis in Section 2, we focus on the markets with only one or two entrants by 1955. We aggregate years before 1949 into *period 1*, while years from 1950 to 1955 into *period 2*. Thus, letting n_t is the number of entrants in period t, the observation for each market $n = (n_1, n_2)$ is classified into the four possible cases: $\{(0,1), (1,0), (0,2), (2,0)\}$.

For market i, we observe $\{n, W, X, Z\}$. Setting $\delta = 0.9$, we estimate $\theta = (\beta, \gamma, \rho_1, \rho_2, \varphi_1, \varphi_2)$. For markets with $(d_1, d_2) = (0,1)$, the contribution of the likelihood is

$$[1 - \sigma_1^* (0; \theta)]^2 \sigma_2^* (0; \theta) [1 - \sigma_2^* (0; \theta)].$$

For markets with $(d_1, d_2) = (1,0)$

$$[1 - \sigma_1^* (0; \theta)] \sigma_1^* (0; \theta) [1 - \sigma_2^* (1; \theta)].$$

For markets with $(d_1, d_2) = (0,2)$

$$[1 - \sigma_1^* (0; \theta)]^2 \sigma_2^* (0; \theta)^2 .$$

Finally, for markets with $(d_1, d_2) = (2,0)$

$$\sigma_1^* (0; \theta)^2 .$$

We estimate the model using the MLE.

The estimates of structural parameters and their standard errors are reported in Table 6. All parameters are estimated precisely. Their signs are mostly intuitive. For example, the size of population, income share, and employment share increase the profitability of drive-in theaters. On the other hand, urban population share has a negative coefficient. Since drive-in theaters are built mainly in suburb areas, counties where most of people live in urban areas do not have large demand. The parameters in entry costs also deserve explanations. First, the entry cost significantly decreases over time. Second, population density and farm value both have a positive coefficient. These variables reflect the value of land, which increases the cost of land acquisition (an important part of entry cost).

Figure 4 shows a scatter plot of predicted entry probabilities in MPE against the frequency of warm days. The figure also shows a fitted curve (quadratic curve). Although it is not as clear as our simulation results, our model can generate non-monotonicity under the estimated parameter values.

5.2 Counterfactual Analysis

To quantify the importance of preemption in the data, we calculate the entry probabilities in the commitment equilibrium, $(\sigma_1^{**}, \sigma_2^{**})$ for each market under the estimated parameter values. For each market, we define the magnitude of preemption incentives by $(\sigma_1^{*} - \sigma_1^{**})/\sigma_1^{*}$. Figure 5 shows a histogram of this magnitude. While in most markets, the share of entry explained by preemption is less than 10%, preemption can explain up to 25% of entry in some other markets.

6 Conclusion

To be concluded.

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[2] Fudenberg, D., and J. Tirole (1985): “Preemption and Rent Equalization in the Adoption of New Technology," The Review of Economic Studies, 52(3): 383-401.

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Year	Obs	Mean	St Dev.	Min	Max
Entry Before 1950	1393	0.123	0.329	0	1
Years Before Entry	1393	6.545	1.916	0	10
Entry Btw 1950 & 1955	1393	0.726	0.446	0	1
Freq Warm Days	1393	0.389	0.140	0.010	0.862
Avg Temperature	1393	20.022	4.580	8.348	30.928
Avg Precipitation	1393	2.335	0.954	0.216	10.799
Population (millions)	1393	0.029	0.090	0.001	2.718
Median Income	1362	4.920	1.591	0	9
Urban Pop Share	1393	0.301	0.230	0	1
Employment Share	1393	0.956	0.044	0.446	0.996
College Share	1393	0.058	0.026	0.014	0.251
Share of Adults	1393	0.603	0.049	0.441	0.737
Share of Black	1393	0.102	0.166	0.000	0.843
Pop Density (1000/miles^2)	1381	0.115	1.397	0.0005	36.029
Farm Value (million $)	1381	6.912	6.193	0.011	52.247

