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

Ricard Gil† Jean-François Houde‡ Shilong Sun§ Yuya Takahashi¶

April 1, 2024

Abstract

This paper studies the role and incidence of entry preemption strategic motives on the dynamics of new industries, while providing an empirical test for entry preemption, and quantifying its impact on market structure. The empirical context is the evolution of the U.S. drive-in theater market between 1945 and 1957. 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 a dynamic entry game that matches the reduced-form prediction and quantify the strength of the preemption incentive. Our counterfactual analysis shows that strategic motives can increase the number of early entrants by as much as 50 percent in mid-size markets without affecting the number of firms in the long run. By causing firms to enter the market too early, we show that strategic entry preemption leads on average to a 5% increase in entry costs and a 1% decrease in firms' expected value (relative to an environment without strategic investments).

JEL Codes: L10, L41, L82

Keywords: strategic entry, preemption, deterrence, non-monotonicity, drive-in theaters

*First version: April 2016. We would like to thank seminar and conference participants at Sogang University, HKUST, University of Pennsylvania, University of Regensburg, IIOC, McGill International Conference on Marketing, the 2017 European Econometric Society Meetings, the Barcelona GSE Summer Forum, the 2019 North American Summer Meetings of the Econometric Society, and the Third Conference on Structural Dynamic Models in Chicago (2019). The usual disclaimer applies.

†Smith School of Business, Queen's University, ricard.gil@queensu.ca

‡Department of Economics, University of Wisconsin - Madison, houde@wisc.edu

§Department of Economics, University of Wisconsin - Madison, ssun226@wisc.edu

¶Department of Economics, University of Washington - Seattle, ytakahas@uw.edu

1. Introduction

A central topic in Industrial Organization is the study of the role and incidence of strategic investments. It is now well known that, in strategic environments, a firm's behavior may deviate from what the stand-alone incentive suggests as optimal, if it can affect its rivals' behavior and enhance its strategic position (Fudenberg and Tirole, 1985; Bulow et al., 1985). While understanding the gains from strategic behavior is fundamental for firms and agents operating in strategic environments, policy makers and government antitrust agencies heavily rely on their capacity to identify anticompetitive strategic behavior before it occurs, and identify it when it takes place.

Strategic investments induce two types of inefficiencies. First, strategic investments may lead markets to be less competitive, and increase market concentration. Second, strategic investments can induce a mis-allocation of resources by incentivizing firms to over-invest in order to maintain their dominance position. This is an important concern for the diffusion of new technologies, such as the one we are studying in this paper. In order to deter entry from rivals, firms can be tempted to introduce new products to the market too early, or pay excessive entry costs. Strategic behavior may take many different shapes and forms such as excess capacity (Lieberman, 1987), product proliferation (Chevalier, 1995), networks (Fudenberg and Tirole, 2003; Calzada and Valletti, 2008), advertising (Schmalensee, 1983; Ellison and Ellison, 2011), and learning-by-doing (Benkard, 2004).[1]

In this paper, we study the decision to enter early in a new market as a tool for firms to *preempt* future entry and limit competition (Dafny, 2005; Schmidt-Dengler, 2006). We contribute to the existing literature by empirically studying how entry deterrence motives affected the diffusion of drive-in movie theaters in the U.S. 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. When anticipating this rapid growth, forward-looking firms may have aimed to deter the entry of future competitors by entering the market at an early date.

Measuring the importance of this deterrence motive represents a substantial identification challenge because strategic investments and behavior respond to a latent threat of entry that is, by definition, unobserved. Therefore, the researcher cannot straightforwardly sep-

[1] These examples of behavior are important in business activity, and consequently, there is an extensive theoretical literature on strategic entry deterrence (Salop, 1979; Bernheim, 1984; Chang, 1993; Waldman, 1987; Gilbert and Vives, 1986)

arate cases without a latent threat from those where entry deterrence is successful. Most importantly, if economists do not observe firms' costs nor profits, it is hard to estimate the optimal behavior that would take place if such deterrence and preemptive incentives were absent. Because of this, empirical evidence supporting existing theories and their implications is scarce.

We address this identification problem by building on the insights of Ellison and Ellison (2011). In short, Ellison and Ellison (2011) show that 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. Alternatively, when the market is too large, the incumbent would not be able to block entry. Only in "intermediate-size" markets can the incumbent deter entry by expanding capacity. Thus, investment capacity by the incumbent is non-monotonic in market size.

We show that this insight can hold true in a game of entry preemption. We first apply the intuition in Ellison and Ellison (2011) to our context and derive a testable hypothesis for detecting preemptive entry motive—there exists a non-monotonic relationship between market size and the probability of early entry. We then build and estimate a dynamic game with stochastic entry and technological progress. We use this model to quantify the effect of entry preemption on firm profits and entry costs.

A key challenge when implementing this identification strategy is to find a relevant and exogenous measure of market size that does not directly impact the cost of entering a new market and is proportional to the variable profit. Ellison and Ellison (2011), for instance, use firms' revenue prior to the expiration of a patent as a proxy for market size. This idea is formalized in Fang and Yang (2023) that a good proxy for market size reflects steady-state payoffs and does not vary over time. In the case of seasonal activities like drive-in theaters, the "size" of the market is affected both by the number and characteristics of potential consumers, but also by the number of days a theater can operate. In our empirical application, we use the percentage of days with warm weather in a county as a measure of market size. The rationale is that inclement weather causes drive-in theaters to shut down, especially given the capabilities of automobiles in the 1950s. In addition, since theaters involved specific investments, the land cannot easily be used to generate other revenue in the off-season, implying that, everything else being equal, theaters in the north are less profitable than in the south. Crucially, this variable affects the potential revenue of a theater (through the number of potential active days), but does not directly impact the willingness-to-pay or cost of operating. We illustrate this by showing that the data exhibit enough variation across markets in average temperature to identify the effect of market size on entry separately from other measures of profitability.

We find robust empirical evidence for our prediction in entry patterns of drive-in theaters across counties in the U.S. between 1945 and 1957. In particular, we show that the probability of entering the market before 1950 is a non-monotonic function of the share of warm days. This result is robust to alternative measures of preemption, as well as the inclusion of a rich set of control variables. We also find that the long-run number of theaters is strictly increasing in the share of warm days, consistent with the work on the theoretical basis of the reduced-form test for entry deterrence, which predicts that market size strictly increases firms' profitability in the steady state.

We use the reduced-form evidence to motivate a dynamic stochastic game in which variable profits and entry costs improve over time in a predictable manner; for instance, due to improvements in the quality of the product (e.g., availability of movies and sound/picture quality), or reduction in the sunk cost of acquiring the equipment. This leads to a non-stationary Markov-perfect entry game that we estimate by Maximum Likelihood using a nested-fixed point algorithm. In addition to quantifying the effect of competition on profits (i.e., deterrence incentive), the model allows us to identify the rate of technological progress in the industry, while accounting for unobserved market heterogeneity. We show that failing to account for unobserved heterogeneity biases downward the rate at which variable profits (e.g., quality) and fixed costs change over time.

Using the estimated parameters, we quantify the magnitude of the preemption incentive by analyzing a counter-factual environment in which firms can commit to specific entry strategies (as opposed to using Markov-perfect strategies). We find that strategic entry preemptive motives increase the number of early entrants by as much as 50 percent in mid-size markets without having an effect on the overall number of entrants. In our model and empirical setting, this means that early strategic entry does not change the number of operating firms in a market in the long run, it just shifts entry to earlier periods where firms in the absence of strategic incentives would have deemed entry to be not optimal. Consequently, our counterfactual exercises can separate the impact of strategic motives on entry costs and the present discounted value of firms. We find that strategic entry preemption lowers firms' expected profits relative to an environment in which firms could commit to a specific entry strategy (Fudenberg and Tirole, 1985), but this effect is overall small. In contrast, the effect of strategic preemption on the overall entry cost incurred by firms is economically large. In mid-size markets where the incentive to enter early is the strongest, firms incur entry costs that are 5% higher on average.

Our paper builds and contributes to the strategic behavior literature. Our work is closest to Ellison and Ellison (2011) on strategic R&D and advertising investments in the pharmaceutical industry, Schmidt-Dengler (2006) in MRI adoption, and Igami and Yang (2016) and Fang and Yang (2021) on entry of fast-food restaurants.[2] Our paper contributes to this literature in a number of ways. First, we build on the insights of Ellison and Ellison (2011) on how to test for strategic preemptive entry, and we improve their test by using an exogenous measure of market size, namely, the share of good weather days in a year. We use this exogenous variation to identify the parameters of a dynamic entry game entry preemption in a transparent way. Third, following Schmidt-Dengler (2006), our model and counter-factual analysis explicitly account for the non-stationary transition of the industry by modeling technological progress as a predictable diffusion process. In contrast, Igami and Yang (2016) and Fang and Yang (2021) use an infinite horizon Markov-perfect industry equilibrium model similar to Aguirregabiria and Mira (2007) to study the entry/exit of firms. The advantage of our approach is that the model generates a unique Markov-perfect equilibrium; which allows us to account for technological process and unobserved heterogeneity when estimating the structural parameters and performing our counter-factual analysis. The existence and uniqueness of MPE follow from the single-direction Markov transition property described in Doraszelski and Judd (2012).

The rest of the paper is organized as follows. In Section 2, we first detail the birth and background of the U.S. drive-in theater industry, and describe the data for our empirical analysis. Section 3 develops a simple entry game and shows by simulation that even a simple model can generate the non-monotonicity observed in the data. In Section 3, we also show

[2] This literature has traditionally had a theoretical flavor (Salop, 1979; Bernheim, 1984; Chang, 1993; Waldman, 1987; Gilbert and Vives, 1986). From an empirical perspective, others have examined strategic behavior in contexts such as hospitals (Dafny, 2005); airlines (Goolsbee and Syverson, 2008; Gil and Kim, 2021); supermarkets (West, 1981; Cotterill and Haller, 1992); pharmaceutical industry (Hünermund et al., 2014); telecommunications (Goldfarb and Xiao, 2011; Seamans, 2012); and entertainment (Takahashi, 2015).

reduced-form evidence of preemptive entry through non-monotonicity of the relation between market size and probability of early entry. In Section 4, we generalize the framework in Section 3 and build a dynamic entry game wherein potential entrants can expedite their entry to deter the future entry of their rivals. Section 5 presents our empirical specifications and estimates of the structural parameters. Section 6 performs several counterfactual analyses to shed light on the mechanisms underlying the impact of strategic entry preemption motives on market structure. Section 7 concludes.

2. Institutional Detail and Data Description

2.1. The industry

A drive-in theater essentially 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 cars where customers can view films from the privacy and comfort of their automobiles. The screen can be as simple as a white wall or as complex as a steel truss structure. While drive-in theaters originally provided sound through speakers on their screens, they eventually transitioned to a sound system of individual speakers for each car in the 1940s and 1950s. This system was not only cheaper but also offered higher quality technology for broadcasting the movie soundtrack to each car. Ultimately, by the 1960s, movie sound was transmitted via an AM or FM radio on often high-fidelity stereos installed in the customers' vehicles.

The first ever known drive-in opened its doors to the public in 1921 in Comanche, Texas. Following the adjudication of U.S. patent 1909537 in 1933, the business concept caught on and spread to several states such as New Jersey, Pennsylvania, California, Massachusetts, Ohio, Rhode Island, Florida, Maine, Maryland, Michigan, New York, Texas and Virginia. The drive-in's popularity peaked in the late 1950s and early 1960s with more than 4,000 drive-in theaters spread across the United States. Drive-ins were particularly popular in rural areas, widening leisure choices and enabling entire families to enjoy movies together at a moderate cost.[3] Unfortunately, this business concept also posed a few challenges on the revenue side. Revenue was more limited compared to regular theaters since showings could only begin at twilight, and operating a drive-in theater during the winter season in some

[3]For example, families with infants could attend to their child while watching a movie, while teenagers and young adults with access to cars found drive-in theaters ideal for dates.

parts of the U.S. was nearly impossible due to inclement weather and the technical equipment (namely heating equipment) of cars during that time. Therefore, drive-ins in locations with harsh weather opened less frequently, resulting in exogenous variation in business profitability across locations in the U.S.

While part of the increase in the number of drive-in theaters is explained by its rising popularity from the demand side, it is also true that fixed entry costs steadily decreased over time between 1933 and their eventual decline in the 1970s due to the continuous emergence of better and cheaper technology along with constant learning-by-doing among industry practitioners. In the end, it is evident that entry costs decreased over time in the drive-in theater industry.

Finally, due to increased competition from home entertainment and economy-wide changes,[4] movie theater attendence declined sharply, making it harder for drive-ins to operate profitably. By the late 1980s, fewer than two hundred drive-ins were in operation in the U.S. and Canada. Only recently have drive-in theaters experienced a resurgence, with 389 in operation across the U.S. by 2013, representing a mere 1.5 percent of all movie screens in the United States, compared to the industry's peak in the early 1960s when 25 percent of the nation's movie screens were drive-ins.

2.2. Data

Our data are obtained from the census of theaters and drive-in theaters in the U.S., published annually in the yearly issues of the Movie Yearbook between 1945 and 1957 (Gil, 2015; Takahashi, 2015). We use information from `www.cinematreasures.org` to determine the approximate location and county of drive-in theaters. We also use this website's information to check whether changes in theater names may have occurred during the sample period. We complement 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.

We drop large counties where markets are segmented and drive-in theaters in different segments do not directly compete against each other.[5] The resulting dataset is a balanced

[4]The 1970s oil crisis and the 1980s real estate interest rate hikes decreased the overall consumption in the economy.

[5]Counties that fall into either one of the following three categories are dropped: (1) having a population of more than 1 million people; (2) a population density above 1000 people per squared miles; or (3) having more than 7 active incumbent drive-in theaters at any point during our sample.

panel of 2,713 counties, 1,996 of which observed drive-in theater entry between 1945 and 1957. The 717 counties which never experienced drive-in entry therefore do not contribute to explaining the intensive margin variation in drive-in theater entry and exit. In our subsequent regression analysis, we use the subsample of 1,996 counties whenever the dependent variable is an intensive-margin measure of entry.

Table 1 provides summary statistics for both data samples. The first sample is composed of the full cross-section of 2,713 counties. Our dependent variables are dummy variables indicating whether a county experienced entry before 1950, or at all, the number of entrants in any given subperiod, and the number of years within our sample that the county took to experience entry. As illustrated in the left columns of Table 1, 15% of counties in our full sample experienced entry prior to 1950, and 74% experienced entry between 1945 and 1957. These values differ for the subsample of 1,996 counties that experienced any entry (e.g., 21% early entry).

Table 1 also shows summary statistics of our measures of county market size, mainly the share of days in a year suitable for operating a drive-in theater business. We use the fraction of warm days (above 25 degree Celsius and below 35 degree Celsius) as the market size indicator. The average county in our full sample had 33% warm days, and 34% in our reduced sample.

We also use other controls such as median family income, urban population share, employment share, college share, share of adults, share of black population, population density, and farm value, obtained from the county and city data set. We include these variables to control for differences across cities that our measures of market size cannot capture and that may affect the potential profitability of a drive-in theater entrant during our sample period. For example, since there is a correlation in the U.S. between temperature and poverty, not controlling for income in our regressions could bias our results. Moreover, our data includes county-level information on the share of college graduates, adult population, black population and population density. Finally, Table 1 includes summary statistics for additional variables such as the number of indoor theaters at the county level, TV penetration, and motorization rates. While the former two variables account for different sources of competition for drive-in theaters, the latter is a demand shifter, as individuals with cars constitute the main demographic attending drive-in theaters.

Table 2 describes entry and exit patterns between 1945 and 1957. Because we do not

Table 1: Summary statistics

	All markets				Max # Driveins > 0			
	Mean	SD	Min	Max	Mean	SD	Min	Max
# drivein entrants (1945–47)	0.01	0.12	0.00	2.00	0.02	0.14	0.00	2.00
# drivein entrants (1948–49)	0.18	0.49	0.00	5.00	0.24	0.56	0.00	5.00
# drivein entrants (1950–51)	0.58	0.85	0.00	5.00	0.78	0.91	0.00	5.00
# drivein entrants (1952–53)	0.40	0.69	0.00	6.00	0.54	0.76	0.00	6.00
# drivein entrants (1954–57)	0.61	0.88	0.00	6.00	0.83	0.94	0.00	6.00
# drivein entrants (1945–49) > 0	0.15	0.36	0.00	1.00	0.21	0.40	0.00	1.00
# drivein entrants (1945–57) > 0	0.74	0.44	0.00	1.00	1.00	0.00	1.00	1.00
Years before first entry					6.38	2.39	0.00	12.00
Fraction warm days	0.33	0.10	0.06	0.81	0.34	0.10	0.06	0.81
Population (millions)	0.03	0.03	0.00	0.54	0.03	0.04	0.00	0.54
Median income	0.50	0.16	0.00	0.90	0.51	0.16	0.00	0.90
Urban population share	0.26	0.24	0.00	1.00	0.32	0.23	0.00	1.00
Employment share	0.96	0.04	0.35	1.00	0.95	0.05	0.35	1.00
College graduate share	0.06	0.03	0.01	0.22	0.06	0.03	0.01	0.22
Adult population share	0.60	0.05	0.43	0.72	0.60	0.05	0.44	0.72
Black population share	0.10	0.17	0.00	0.84	0.10	0.16	0.00	0.84
Population density	0.05	0.13	0.00	3.87	0.06	0.15	0.00	3.87
Farmland value (millions $)	0.01	0.01	0.00	0.10	0.01	0.01	0.00	0.10
# indoor theaters	3.83	2.84	0.00	19.00	4.33	3.03	0.00	19.00
TV rate	0.54	0.25	0.00	1.00	0.57	0.25	0.00	1.00
Motorization	0.74	0.25	0.00	1.61	0.73	0.23	0.12	1.38
Observations	2,713				1,996			

Note: This table provides summary statistics of all variables used in our empirical analysis for different samples conditioning on the maximum number of entrants in a market.

observe data prior to 1945, we take 1945 as a departure point and show the number of U.S. counties experiencing net entry and net exit as well as the number of drive-in entrants and exitors in five different time periods: 1945–47, 1948–49, 1950–51, 1952–53 and 1954–57. On the one hand, Table 2 shows how net exit is rather rare for all years except for the years between 1954 and 1957 when more counties experienced net exit. On the other hand, net entry was sparse during the first years of our sample (1945 to 1949) and sped up between 1950 and 1957. Figure 1 shows geographical dispersion in adoption. Consistent with Table 2, most entry occurred between 1948 and 1950, and by 1957 almost all U.S. counties had experienced entry of at least one drive-in theater.

Table 2: Entry and exit per year

Period	Counties with entry	Drive-in entrants	Counties with exit	Drive-in exitors
1945–47	39	40	0	0
1948–49	377	479	2	2
1950–51	1079	1562	16	16
1952–53	817	1074	13	13
1954–57	1131	1662	169	194

Note: This table shows the number of counties with net entry and net exit in five different periods in our sample.

In any case, these data are consistent with anecdotal evidence that drive-in theaters spread quite rapidly between the 1940s and 1950s, and slowed down in the 1960s. A cautionary note is due regarding the information on net exit in Table 2. Exit information (drive-in theaters disappearing from our data sample) is usually followed by entry. Therefore, exit may be disguised by changes in ownership, renaming or rebranding of existing drive-in theaters. We do our best to attenuate the impact of such noise by matching addresses of exiting and entering drive-in theaters over time. In the next section, we derive testable predictions regarding non-monotonicity between market size and early strategic entry, which we then take to data.

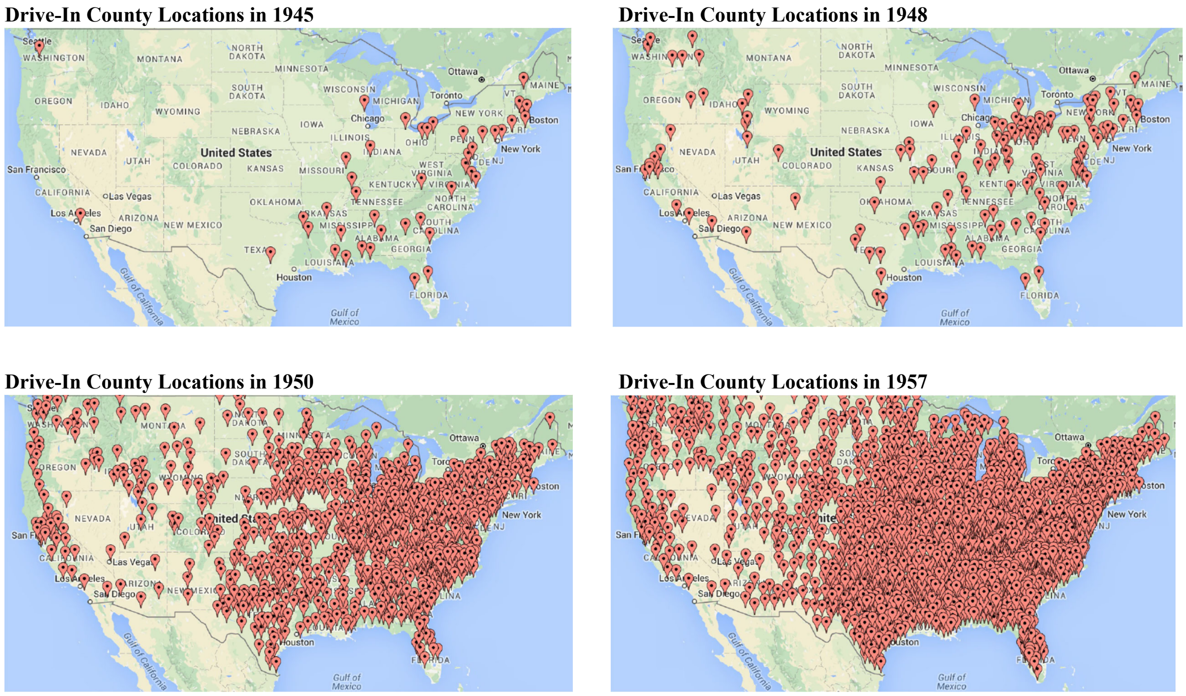


Figure 1: Diffusion graph of drive-in movie theaters at the county level for 1945, 1948, 1950 and 1957

3. Reduced-Form Evidence

3.1. The relation between early entry and market size

In this subsection, we build on the work by Ellison and Ellison (2011) to gain intuition on how strategic entry may change with market size, that is, why the probability of early entry into an empty market may be non-monotonic in market size. In a world with uncertain but decreasing fixed costs of entry, a firm would unambiguously benefit from delaying entry, all else equal, when its entry does not affect other potential entrants' entry decisions.