Table 1: **Summary Statistics.**

Year	# of Counties with Entry	# of Counties with Exit
1946	0	0
1947	6	3
1948	20	0
1949	146	15
1950	342	7
1951	365	7
1952	226	15
1953	296	106
1954	302	274
1955	266	7
Total	1,969	434

Table 2: **Number of Counties with Entry and Exit.**

Prob of Early	(1)		(2)		(3)		(4)		(5)	
Entry	dF/dx	P Val	dF/dx	P Val	dF/dx	P Val	dF/dx	P Val	dF/dx	P Val
Freq Warm Days	0.490	0.002	0.457	0.089	2.1269	0.003	2.313	0.000	0.923	0.418
$(\text{Freq Warm Days})^2$	-0.499	0.005	-0.447	0.139	-2.440	0.007	-2.403	0.001	-0.377	0.818
POP	1.951	0.000	–	–	–	–	–	–	–	–
$(\text{POP})^2$	-7.028	0.000	–	–	–	–	–	–	–	–
Median Income	0.009	0.011	-0.003	0.542	0.028	0.009	0.035	0.019	0.050	0.060
Urban Pop Share	-0.009	0.656	-0.000	0.998	-0.131	0.113	0.086	0.330	0.265	0.125
Employment Share	0.114	0.175	0.233	0.602	-0.018	0.948	0.406	0.104	0.238	0.664
College Share	0.203	0.169	0.690	0.112	0.670	0.204	0.167	0.866	0.924	0.424
Adult Share	-0.097	0.370	-0.011	0.962	-0.512	0.130	-1.228	0.016	0.568	0.552
Black Share	-0.002	0.959	0.044	0.486	0.031	0.772	-0.182	0.181	0.017	0.962
Pop Density	0.129	0.042	0.497	0.331	0.434	0.543	1.262	0.083	-0.042	0.037
Farm Value	-0.569	0.360	1.363	0.508	4.219	0.169	4.219	0.169	-5.196	0.211
Sample	All		Q1 POP		Q2 POP		Q3 POP		Q4 POP	
Observations	1,362		338		345		342		337	

Table 3: **Probit Regressions of Entry Prior to 1950 on Market Size**.

Note: Marginal effects reported of probit regressions at the county level for all counties that either had one or two drive-in theaters in our sample. Column (1) uses both population and frequency of warm days. Columns (2) to (5) divides the sample into quartiles of population.

Years Before	(1)		(2)		(3)		(4)		(5)	
1st Entry	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Freq Warm Days	-7.459	2.193	-1.403	2.960	-9.889	4.486	-11.715	3.209	-8.271	3.867
(Freq Warm Days)^2	8.210	2.842	0.474	3.148	9.289	5.145	11.829	3.329	7.485	5.289
POP	-12.375	7.786	–	–	–	–	–	–	–	–
(POP)^2	3.237	1.723	–	–	–	–	–	–	–	–
Median Income	-0.121	0.065	-0.071	0.103	-0.400	0.132	-0.098	0.086	-0.267	0.111
Urban Pop Share	-2.316	0.431	-1.124	0.445	-0.711	0.864	-2.834	0.763	-2.008	0.569
Employment Share	-0.321	0.799	-4.651	2.080	2.138	1.587	-1.927	1.880	-1.652	1.944
College Share	-0.229	3.475	-10.432	5.590	-7.907	8.390	-12.326	6.365	0.425	4.107
Adult Share	1.619	1.780	0.956	2.314	7.206	2.082	8.736	2.541	0.491	2.558
Black Share	-0.538	0.487	-0.348	1.132	0.339	1.021	1.170	0.608	0.005	0.745
Pop Density	0.337	0.216	-31.776	8.292	-0.795	5.998	-11.263	4.415	0.066	0.011
Farm Value	-19.962	10.821	3.137	24.421	34.955	28.160	-52.844	28.422	15.459	11.650
Sample	All		Q1 POP		Q2 POP		Q3 POP		Q4 POP	
Observations	1,362		338		345		342		337	

Table 4: **OLS Regressions of Years Before Entry in a County on Market Size**.