However, if firms are strategic, they will take into account the impact of their entry decisions in the current period on the incentives and entry decisions of others in the future, which may in turn affect their future profits. It is straightforward to note that if a firm enters as a monopolist, its profit will depend only on market characteristics and demographics and will increase with market size. Profits will be lower if others enter and the firm engages in oligopolistic competition. Yet, in some markets, oligopoly profits may not cover entry costs. In these cases, strategic motives may drive firms to enter a market earlier than absent strategic incentives—early entry may decrease the expected gains of competitors' entry in later periods and, thus, deter future entry.

To understand the extent to which strategic entry incentives affect the timing of firm entry, it is important to separate markets into small, intermediate and large size markets. The probability of any entry is close to zero in very small markets even when the market is empty, and very high in large markets where all potential entrants can enter and earn positive net profits. Therefore, the efficacy of entry deterrence is low in these two types of markets. Consequently, the probability of early entry is close to zero in small markets (no profits either way) and in large markets (early entry does not deter entry in later periods and so it has no strategic value). In contrast, in mid-size markets, only some but not all of the potential entrants can enter and earn positive net profit, thus the likelihood of late entry decreases with early entry. This creates a gain from entering earlier because it directly preempts late entry. Therefore, the probability of early entry is higher in intermediate-sized markets compared to small- and large-sized markets.

Appendix B.1 presents a heuristic two-player, two-period model that highlights the forces at play described in this subsection. We extend that model into a multi-player, multi-period dynamic entry game in Section 4 and show in Section 6 that the intuition applies in this setting of entry game.

3.2. Market size

A key challenge when implementing the identification strategy described in Section 3.1 is to find a relevant and exogenous measure of market size. A defining feature of "market size" in the literature on strategic investment and entry preemption is its positive association with static payoffs. Ellison and Ellison (2011) develop a two-period model and identify two sufficient conditions under which the relationship between market size and strategic investment is *monotonically* increasing when strategic deterrence is infeasible, and *non-monotonic* when deterrence is feasible.[6] Recent research by Fang and Yang (2023) extends this finding to an environment of an infinite-horizon entry game. Their key insight is that market size needs to increase with payoffs in the steady state and remains constant over time.

[6]The two conditions are: (1) market size raises the marginal benefit from the investment more than it raises the marginal cost of the investment; (2) the marginal benefit of the investment is larger when the incumbent faces a rival.

While population is widely used to measure market size, it is not a priori clear to satisfy the above criteria. In particular, population affects economic activities in many different ways. It affects the number of customers, which is directly related to market size. However, it could also affect entry costs and variable costs (such as labor).

In our empirical context, weather variables offer a more direct and transparent measure of market size. Because drive-in theaters operate outdoors, weather affects its actual appeal to consumers. The expected profit from a potential entrant's perspective is multiplicative in the number of days suitable for operating a drive-in theater business each year (e.g., warm weather). Consequently, after accounting for other variables influencing profit and entry cost, the static payoff in each period increases with the share of warm days.

We control for population and population density in our reduced-form test and measure warm weather as maximum daily temperature above 25 degrees Celsius and below 35 degrees Celsius. In Appendix B.2.2, we provide evidence that the fraction of warm days is widely known to the public and very stable over time.

3.3. Reduced-form test for entry preemption

Let us now start our empirical exploration using reduced-form specifications that aim to capture the non-monotonicity in the probability of early entry with market size. We do this in two ways. Our first approach uses a probit model to estimate the probability of entry in a given county prior to 1950, subject to market size measured by the fraction of warm days in that county and its square, while controlling for a wide range of other market characteristics as described in Section 2.2. We include these market characteristics to ensure that our coefficient estimates on weather-related terms capture their effects on entry decisions through differences in market size and to alleviate the concern that weather is correlated with other variables that affect the expected profit of drive-in theaters in a market.

Table 3 reports the estimated coefficients of the probit model. In column (1), we show that the probability of early entry is an inverse U-shaped function of the fraction of warm days, and the maximum probability of early entry is reached at a share of warm days of 46.8% (standard error = 3.2%). We then partition the support of county-level fraction of warm days into 65 bins of 1% width and compute the average early entry probability predicted by our estimates in column (1) of Table 3 for each bin. In Figure 2, we plot the histogram of the fraction of warm days using this partition and these average predicted probabilities. The non-monotonic relationship between market size and early entry is present in this figure.

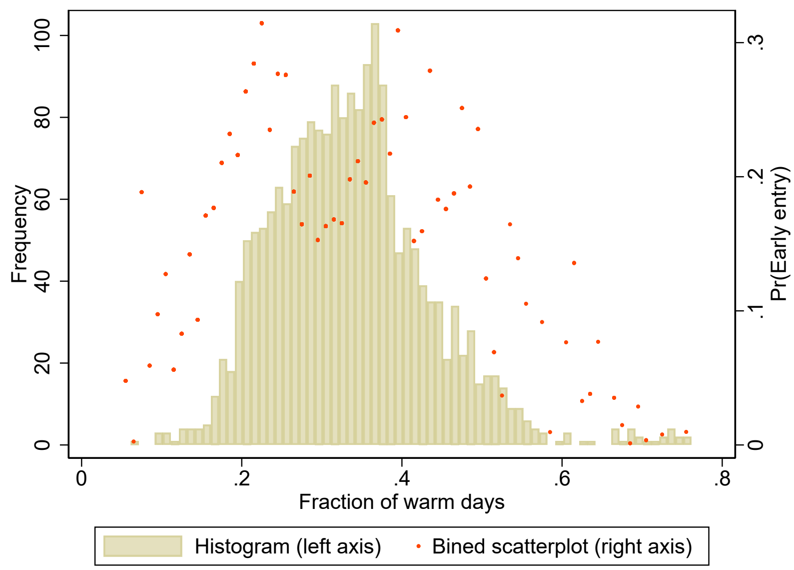


Figure 2: The relationship between early entry probability and the fraction of warm days

Notes: This figure shows the histogram of the fraction of warm days using 65 bins of 1% width and the average early entry probability predicted by the estimates in column (1) of Table 3.

A potential concern with the analysis in column (1) of Table 3 is that a linear and quadratic term of market size cannot adequately control for highly non-linear effects of market size that may be correlated with early entry. To control for such potential unobserved heterogeneity, the specification in column (2) of Table 3 divides our sample of counties by quintiles in the fraction of warm days and runs a probit regression of the probability of entry prior to 1950 on quintile dummies, while controlling for differences in other variables across counties. Our results in column (2) show non-monotonicity in the four quintile dummies of fraction of warm days, with counties in the first quintile as the reference group. Counties in the second to fifth quintiles exhibit a statistically significant higher probability of early entry prior to 1950, and the fifth quintile displays a lower (yet statistically significant) probability relative to the fourth quintile but higher than the first to third quintiles. Furthermore, based on the estimates in column (2), we conduct a statistical test for non-monotonicity where the null hypothesis is $(\beta_4 - \beta_3)(\beta_5 - \beta_4) \geq 0$, with β_q representing the coefficient on the dummy for the q^{th} quintile

Table 3: Regression analysis of early entry and entry timing

	Entry before 1950		Years until first entry	
	(1)	(2)	(3)	(4)
Fraction warm days	12.729***		-10.934***	
	(3.812)		(2.958)	
(Fraction warm days)^2	-13.601***		9.473***	
	(4.468)		(3.402)	
2nd quintile freq warm days		0.386*		-0.257
		(0.213)		(0.229)
3rd quintile freq warm days		0.816***		-0.793***
		(0.236)		(0.231)
4th quintile freq warm days		1.108***		-1.344***
		(0.252)		(0.251)
5th quintile freq warm days		0.845***		-0.962***
		(0.264)		(0.279)
Population (millions)	24.350***	25.867***	-33.475***	-34.274***
	(4.791)	(4.799)	(7.125)	(6.918)
Population^2	-37.662***	-39.615***	64.867***	64.735***
	(11.583)	(11.547)	(23.425)	(22.553)
Median income	0.678	0.739	-0.581	-0.743
	(0.601)	(0.629)	(0.664)	(0.683)
Urban population share	0.715**	0.794***	-2.702***	-2.797***
	(0.298)	(0.291)	(0.399)	(0.391)
Employment share	-0.250	-0.108	0.865	0.705
	(0.858)	(0.816)	(0.925)	(0.885)
College graduate share	3.451	3.179	-2.994	-2.598
	(2.606)	(2.673)	(3.256)	(3.344)
Adult population share	-6.192***	-6.955***	4.556***	5.029***
	(1.822)	(1.801)	(1.492)	(1.467)
Black population share	0.245	0.449	-0.150	-0.658
	(0.424)	(0.306)	(0.506)	(0.414)
# indoor theaters	0.015	0.010	-0.048	-0.042
	(0.026)	(0.026)	(0.029)	(0.027)
TV rate	0.754***	0.730***	-1.033***	-0.942***
	(0.174)	(0.172)	(0.277)	(0.277)
Motorization	1.482***	1.892***	-0.831*	-1.321***
	(0.402)	(0.455)	(0.429)	(0.473)
Population density	-0.740**	-0.762**	0.936	0.951
	(0.351)	(0.350)	(0.654)	(0.654)
Farmland value (millions $)	-18.229***	-18.253***	14.817**	13.310*
	(6.903)	(6.935)	(6.945)	(7.151)
N	1,996	1,996	1,996	1,996
Psudo R^2	0.238	0.248		
R^2			0.316	0.322
M^*	0.468 (0.032)		0.577 (0.071)	
p-value (non-monotonicity test)		.045		.069
Sample	Max # drive-ins > 0			

Notes: Columns (1) and (2) report coefficient estimates from the probit model examining drive-in entry before 1950. Columns (3) and (4) report OLS estimates for regressions with years before the first entry as dependent variables. The sample consists a cross-section of 1,996 counties with at least one drive-in theater between 1945 and 1957. Standard errors clustered at the state level are reported in parentheses.

of the fraction of warm days.[7] The p-value for this test based on the estimates in columns (2) is 0.045, as reported in Table 3.

A second way to estimate the non-monotonic relationship between market size and early entry is to construct another dependent variable measuring the number of years observed before entry since 1945 (our first year of data). Once we create this variable, we follow the same strategy as in columns (1) and (2) and run OLS regressions that contain the fraction of warm days, population and their squared variables, as well as other demographic controls also used in the probit regressions. We present the results of this second empirical strategy in columns (3) and (4) of Table 3. Our results here are qualitatively similar to those in columns (1) and (2).

The effects of other variables on early entry behaviors are consistent with our priors. First, we include both population and population squared terms in the regressions, and both terms are significant across all specifications. However, the inflection points of the estimated quadratic functions range from 0.26 to 0.33, which are above the population of most counties in our sample. This evidence suggests that the effect of population on early entry behaviors follows a monotonically increasing concave function. Moreover, the share of urban population and motorization rate increase the occurrence of early entry, while population density and farmland value, two variables we include to proxy for entry costs, are negatively correlated with early entry.

In a nutshell, we find evidence of a non-monotonic relationship between market size (measured with the fraction of warm days) and the probability of entry prior to 1950 and the number of years before observing the first entry: early entry is more likely to happen in "intermediate size" markets than in small and large markets.

3.4. Additional regression results

The previous analysis used variation in market size to identify the incentive of firms to preempt entry. Another implication of the theoretical work summarized in Section 3.2 is that the number of firms that choose to enter the market in the long run is strictly increasing in market size. We use this second prediction to validate our proxy variable for market size.

Table 4 examines the relationship between the terminal period number of drive-in theaters

[7] We compute the standard error of $(\hat{\beta}_4 - \hat{\beta}_3)(\hat{\beta}_5 - \hat{\beta}_4)$ using the Delta method, and use this statistic for the hypothesis testing.

in a county and our market-size proxy. To do so, we run OLS regressions of the terminal period number of drive-ins on the same set of explanatory variables used in Section 3.3. We run the regressions on both the reduced sample with only counties experiencing entry between 1945 and 1957 and the full sample. In columns (1) and (3), we estimate a quadratic function of the fraction of warm days, and the second-order term in both regressions loses statistical significance. Moreover, the inflection points of the two quadratic functions are 0.825 and 0.739. These values are above most of the data points in our sample, so we can conclude that non-monotonicity cannot be found in these regressions (see in Table 1 for the maximum value of the fraction of warm days, which is 0.81). Moreover, specifications in columns (2) and (4) use dummies per quintile of the fraction of warm days and clearly show a positive relationship between the terminal period number of drive-in theaters and the fraction of warm days. Lastly, the p-values associated with the non-monotonicity tests based on the estimates in columns (2) and (4) are 0.421 and 0.415, respectively, further reinforcing the conclusion that non-monotonicity cannot be detected from these regressions.

3.5. Discussions on reduced-form evidence on entry preemption

3.5.1. An alternative interpretation of the non-monotonicity test results

An alternative interpretation of the results in Section 3.3 is that (1) market size is a non-monotonic transformation of the fraction of warm days (e.g., the distance between average temperature and a bliss-point temperature), and (2) there is no entry preemption in the data, so early entry increases with that market size and varies non-monotonically with the fraction of warm days. The exercise in Section 3.4 invalidates this alternative interpretation by showing that steady-state market structure increases with the fraction of warm days. Therefore, as discussed in Section 3.2, any non-monotonic transformation of our market size measure does not satisfy the criteria of market size.

3.5.2. Robustness checks

We present the results of three robustness checks in Appendix C. In the first exercise, we experiment with the entry dependent variable. Table C1 reports estimates from probit models with the same specification as column (1) of Table 3. Specifically, we use eight dummy variables indicating at least one drive-in theater entry before year $t = 1949, ..., 1956$ as de-

Table 4: OLS regressions of the maximum number of entrants and market size

	Terminal period incumbent count			
	(1)	(2)	(3)	(4)
Fraction warm days	4.667**		6.388***	
	(1.986)		(2.102)	
(Fraction warm days)^2	-2.830		-4.319*	
	(2.156)		(2.522)	
2nd quintile freq warm days		-0.082		-0.010
		(0.131)		(0.102)
3rd quintile freq warm days		0.538***		0.543***
		(0.133)		(0.134)
4th quintile freq warm days		0.763***		0.890***
		(0.160)		(0.159)
5th quintile freq warm days		0.795***		0.927***
		(0.204)		(0.216)
Population (millions)	29.782***	30.835***	33.756***	34.456***
	(4.771)	(4.272)	(5.685)	(5.272)
Population^2	-51.874***	-52.454***	-62.920***	-62.513***
	(17.006)	(16.249)	(22.262)	(21.402)
Median income	1.023***	1.249***	0.609	0.813**
	(0.373)	(0.359)	(0.365)	(0.327)
Urban population share	0.222	0.194	1.360***	1.317***
	(0.221)	(0.223)	(0.204)	(0.202)
Employment share	-2.135***	-2.030***	-2.561***	-2.356***
	(0.734)	(0.706)	(0.740)	(0.708)
College graduate share	-0.140	-0.112	0.898	0.979
	(2.247)	(2.226)	(2.246)	(2.218)
Adult population share	-1.514	-1.719	-1.969*	-2.169*
	(1.178)	(1.199)	(1.157)	(1.200)
Black population share	-0.226	-0.142	-0.568	-0.420
	(0.365)	(0.331)	(0.386)	(0.360)
# indoor theaters	0.092***	0.087***	0.098***	0.093***
	(0.018)	(0.017)	(0.019)	(0.018)
TV rate	0.010	-0.073	0.017	-0.044
	(0.139)	(0.130)	(0.148)	(0.142)
Motorization	0.100	0.516	0.021	0.357
	(0.311)	(0.327)	(0.278)	(0.297)
Population density	-1.261***	-1.222***	-1.433***	-1.400***
	(0.434)	(0.430)	(0.464)	(0.452)
Farmland value (millions $)	-18.543***	-16.081***	-16.815**	-13.777**
	(6.641)	(5.596)	(6.444)	(5.228)
N	1,996	1,996	2,713	2,713
R^2	0.344	0.356	0.456	0.464
M^*	0.825 (0.295)		0.739 (0.21)	
p-value (non-monotonicity test)		.421		.415
Sample	Max # drive-ins > 0		All markets	

Notes: Coefficients of OLS regressions reported at the county level for all counties and those with at least one entrant in our sample. Columns (1) and (3) use both population and fraction of warm days. Columns (2) and (4) use quintiles of fraction of warm days. Standard errors clustered at the state level are reported in parentheses.

pendent variables. In Panel A, only the fraction of warm days is included. In Panel B, we in addition include its square term. All specifications in Table C1 control for the same covariates as in column (1) of Table 3. Notably, the statistical significance of the fraction of warm days squares diminishes for regressions in the last two columns where the dependent variables are entry before 1955 and 1956, respectively. The inflection point of the estimated quadratic function of the fraction of warm days (M) exceeds most observed M values in our data when the dependent variable is an indicator of having an entry before 1953, 1954, 1955, or 1956.

We draw two conclusions from the exercise. First, our findings in Table 3 are robust to alternative definitions of early entry. Second, whether a county had experienced an entry in later periods does not vary non-monotonically with market size.

Our second exercise investigates whether our results in Table 3 are sensitive to alternative definitions of warm days used for constructing the market size proxy. We compute the fraction of warm days where warm days are defined as days with maximum daily temperature falling within the following ranges: (1) $> 25°C$, (2) $25°C - 30°C$, (3) $25°C - 35°C$, (4) $> 25°C$, and (5) $25°C - 35°C$. We use different market size proxies and re-estimate the model presented in Table 3, column (1). All specifications control for the same covariates as in column (1) of Table 3.

The results are presented in Table C2. To interpret the estimates in each column, we report the mean of market size under the associated definition of warm days and compare it with the inflection point of the estimated quadratic function. We find that across specifications, we observe a robust non-monotonic relationship between the fraction of warm days and early entry, which suggests that our baseline results are not driven by our definition of warm days.

Finally, we conduct the statistical test in Ellison and Ellison (2011) and report the results in Appendix C.3. The results are generally consistent with our baseline findings.

4. A model of entry and technology diffusion

In this section, we formalize our analysis of entry with preemption gains presented in Section 3 to pursue structural estimation. By doing so, our objective is twofold. First, we aim to quantify the importance of technological progress that occurred over time within the industry. As described in Section 3.1, in contrast to entry deterrence, this economic force postpones the timing of potential entrants' entry. Second, we use the estimated model to quantify the effect of strategic entry preemption on market structure and the resulting waste in entry costs.

4.1. Market structure and timing

Markets are indexed by $i = 1, ..., m$ and firms are denoted as $j = 1, ..., N$. Time is discrete and infinite, $t = 1, ..., \infty$. All markets have zero incumbent firms and N symmetric potential entrants in period 1. In each period t, there are n_{it} incumbent firms entering the market before period t, and $N - n_{it}$ potential entrants.

The timing of the game proceeds as follows: (i) potential entrants observe the number of incumbent firms n_{it} and decide whether to enter; (ii) the number of entrants is realized, and the number of firms in the market becomes $n_{i,t+1}$;[8] (iii) non-entering potential entrants and entrants draw an independently and identically distributed Type-1 extreme valued payoff shock (denoted as ϵ_{ijt0} and ϵ_{ijt1}, respectively), entrants pay sunk entry cost, and the $n_{i,t+1}$ active firms in the market earn the profit $\pi_{it}(n_{i,t+1})$;[9] (iv) the game moves to period $t+1$ with $n_{i,t+1}$ as the new number of incumbents; (v) market structure is fixed after period T, and all the $n_{i,T+1}$ firms in the market receive a perpetual stream of profit $\pi_{iT}(n_{i,T+1})$ in periods $t = T + 1, ..., \infty$.