Note: Results from OLS regressions at the county level for all counties that either had one or two drive-in theaters in our sample. Column (1) uses both population and frequency of warm days. Columns (2) to (5) divides the sample into quartiles of population.

	(1)		(2)		(3)		(4)	
Dependent	Prob of Late Entry		Prob of Early Entry		Prob of Early Entry		Prob of Early Entry	
Variable	dF/dx	P Val	dF/dx	P Val	dF/dx	P Val		
Freq Warm Days	-0.321	0.348	–	–	–	–	1.404	0.008
(Freq Warm Days)^2	0.482	0.216	–	–	–	–	-1.594	0.012
Ave Temperature	–	–	0.027	0.003	–	–	–	–
(Ave Temperature)^2	–	–	-0.0006	0.007	–	–	–	–
Ave Precipitation	–	–	–	–	0.009	0.531	–	–
(Ave Precipitation)^2	–	–	–	–	-0.0008	0.625	–	–
POP	-2.287	0.001	1.924	0.000	2.015	0.411	5.650	0.000
(POP)^2	21.939	0.001	-6.994	1.094	-7.588	1.114	-27.936	0.001
Other Controls	Yes		Yes		Yes		Yes	
Observations	1,362		1,362		1,362		1,362	

Table 5: **Other Specifications/Variables**.

Note: Marginal effects reported of probit regressions at the county level for all counties that either had one or two drive-in theaters in our sample. Column (1) uses the probability of late entry for the dependent variable. Columns (2) and (3) uses different weather variables.

	Coef.	S.E.
In Profit Function		
Constant (Period 1)	3.131	0.050
Constant (Period 2)	1.152	0.053
Population	52.796	0.439
Median Income	1.712	0.081
Urban Pop Share	-0.520	0.075
Employment Share	0.126	0.040
College Share	1.316	0.262
Adult Share	-3.557	0.063
Black Share	-0.877	0.102
In Entry Cost		
Constant (Period 1)	2.636	0.026
Constant (Period 2)	-1.823	0.031
Pop Density	5.079	0.393
Farm Value	41.667	0.328
Log Likelihood	-2123.901	

Table 6: **Estimates of Structural Parameters**.