There are three comments about our model setups. First, entry is a terminating action, so incumbent firms do not make dynamic choices such as exit. While a simplifying assumption, it is consistent with the data pattern presented in Table 2 that exit is fairly rare and often reflects rebranding or changes of ownership/name. Second, entry decisions are made in the first T periods. This modeling choice is important as it guarantees a unique solution to a dynamic game while acknowledging the presence of fundamental non-stationarity in the data, a defining feature of evolving industries such as high-tech manufacturing (Igami, 2017; Yang, 2020) and wind and solar power generation (Elliott, 2022). Lastly, potential entrants make entry decisions before firm-specific payoff shocks and profits are realized. Therefore, the decisions are made based on beliefs about how $n_{i,t+1}$ will evolve and the distribution of payoff shocks.

[8] $n_{i,t+1}$ is equal to the sum of n_{it} and the number of firms entering in period t.

[9] Because we assume firms in market i are symmetric, the profit $\pi_{it}(n_{i,t+1})$ is common to all firms in market i, and depends on technology in period t, market size and demographics.

4.2. Dynamic optimization

4.2.1. Beliefs

We refer to $\sigma_i = \{\sigma_{it}(n)\}_{n=0,\ldots,N;t=2,\ldots,T} \cup \{\sigma_{i1}(0)\}$ as the strategy profile of potential entrants in market i.[10] Each element in σ_i is a strategy function (i.e., entry probability) of the state variable n (the number of incumbents at the beginning of the period). We index strategy by t due to the non-stationarity of the game, and by i to indicate that strategy is dependent on market size and other characteristics of i. There is no subscript indexing firms because we assume firms are symmetric, and solve for the symmetric equilibrium.

Incumbent firms' beliefs about the evolution of the number of incumbents under σ_i follow a Markov process determined by potential entrants' entry probability $\sigma_{it}(n_{it})$:

$$P_{it}^{\sigma}(n_{i,t+1}|n_{it}) = \mathrm{B}(N - n_{it}, n_{i,t+1} - n_{it}, \sigma_{it}(n_{it})), \tag{1}$$

which represents the Binomial probability of $n_{i,t+1} - n_{it}$ entries out of the $N - n_{it}$ potential entrants.

Denote entry decisions by a, where $a = 0$ and $a = 1$ index not entering and entering, respectively. From the potential entrants' point of view, under strategy profile σ_i, the probability of facing competition from $n_{i,t+1}$ firms, conditional on taking action a, is given by

$$P_{it}^{\sigma}(n_{i,t+1}|a, n_{it}) = \mathrm{B}(N - n_{it} - 1, n_{i,t+1} - a - n_{it}, \sigma_{it}(n_{it})), \tag{2}$$

which represents, out of the $N - n_{it} - 1$ rival potential entrants, the Binomial probability of $n_{i,t+1} - n_{it} - 1$ entries if the focal potential entrant enters and the probability of $n_{i,t+1} - n_{it}$ entries if the focal potential entrant does not enter. Note that the Binomial probability is well-defined in equations (1) and (2) when their respective first argument is equal to zero.

[10] $\sigma_{i1}(n)$ is only defined for $n = 0$ because the market is empty at the beginning of period 1.

4.2.2. Incumbents' value

Since entry is a terminating action, incumbents do not make dynamic choices after entry. The net present value of being an incumbent in market i and period t is defined recursively as:

$$W_{it}^{\sigma}(n_{it}) = \begin{cases} \sum_{t=T}^{\infty} \delta^{t-T} \pi_{iT}(n_{i,T+1}) & \text{if } t = T \\ \sum_{n_{i,t+1} \geq n_{it}} P_{it}^{\sigma}(n_{i,t+1}|n_{it}) \left[\pi_{it}(n_{i,t+1}) + \delta W_{i,t+1}^{\sigma}(n_{i,t+1})\right] & \text{If } t < T \end{cases} \tag{3}$$

where $\delta = 0.9$ is the discount factor and $P_{it}^{\sigma}(n_{i,t+1}|n_{it})$ is defined in equation (1).

4.2.3. Potential entrants' problem

For potential entrants, the value of entering the market (net of payoff shock ϵ_{ijt1}) is given by:

$$v^{\sigma}(a = 1|n_{it}) = \sum_{n_{i,t+1} \geq n_{it}+1} P_{it}^{\sigma}(n_{i,t+1}|a = 1, n_{it}) \left[\pi_{it}(n_{i,t+1}) - F_{it} + \delta W_{i,t+1}^{\sigma}(n_{i,t+1})\right], \tag{4}$$

where F_{it} is market-time specific sunk entry cost, $P_{it}^{\sigma}(n_{i,t+1}|a = 1, n_{it})$ is defined in Equation (2), and $W_{i,t+1}^{\sigma}(n_{i,t+1})$ can be calculated using Equation (3).

Similarly, the value of not entering (net of payoff shock ϵ_{ijt0}) is determined by the option value of being a potential entrant in $t + 1$:

$$v_{it}^{\sigma}(a = 0|n_{it}) = \sum_{n_{i,t+1} \geq n_{it}} P_{it}^{\sigma}(n_{i,t+1}|a = 0, n_{it}) \left[\delta V_{i,t+1}^{\sigma}(n_{i,t+1})\right], \tag{5}$$

where

$$\begin{aligned} V_{it}^{\sigma}(n_{it}) &= E_{\epsilon}\left[\max\{v_{it}^{\sigma}(a = 1|n_{it}) + \epsilon_{ijt1}, v_{it}^{\sigma}(a = 0|n_{it}) + \epsilon_{ijt0}\}\right] \\ &= \ln\left(\sum_{a=0,1} \exp(v_{it}^{\sigma}(a|n_{it}))\right) + \gamma \end{aligned} \tag{6}$$

is the expected value function of potential entrants with γ being the Euler constant. As in Rust (1987), the second equality follows from the assumption of type-1 extreme value distribution on payoff shocks ϵ_{ijt0} and ϵ_{ijt1}.

Given belief $P_{it}^{\sigma}(n_{i,t+1}|a = 1, n_{it})$, which is a function of strategy profile σ_i, the optimal entry strategy of a potential entrant can be summarized by the following entry probability:

$$\begin{aligned}\Lambda_{it}(\sigma_i, n_{it}) &\equiv \Pr(a = 1|\sigma_i, n_{it}) \\ &= \frac{\exp(v_{it}^{\sigma}(a = 1|n_{it}))}{\exp(v_{it}^{\sigma}(a = 0|n_{it})) + \exp(v_{it}^{\sigma}(a = 1|n_{it}))}.\end{aligned}$$

As in Aguirregabiria and Mira (2007), we refer to this mapping as the best-response probability function.

4.3. Equilibrium solution

We focus on symmetric Markov-Perfect Bayesian Nash equilibrium (MPE). We follow Aguirregabiria and Mira (2007) in defining our equilibrium in terms of entry probabilities. A strategy profile $\sigma^* = \{\sigma_{it}^*(n)\}_{n=1,\ldots,N;t=2,\ldots,T} \cup \{\sigma_{i,1}^*(0)\}$ is an MPE if the vector of entry probabilities are consistent with firms' best-response strategies in every state n and time period t. Definition 1 formally defines the equilibrium of this game.

Definition 1. Strategy profile σ^* is a Markov-perfect Bayesian Nash equilibrium for market i if $\sigma^* = \{\sigma_{it}^*(n)\}_{n=1,\ldots,N;t=2,\ldots,T} \cup \{\sigma_{i,1}^*(0)\}$ is a fixed-point to the following best-response entry probability mapping:

$$\sigma_{it}^*(n_{it}) = \Lambda_{it}(\sigma^*, n_{it}) = \frac{\exp(v_{it}^{\sigma^*}(a = 1|n_{it}))}{\exp(v_{it}^{\sigma^*}(a = 0|n_{it})) + \exp(v_{it}^{\sigma^*}(a = 1|n_{it}))}, \quad \text{for all } n_{it} \text{ and } t.$$

We obtain the solution to this MPE using backward induction. In period $t = T$ and state n_{iT}, the model reduces to a static entry game with $N - n_{iT}$ symmetric potential entrants and incomplete information. Since $(\epsilon_{ijt0}, \epsilon_{ijt1})$ has full support, there exists a unique symmetric Bayesian Nash equilibrium for this stage game. This equilibrium and associated value functions $(W_{iT}^{\sigma*}(n_{iT}), V_{iT}^{\sigma*}(n_{iT}))$ can be found easily by iterating on the best-response probability mapping. In period $T - 1$, firms play a similar entry game, taking as given the equilibrium value of being an incumbent in period T, $W_{i,T}^{\sigma^*}(n_{iT})$ and the option value as a potential entrant, $V_{iT}^{\sigma*}(n_{iT})$. Using the same argument, there exists a unique Bayesian Nash equilibrium in period $T - 1$, as well as in all periods $t < T - 1$. Crucially, these steps imply that there exists a unique symmetric MPE.

The existence and uniqueness of an MPE in this context is consistent with arguments in previous work on stochastic dynamic games. An equilibrium exists because of our assumption that the private-information payoff shocks have full support, guaranteeing the existence of an interior solution to the best-response probability fixed-point (see Pesendorfer and Schmidt-Dengler, 2008). Uniqueness is guaranteed because of our assumption that incumbents cannot exit the market, ensuring that the number of incumbent firms in the market cannot decrease over time. As pointed out by Doraszelski and Satterthwaite (2010), industry dynamic models with single-direction Markov transitions exhibit a unique Markov-perfect Bayesian equilibrium. We exploit the properties of existence and uniqueness in the next section when constructing our estimator.

5. Empirical Specification and Estimation Results

5.1. Time aggregation

We aggregate our data into 5 multi-year periods when estimating the structural model: 1945–1947, 1948–1949, 1950–1951, 1952–1953, and 1954–1957. Besides, we assume the terminal period is not observed in the data (i.e., 1957 corresponds to the end of period $T-1$). Although we do not have data in period $T = 6$, we include an extra period since the growth rate in the number of drive-in movie theaters per market was still positive in the last period of our data-set.

There are two considerations for the choice of time aggregation. First, entry is relatively rare, and on average the first theater enters after 5 years (see Table 1). On an annual basis, 70% of observations exhibit no entry. Rationalizing these patterns with the model would inflate the importance of idiosyncratic profit shocks. On the other hand, using too few periods would limit our ability to measure an S-shaped diffusion pattern from the number of theaters per market. The shape of the diffusion pattern is important to identify the relative importance of entry preemption incentive and technological progress. We balance these two issues by defining a period as a two- or three-year interval.

Second, as we discussed in the data section above, our data on the number of movie theaters is likely measured with error; either due to the data extraction process itself, imperfect recording on entry dates, or theater exit. Using finer time aggregation results in a more volatile measure of entry and can lead to “false” exits. This is particularly relevant later in the sample since the 1954 recession caused temporary exits and/or changes of theater names. Since our model does not rationalize exit, aggregating across years leads to a more stable measure of the number of active theaters.

5.2. Parameterization

5.2.1. Profits

We approximate the profit of active firms in market i in period t using the following reduced-form function:

$$\pi_{it}(n) = M_i \frac{\log(1 + \exp(x_i\beta_x + \beta_t \log t + u_i))}{(1+n)^\theta}, \tag{7}$$

$$u_i \overset{iid}{\sim} N(0, \sigma_u^2),$$

where M_i is the fraction of warm days (our proxy for market size), x_i is a vector of market characteristics used in our reduced-form analysis,[11] and u_i is a time-invariant random effect measuring unobserved market profitability. We also include a time trend $\beta_t \log t$ in the profit function, which captures exogenous technological progress (e.g., declining marginal costs) and/or the increase in demand for drive-in theaters over time. The second term in Equation (7) represents the average profit per day open. Its numerator is proportional to the monopolistic profit in market i in period t, with the $\log(1 + \exp(.))$ functional form bounding variable profits above zero.[12] The functional form of its denominator nests the Cournot profit function if $\theta = 2$.[13]

Under this specification, differences in monopoly profits across market-period pairs are monotonically increasing in market size M_i and in the term $(x_i\beta_x + \beta_t \log t + u_i)$. We incorporate observed differences in demographic characteristics across markets in x_i. Finally, β_t measures the rate of technical progress affecting the variable profit. A positive value for β_t is

[11] x_i includes an intercept, population, median family income, urban population share, employment share, college share, share of adults, and share of black population.

[12] Since the profit shock u_{it} has full support, we employ the $\log(1 + \exp(\cdot))$ transformation to moderate the rate at which the profit function increases with u. Specifically, when using the profit function $\pi_{it}(n) = M_i \times \exp(x_i\beta_x + \beta_t \log t + u_i)/(1+n)^\theta$, large realizations of u_i can imply a zero probability of staying out of the market for certain parameter values, leading to numerical difficulties when maximizing the likelihood function.

[13] Under the assumption of Cournot competition, denote firm i's residual demand curve by $P_{it}(Q) = a_{it} - bQ$ and variable cost curve by $C_{it}(q) = c_{it}q$, where q and Q are firm i's output and industry output, respectively. The equilibrium price, quantity, and profit are given by $P^*_{it} = (a_{it} + c_{it}n_{i,t+1})/(1+n_{i,t+1})$, $q^*_{it} = (a_{it} - c_{it})/(b(1+n_{i,t+1}))$, and $\pi^*_{it} = (a_{it} - c_{it})^2/(b(1+n_{i,t+1})^2)$.

consistent with improvements in the quality of the product over time (e.g., variety of movies available) or a reduction in the marginal cost of serving consumers.

5.2.2. Entry costs

We assume that the sunk entry cost paid by actual entrants changes over time as the technology matures:

$$F_{it} = z_i \gamma_z + \gamma_t \log t, \tag{8}$$

where z_i is a vector of proxies for the cost of acquiring land that are not included in x_i, such as population density and the value of farm products, along with an intercept. We also incorporate an exogenous time trend in sunk entry costs, $\gamma_t \log t$, in F_{it} to capture the decline over time in the upfront installment cost of drive-in theater equipment. We interpret the parameter γ_t as the rate of this technological progress. Since we normalize the profit of non-entering to zero, $z_i \gamma_z$ measures the sunk cost of entering net of the value of staying out.

5.3. Maximum likelihood estimator

The parameter vector to be estimated is $\mathbf{\Theta} = (\beta_x, \beta_t, \gamma_z, \gamma_t, \theta, \sigma_u)$, where β_x, β_t, θ, and σ_u are from equation (7), and γ_z and γ_t are from equation (8). Let $X_i = \{x_i, z_i\}$ denote the vector of observed demographic characteristics of market i. We use the full-solution approach to estimate $\mathbf{\Theta}$ via the nested-fixed point algorithm.

Given a guess of the parameters $\mathbf{\Theta}$ and a random effect u_i, we solve for the MPE $(\sigma^*_{it}(n_{it}))$ by backward induction as described in Section 4.3. The probability of observing the sequence of states $(n_{i0} = 0, n_{i1}, ..., n_{iT})$ in market i is given by:

$$\Pr(n_{i2}, ..., n_{iT}; u_i, n_{i1} = 0, X_i, \mathbf{\Theta}) = \prod_{t=1}^{T-1} P^{\sigma*}_{it}(n_{i,t+1}|n_{it}), \tag{9}$$

where $P^{\sigma*}_{it}(n_{i,t+1}|n_{it})$, the probability of observing $n_{i,t+1}$ incumbents in period $t+1$ conditional on having n_{it} in period t, is given by equation (1) evaluated at the solved MPE $(\sigma^*_{it}(n_{it}))$. As mentioned in Section 5.1, we only have data before period T, so the probability is calculated from $t = 1$ to $T - 1$. The likelihood contribution of observation i is computed by integrating over the distribution of random effects (i.e., $N(0, \sigma_u^2)$)

$$\mathcal{L}_i(\mathbf{\Theta}) = \int_u \phi\left(\frac{u}{\sigma_u}\right) \Pr(n_{i2}, ..., n_{iT}; u, n_{i1} = 0, X_i, \mathbf{\Theta}) du. \tag{10}$$

The log-likelihood function of the sample is

$$l(\mathbf{\Theta}) = \sum_i \log\left(\mathcal{L}_i(\mathbf{\Theta})\right). \tag{11}$$

We use simulated maximum likelihood method to estimate the model where parameter estimates maximize the likelihood function (11).[14] For computing the integral in equation (11), we use the Gauss-Hermite quadrature method.[15] The full sample utilized in our reduced-form analysis is used for estimating the structural model in this section. We fix the number of potential entrants at 7, corresponding to the maximum number of firms observed in the dataset.

5.4. Parameter estimates

The estimation results are reported in Table 5. Column (1) reports the baseline specification outlined in the previous subsection. Columns (2)–(5) report the estimates from four restricted models. Model (2) imposes the assumption of Cournot competition where the competition parameter θ in the profit function is restricted to 2. Models (3) and (4) eliminate the time trend in sunk entry cost and variable profit, respectively. Model (5) eliminates the market-level unobserved heterogeneity in variable profit (i.e., $\sigma_u = 0$). For the restricted models, a χ^2 statistic for the likelihood ratio test against the baseline model (1) is also reported. The χ^2 statistic is calculated as $2(\ell - \ell_0)$ where ℓ_0 and ℓ are respectively the log-likelihood of the baseline unrestricted model and that of the restricted model.

The parameter estimates in the variable profit are consistent across different specifications. First, as the number of incumbents increases, variable profit declines at a lower rate than that in a Cournot model (except for Model (2) where Cournot competition is imposed). Second, average daily variable profit increases with population size, median income, share of urban

[14] To make sure that the estimates are not local maxima, we initialize the estimation algorithm with different starting values for the parameter guess. Most starting values converge to the same, greatest likelihood.

[15] The approximation is $\mathcal{L}_i(\mathbf{\Theta}) \approx (1/\sqrt{\pi}) \times \sum_k \omega_k \Pr(n_{i2}, ..., n_{i,T-1}; u_k, X_i, \mathbf{\Theta})$, where u_k and ω_k are the node and weight of the Gaussian-Hermite quadrature, respectively. Further details can be found in Chapter 5.2 of Miranda and Fackler (2004).

population, and share of college graduates. All else equal, variable profit decreases with share of the black population, share of employment, and share of the adult population. Lastly, there is a rising time trend in variable profit ($\beta_t > 0$).

The parameter estimates in the entry cost are also consistent across different specifications. Our results show, across all specifications, that entry cost increases with population density and farm land value. It follows that both population density and farm land value increase the cost of land acquisition. Moreover, there is a declining time trend in entry cost ($\gamma_t < 0$) as anticipated.

Specifications (3) and (4) restrict technological progress to operate only through variable profit or fixed-cost. Both restrictions are clearly rejected from the data. Based on the magnitude of the likelihood ratio tests and the parameter estimates, growth in variable profits due to quality or marginal cost is the most important factor to explain the data. Also, accounting for both trends has an important impact on our estimate of θ (i.e. effect of competition on profits). This is because the competitiveness of the market and technology jointly determine the predicted speed of diffusion of drive-in theaters. Failing to account for the two sources of technological progress leads to a biased estimate of the competition parameter.

Finally, controlling for unobserved market heterogeneity is crucial for fitting the data, and to consistently estimating the magnitude of the trade-off between technological progress and entry preemption. Specification (5) shows that accounting for unobserved heterogeneity has the most substantial impact on the model fit. Setting $\sigma_u = 0$ also biases towards zero our estimate of technological improvement, and reduces the competition parameter. This attenuation effect on parameter estimates from omitting unobserved market heterogeneity is also found in Aguirregabiria and Mira (2007) and Igami and Yang (2016).

5.5. Model fits and source of identification

In this subsection, we discuss how well the baseline model fits a set of data moments and how the constraints on structural parameters in specifications (2)–(5) of Table 5 limit their ability to capture certain data features. We use this exercise to shed light on the source of identification of structural parameters.