Figure 1: Entry Probabilities as Market Size Increases

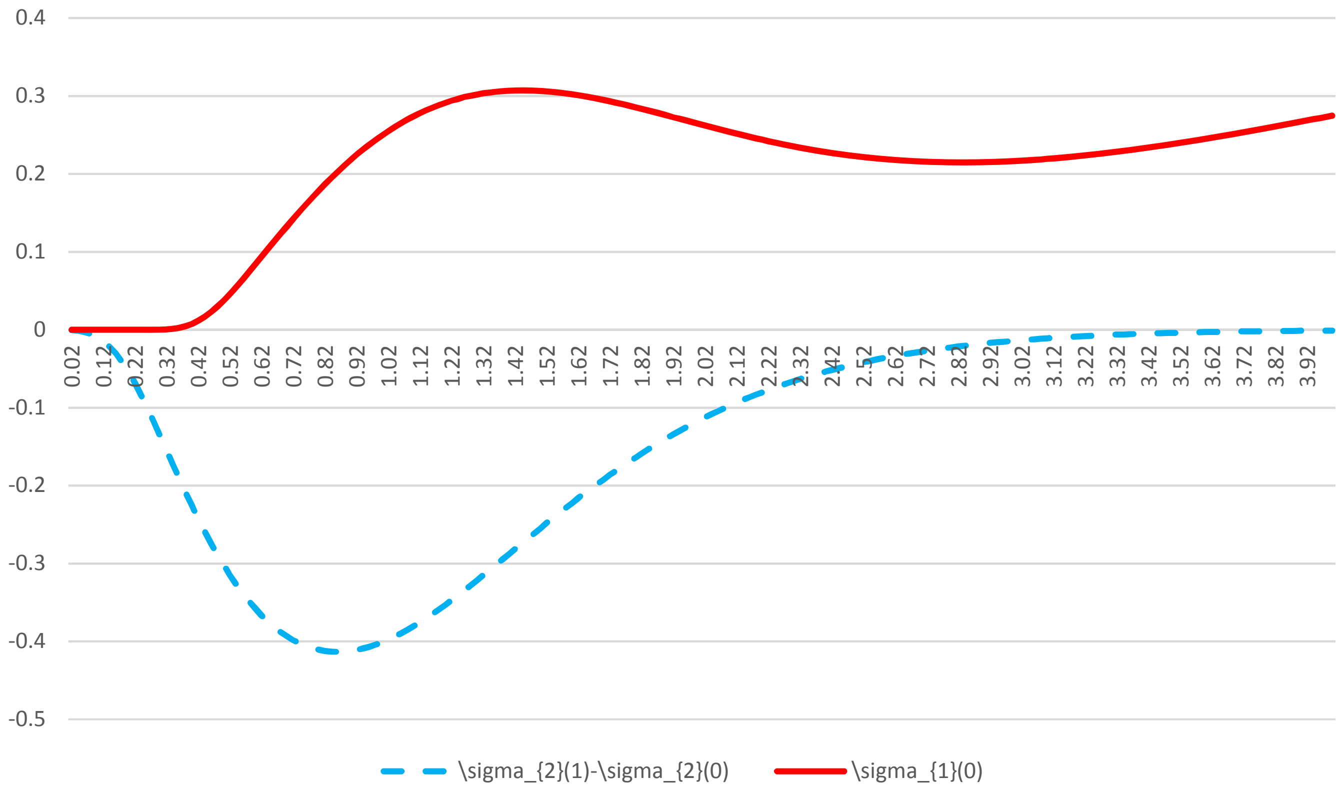


Figure 2: Entry Probability for Different Parameter Values