Specifically, we use the estimates from specifications (1)–(5) of Table 5 to simulate 2,000 market structure sequences for each of the 2,713 markets in the sample. Each simulation

Table 5: Simulated maximum likelihood estimates of the structural model

	(1) Baseline	(2) Cournot	(3) $\gamma_t = 0$	(4) $\beta_t = 0$	(5) $\sigma_u = 0$
σ_u	3.008	9.203	2.956	1.719	
	(0.083)	(0.2)	(0.083)	(0.055)	
θ	1.196	2.0	1.037	0.967	1.178
	(0.023)		(0.036)	(0.014)	(0.022)
Variable profit (β)					
Population (10k)	1.452	3.639	1.183	1.055	1.278
	(0.047)	(0.089)	(0.053)	(0.038)	(0.052)
Income	1.921	3.855	2.325	1.424	1.092
	(0.426)	(1.145)	(0.305)	(0.27)	(0.247)
Urban share	7.636	24.121	6.76	4.553	5.197
	(0.408)	(0.849)	(0.541)	(0.267)	(0.261)
Employment share	-8.17	-22.354	-8.877	-4.341	-4.945
	(0.748)	(2.075)	(0.859)	(0.465)	(0.451)
College share	10.587	30.887	9.701	6.594	5.858
	(2.151)	(6.991)	(1.46)	(1.348)	(1.171)
Adult share	-9.207	-27.512	-7.994	-6.509	-7.682
	(1.945)	(4.653)	(1.331)	(1.101)	(1.101)
Black share	-2.772	-4.83	-2.779	-2.262	-2.153
	(0.513)	(1.565)	(0.33)	(0.317)	(0.272)
# Indoor Theaters	1.248	4.851	1.029	0.913	0.915
	(0.25)	(0.761)	(0.17)	(0.146)	(0.123)
TV rate	-0.254	-5.613	-0.052	0.261	0.08
	(0.548)	(1.46)	(0.405)	(0.333)	(0.287)
Motorization	0.32	1.07	0.347	0.186	0.177
	(0.019)	(0.054)	(0.025)	(0.011)	(0.01)
Intercept	-1.241	-14.471	-6.021	6.137	1.203
	(1.282)	(3.35)	(0.859)	(0.757)	(0.685)
Log-trend (β_t)	7.553	26.131	10.852		3.253
	(0.256)	(0.782)	(0.626)		(0.133)
Fixed entry cost (γ)					
Population density	7.282	3.902	8.333	6.669	5.53
	(0.242)	(0.09)	(0.215)	(0.197)	(0.118)
Farm value	35.355	4.47	41.512	40.943	34.96
	(3.956)	(4.117)	(3.495)	(3.817)	(2.613)
Intercept	6.321	5.209	6.659	6.682	4.409
	(0.175)	(0.159)	(0.242)	(0.217)	(0.093)
Log-trend (γ_t)	-0.976	-1.085		-1.987	-1.045
	(0.014)	(0.012)		(0.052)	(0.018)
Log-likelihood	-8888.627	-8936.356	-8943.306	-8972.9	-9023.98
$\chi^2(df)$		95.459(1)	109.359(1)	168.547(1)	270.708(1)

Notes: $N = 2713$. Standard errors clustered at the state level are reported in parentheses. The last row reports the χ^2 statistic for likelihood ratio tests of restricted models (2)–(5) against the full model (1).

yields a panel dataset of 2,713 markets, from which we compute four sets of moments, as presented in Panels A–D of Table 6.

5.5.1. Model fits of market structures

Panels A and B summarize market structures. Panel A reports the number of incumbents in each period (note that all markets were empty before 1945, so $n_{i1} = 0$). Panel B reports the share of empty markets in the cross-section of 2,713 markets in each period. All specifications exhibit similar fits and tend to over-predict the number of incumbents in earlier periods. Additionally, these models tend to under-predict the share of empty markets in early periods, with the unconstrained baseline model (column (1)) and the model with Cournot restrictions (column (2)) performing the best.

5.5.2. Identification of the competition effect and unobserved heterogeneity

The importance of unobserved heterogeneity across markets σ_u and the competition effect θ are related to the degree of serial correlation in the number of entrants within each market (conditional on time trends). In particular, unobserved heterogeneity implies a positive correlation between entry ($e_{it} \equiv \Delta n_{i,t+1}$) and the number of incumbents n_{it}. Markets with high unobserved profits (u_i) exhibit a higher probability of entry, and a large number of incumbents in period $t-1$ (and vice versa for low u_i markets). By contrast, the effect of competition ($\theta > 0$) implies a negative relationship between the number of incumbents and the probability of entering.

This identification argument is consistent with results in Table 6, Panel C, where we report the coefficients reflecting the degree of serial correlation in the number of entrants within each market by estimating the following three regressions:

$$e_{it} = \alpha + \beta^{OLS} n_{it} + \tau_t + u_i + \epsilon_{it}, \qquad \text{(Pooled OLS)}$$

$$\Delta e_{it} = \alpha + \beta^{FD} \Delta n_{it} + \tau_t + \Delta\epsilon_{it}, \qquad \text{(First difference)}$$

$$e_{it} = \alpha + \beta^{OLS}_{xz} n_{it} + \tau_t + (x_i, z_i)'\lambda + (u_i - (x_i, z_i)'\lambda) + \epsilon_{it}, \quad \text{(Pooled OLS with controls)}$$

where τ_t is the period fixed effect, and (x_i, z_i) is the vector of profit and entry cost covariates. The coefficient estimate $\hat{\beta}^{OLS}$ in the pooled OLS regression reflects the effect of having one more incumbent on entry (i.e., the negative competition effect β^{OLS}) and the correlation between u_i and n_{it}. Both observed and unobserved time-invariant market heterogeneities are controlled in the first-difference regression, while only the observed heterogeneity is controlled in the pooled OLS regression with controls. The difference between the coefficient estimates from the first-difference regression and pooled OLS regression, $\hat{\beta}^{FD} - \hat{\beta}^{OLS}_{xz}$, is suggestive of fraction of time-invariant market heterogeneity $(u_i - (x_i, z_i)'\lambda)$ that is unobserved.

The positive estimate $\hat{\beta}^{OLS} = 0.089$ from our data (column (6)) suggests the existence of unobserved heterogeneity u_i. Moreover, estimating the same regression using the dataset generated from a greater competition effect ($\hat{\beta}^{OLS} = 0.037$ in column (2)) or from removing unobserved heterogeneity ($\hat{\beta}^{OLS} = 0.046$ in column (5)) yields estimates of smaller magnitude. Lastly, the moment $\hat{\beta}^{FD} - \hat{\beta}^{OLS}_{xz}$ helps distinguish smaller unobserved heterogeneity from a high competition effect. This moment in specifications (1)–(4) is closer to the data counterpart, while the moment in specification (5) is of smaller absolute magnitude, suggesting a lower importance of unobserved heterogeneity.

Lastly, we provide additional discussion on the identification of unobserved heterogeneity based on the evolution of the hazard function of the first entry $P(n_{i,t+1} > 0 | x_i, z_i, n_{it} = 0)$ in the spirit of the previous literature on unobserved heterogeneity (e.g., Reeling et al., 2020).

5.5.3. Identification of other parameters

After discussing the identification of θ and σ_u, we now address the identification of (β_x, γ_z) and (β_t, γ_t). As we will demonstrate in Section 6.2, the preemption motive only affects the timing of entry but not the steady-state market structure. Therefore, the standard identification argument in the static entry literature which examines the determinants of long-run market structure (Bresnahan and Reiss, 1991; Berry, 1992) can be applied here: given that $x_i\beta_x$ and $z_i\gamma_z$ monotonically increase steady-state monopolistic profit and entry cost, respectively, coefficients β_x and γ_z can be identified by comparing the steady-state number of firms across markets with observably different characteristics.

Moreover, the diffusion pattern of drive-in theaters over time is determined by the rate of technological progress (γ_t, β_t). The identification is facilitated by the exclusion restriction imposed by the model: the variables in z_i are not included in x_i. The variation in the diffusion pattern across markets with observably different characteristics is suggestive of the magnitudes of γ_t and β_t. While it is common in economic models that entry cost shifters are different from the ones in profits (i.e., demand and marginal cost shifters), we construct x_i and z_i based on the institutional background outlined in Section 2: population density and farm value affect the fixed cost, while other socio-demographic characteristics (such as motorization rate and the number of theaters) of the county affect the variable profit.

Admittedly, the assumption of common time trends in profit and entry cost is important for our identification argument outlined above. If the time trends β_t and γ_t are contingent upon market characteristics (x_i, z_i), the intuition behind identification may not hold. Nevertheless, we maintain that this assumption largely aligns with the institutional background detailed in Section 2. Specifically, the time-varying component in sunk entry costs is attributed to the installation of screening and sound systems, which were purchased from a national market of drive-in theater equipment. On the other hand, the time-varying component in static profit is driven by changes in marginal costs and/or consumer demand. While these factors may exhibit cross-market heterogeneity, we include market-level unobserved heterogeneity to mitigate this concern to some extent.

Table 6: Model fit

	(1)	(2)	(3)	(4)	(5)	(6)
	Model estimates					Data
	Baseline	Cournot	$\gamma_t = 0$	$\beta_t = 0$	$\sigma_u = 0$	
Panel A: average number of incumbents						
$\bar{n}_2$	0.085	0.085	0.099	0.104	0.096	0.015
$\bar{n}_3$	0.266	0.264	0.287	0.289	0.275	0.191
$\bar{n}_4$	0.578	0.575	0.614	0.572	0.568	0.767
$\bar{n}_5$	1.07	1.071	1.121	1.021	1.039	1.163
$\bar{n}_6$	1.807	1.811	1.807	1.779	1.807	1.776
Panel B: share of empty markets						
$P(n_{i2} = 0)$	0.934	0.934	0.919	0.919	0.924	0.986
$P(n_{i3} = 0)$	0.812	0.812	0.793	0.796	0.8	0.849
$P(n_{i4} = 0)$	0.637	0.635	0.616	0.639	0.627	0.538
$P(n_{i5} = 0)$	0.437	0.432	0.424	0.454	0.417	0.416
$P(n_{i6} = 0)$	0.266	0.262	0.274	0.263	0.211	0.264
Panel C: panel regressions						
$\hat{\beta}^{OLS}$	0.066	0.037	0.069	0.086	0.046	0.089
$\hat{\beta}^{FD} - \hat{\beta}^{OLS}_{xz}$	-0.845	-0.849	-0.844	-0.845	-0.81	-0.861

Notes: In columns (1)–(5) report moments calculated from 2,000 simulations of panel dataset using the estimated structural parameters in columns (1)–(5) in Table 5, respectively. Column (6) presents data moments.

6. Measuring the value of commitment

6.1. Commitment equilibrium

To quantify the magnitude of the preemption incentive, we consider a counter-factual environment in which firms could commit to an entry probability profile. In the first period, each potential entrant specifies and commits to a sequence of strategies $\sigma_i = \{\sigma_{it}\}_{t=1,\ldots,T}$ for the following periods. Potential entrants cannot condition their strategy on the number of incumbents because it is not observed when they specify their strategy. This eliminates the possibility of preemption, since firms cannot affect future market structure by deciding to enter early. Instead, each player forms a belief of its rivals' sequence strategy such that its strategy is a best response to the rivals' strategy. Under a strategy profit σ, the choice-specific value functions associated with entering and not entering market i are respectively defined as

$$\bar{v}^{\sigma}_{it}(a=1) = \sum_{n_{it}} Q^{\sigma}(n_{it})\bar{v}^{\sigma}_{it}(a=1|n_{it}), \tag{12}$$

$$\bar{v}^{\sigma}_{it}(a=0) = \sum_{n_{it}} Q^{\sigma}(n_{it})\bar{v}^{\sigma}_{it}(a=0|n_{it}), \tag{13}$$

where $Q^{\sigma}(n_{it})$ measures the probability of facing n_{it} incumbents perceived by a potential entrant in period t,[16] and $\bar{v}^{\sigma}_{it}(a=1|n_{it})$ and $\bar{v}^{\sigma}_{it}(a=0|n_{it})$ are given by equations (4) and (5), respectively. Similarly, the value functions used in calculating $\bar{v}^{\sigma}_{it}(a=1|n_{it})$ and $\bar{v}^{\sigma}_{it}(a=0|n_{it})$, $W^{\sigma}_{it}(n_{it})$ and $V^{\sigma}_{it}(n_{it})$, are calculated by the formula in equations (3) and (6) in which the entry probabilities in the MPE strategy profile $\sigma_{it}(n_{it})$ are replaced by those in the strategy profit under commitment σ_{it}.[17]

Using equations (12) and (13), we can define the best-response entry probability mapping with commitment as follows:

$$\Lambda^{c}_{it}(\sigma) = \frac{\exp(\tilde{v}^{\sigma}_{it}(1))}{\exp(\bar{v}^{\sigma}_{it}(0)) + \exp(\bar{v}^{\sigma}_{it}(1))}. \tag{14}$$

Definition 2 formally defines the equilibrium of this game.