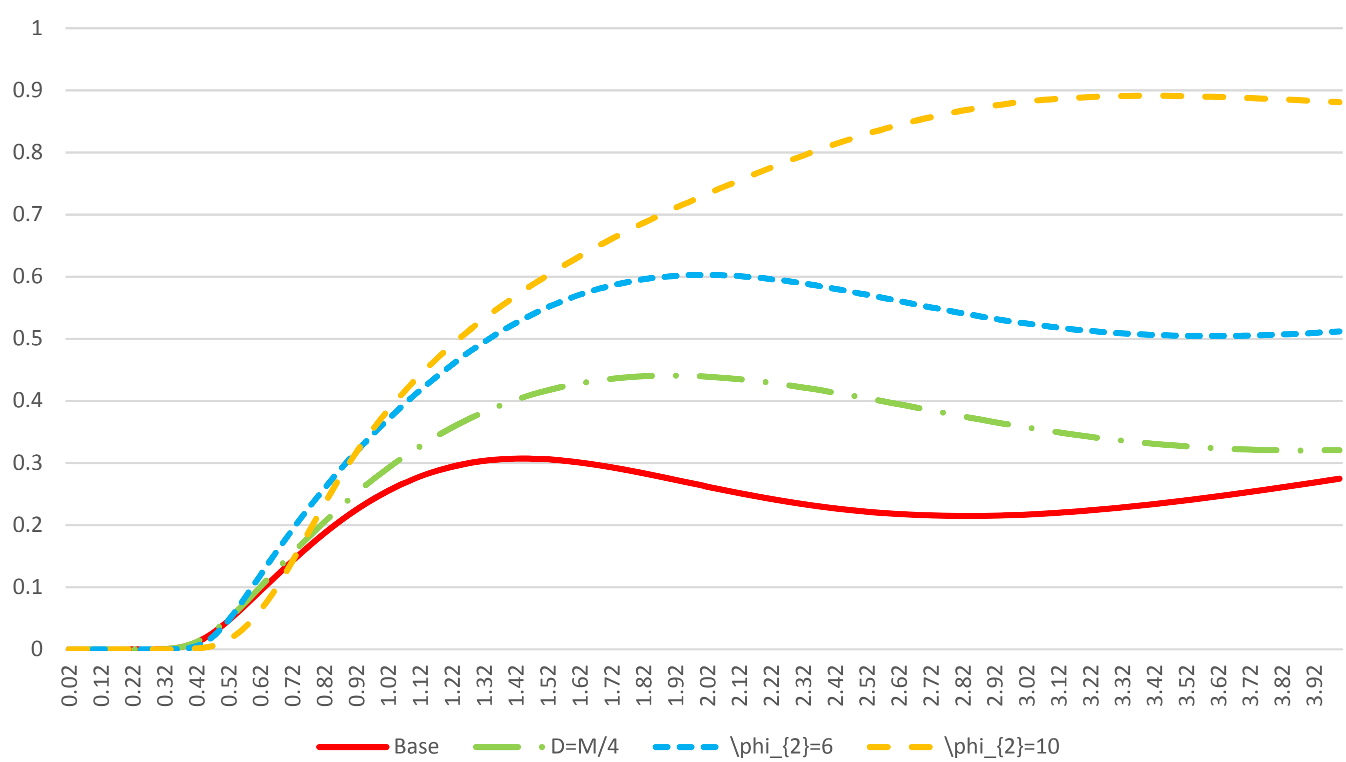


Figure 3: MPE and Commitment Equilibrium

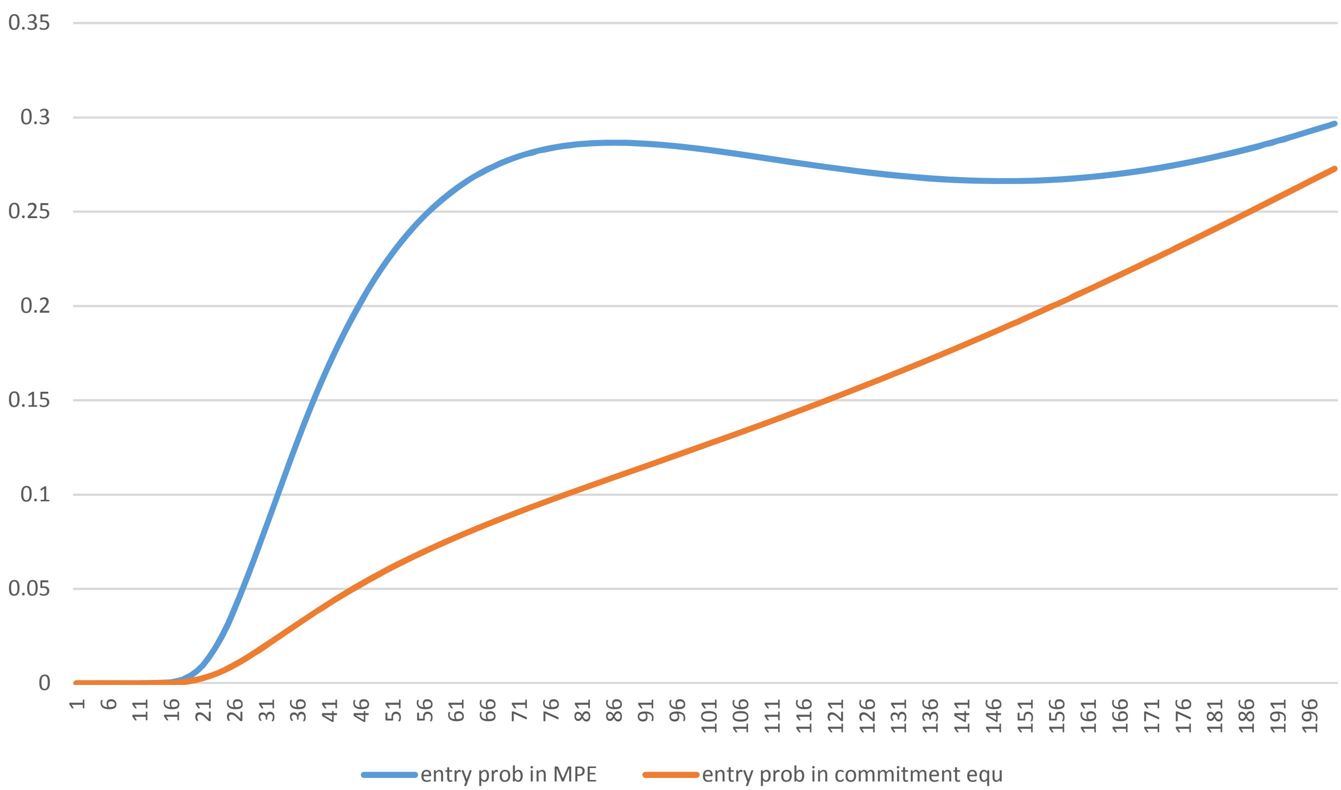


Figure 4: Entry Probability in MPE

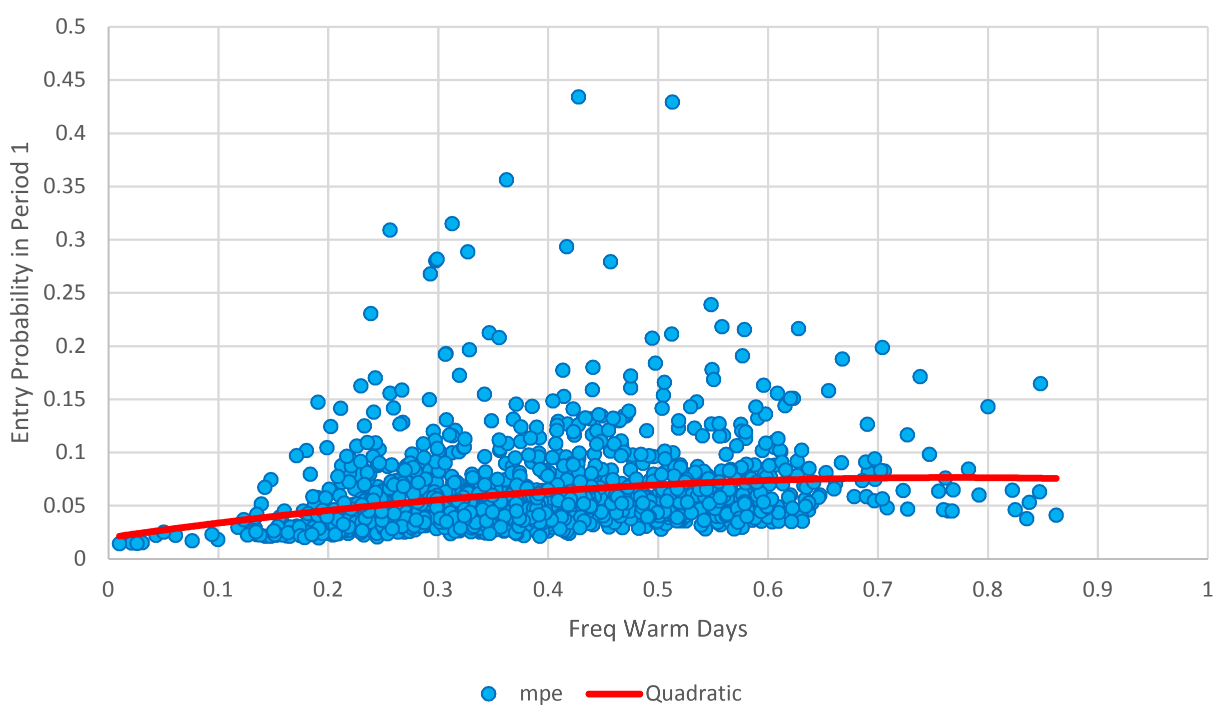
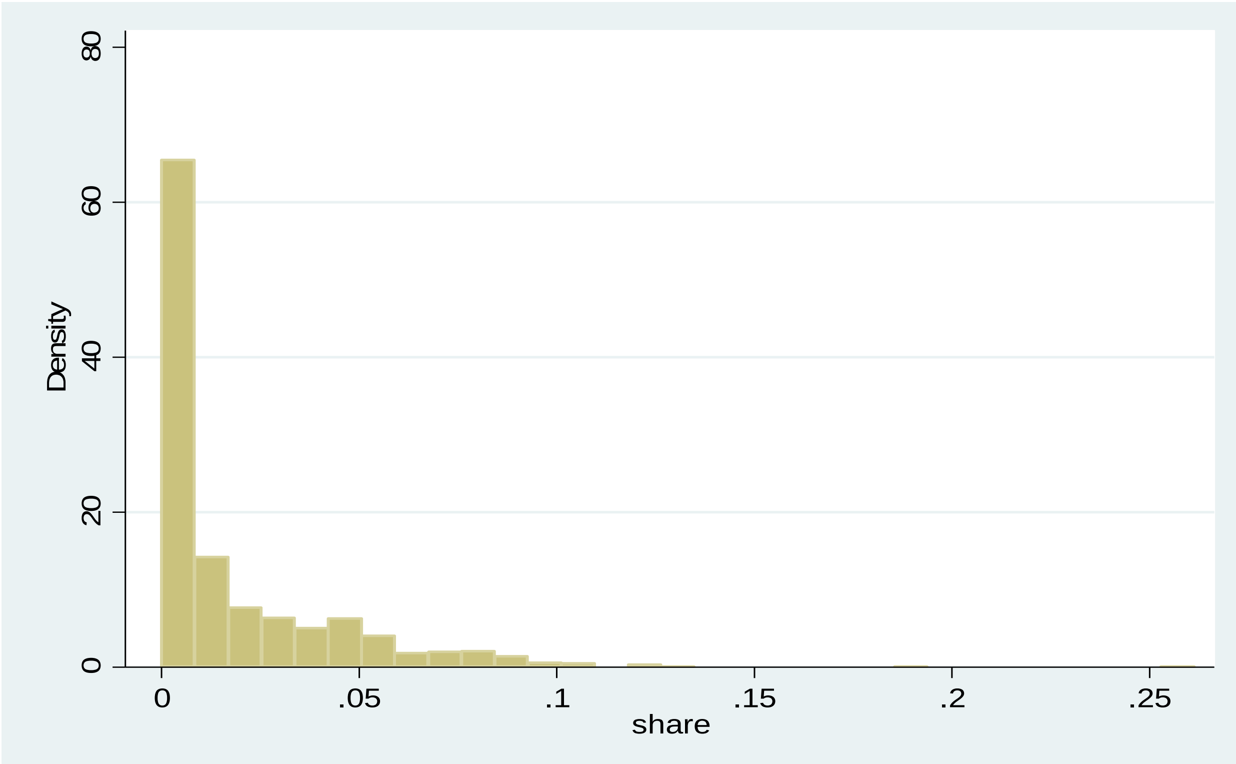


Figure 5: Entry Probability Explained by Preemption Incentive



Note: Entry probability in MPE - entry probability in commitment equilibrium as a share of entry probability in MPE