[16] The distribution of incumbents perceived by potential entrants, $Q^{\sigma}(n_{it})$ is calculated by integrating over all possible sequences of entry from period 1 to t. We show in Appendix E that $Q^{\sigma}(n_{it})$ can be calculated recursively using the Law of Total Probability.

[17] That is, under commitment equilibrium the entry probability in any period is the same regardless of the possible payoff-relevant state n_{it}.

Definition 2. Strategy profile $\sigma^c = \{\sigma^c_{it}\}_{t=1,...,T}$ is a Bayesian-Nash equilibrium of the game with commitment for market i if σ^c is a fixed-point to the following best-response entry probability mapping for all periods:

$$\sigma^c_{it} = \Lambda^c_{it}(\sigma^c) = \frac{\exp(\tilde{v}^{\sigma^c}_{it}(a=1))}{\exp(\bar{v}^{\sigma^c}_{it}(a=0)) + \exp(\bar{v}^{\sigma^c}_{it}(a=1))}, \quad \forall t. \tag{15}$$

The algorithm used to solve for σ^c is described in the Appendix E.2.

6.2. Quantifying the effects of preemption

To quantify the effects of preemption, we first estimate the posterior expectation of the random coefficients:

$$\begin{aligned} \mathrm{E}(u_i|n_{i2},...,n_{i,T+1}) &= \int u f(u|n_{i2},...,n_{i,T+1}) du \\ &= \int \frac{u f(n_{i2},...,n_{i,T+1}|u)}{\int f(n_{i2},...,n_{i,T+1}|u) f(u) du} f(u) du \\ &= \int \frac{u f(n_{i2},...,n_{i,T+1}|u)}{\mathcal{L}_i(\mathbf{\Theta})} f(u) du, \end{aligned} \tag{16}$$

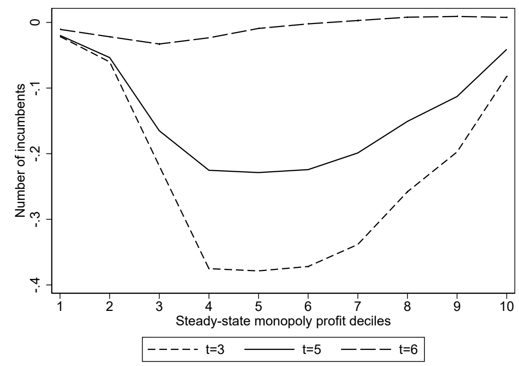
where $f(u)$ is the prior probability density function of $u_i \sim N(0, \sigma^2_u)$, $\mathcal{L}_i(\mathbf{\Theta})$ is the likelihood contribution from market i defined in equation (10), and $f(n_{i2},...,n_{i,T+1}|u)$ is the likelihood of observing the sequence of the numbers of incumbents $(n_{i2},...,n_{i,T+1})$ in market i conditional on the unobserved variable profit intercept u defined in equation (9).

Denote by $\bar{u}_i$ our estimated posterior expected market-specific random effect in equation (16).[18] Together with variable profit and entry cost covariates (x_i, z_i) and the estimated structural parameters $\hat{\mathbf{\Theta}} = (\hat{\theta}, \hat{\beta}_x, \hat{\beta}_t, \hat{\gamma}_z, \hat{\gamma}_t, \hat{\sigma}_u)$ reported in Column (1) of Table 5, we can solve the dynamic entry game for each market under the two equilibrium concepts. This gives us the equilibrium entry probability in each period and the associated value functions.

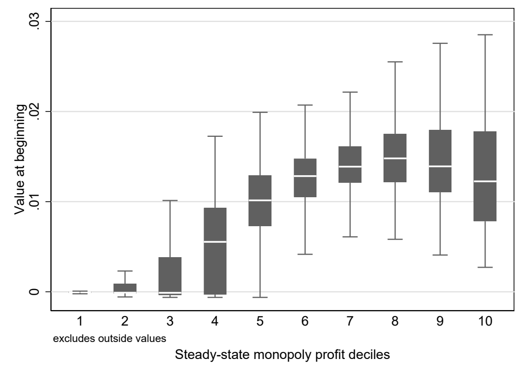
To illustrate the relationship between preemption, market structure, and the value of a potential entrant, we group markets in terms of profitability as measured by the profit of a monopolist in the steady state $\pi_{iT}(n_{i,T+1} = 1) = M_i \times \log(1 + \exp(x_i\hat{\beta}_x + \hat{\beta}_t \log T + \bar{u}_i)) \times 2^{-\hat{\theta}}$. We use monopoly profit instead of market size to illustrate the preemption motive because in the data markets differ both in terms of M and in terms of demographic characteristics (and

[18]The steps of estimating equaton (16) are given in Appendix E.3.

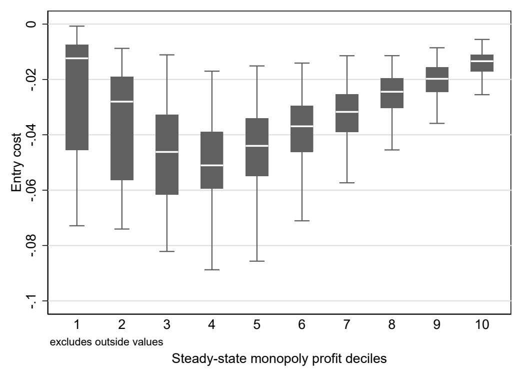
$\bar{u}_i$). The profit of a monopolist summarizes this heterogeneity in a single index.[19] Everything else being equal, markets with intermediate values of monopoly profits generate the largest benefit from preemption. In practice, markets also differ in their fixed costs, so there is not a one-to-one mapping between preemption incentives and profitability.



(a) Number of Incumbent



(b) V_{i1}



(c) Entry Cost

Figure 3: Differences in market structure and profitability with and without commitment

Notes: The figures plot the proportional change in their respective variables on the y-axis Y under commitment relative to the MPE benchmark: $(Y_i^{\text{Commit}} - Y_i^{\text{MPE}})/Y_i^{\text{MPE}}$ for the expected number of (end of period t) incumbents $\mathrm{E}(n_{i,t+1})$ in Figure 3(a), the ex ante value of a potential entrant in market i, V_{i1} in Figure 3(b), and the expected discounted sum of entry cost incurred $\mathrm{EC} = \sum_{t=1}^{T} \delta^t \mathrm{E}_{n_{i,t+1}}[(n_{i,t+1} - n_{it})F_{it}]$ in Figure 3(c). The horizontal axis consists of the ten deciles of markets ranked by monopoly profitability in the steady-state: $\pi_{i,6}(n=1)$. Figure 3(a) plots the median value within each bin. Figures 3(b) and 3(c) plot the distribution of each variable within each profitability group, after winsorizing the top and bottom percentiles.

Figure 3(a) illustrates the effect of preemption on market structure. We calculate the

[19] Note that the steady-state monopoly profit is the "perfect" measure of market size in the theoretical framework of Fang and Yang (2023) and exhibits a non-monotonic relationship with preemptive entry occurrence in theory. However, as monopolistic profit is not readily observed in the data, we use the fraction of warm weather, which monotonically raises monopolistic profit in the steady state, to proxy for market size in our reduced-form test, and control other market-level characteristics that affect profit. In the counterfactual section, we instead use the monopolistic profit implied by our estimates of the structural model—the "perfect" market size variable that incorporates all the variation in the data—and investigate its relationship with the cost and value of preemptive entry implied by our estimates of the structural model.

percentage change in the number of incumbents between the commitment equilibrium and MPE at each stage of the game. A negative value indicates a strong effect of entry preemption. The x-axis corresponds to each decile of the distribution of monopoly profits, with each curve representing the median value of the outcome variable within each decile.

The first thing to note is that the commitment and Markov equilibria generate roughly the same number of firms in the final stage (i.e., the median of $E\left(n_{i,T}^{\text{Commit}}\right) - E\left(n_{i,T}^{\text{MPE}}\right)$ at $T = 6$ is close to zero for all deciles). Instead, preemption affects the timing of entry, and this effect is the largest in the early stages of the game. For markets in the middle of the profitability distribution, the model predicts that the number of incumbents is 40% smaller with commitment in $t = 3$, compared to only 20% in $t = 5$. Moreover, at each stage, preemption leads to a non-monotonic relationship between the number of incumbents and profitability. In $t = 3$, expected differences in market structure are nearly zero for markets in the bottom and top deciles but rise to nearly 40% near the median of the profitability distribution.

To evaluate the effect of these market structure differences on profitability, we calculate the ex ante value of a potential entrant in market i, V_{i1}, and the expected discounted sum of entry costs incurred in each market, $\text{EC} = \sum_{t=1}^{T} \delta^t \text{E}_{n_{i,t+1}}[(n_{i,t+1} - n_{it})F_{it}]$. Differences in V_{i1} measure the change in firm value between the commitment equilibrium and the MPE. A positive value implies that firms are better-off with commitment. Similarly, a negative value for the difference in entry costs implies that markets exhibit larger fixed costs under MPE.

In the Markov-perfect equilibrium, firms enter early to deter future entry, which leads to incurring higher fixed costs. The effect on variable profits is more ambiguous. On the one hand, firms that successfully delay entry of rivals earn lower profits upon entry (due to $\beta_t > 0$), but earn higher profits afterwards due to deterrence. On the other hand, firms that delay their entry because of preemption earn positive profits for fewer periods and face more competition upon entry. The net effect captures the expected value of entry preemption on firm value.

We illustrate these two variables using a series of box plots. Before plotting the graphs, we winsorize the variables at the top and bottom percentiles. As before, we divide counties into groups based on their profitability. Figures 3(b) and 3(c) present the results. Overall, we find that firms are worse off under MPE ex-ante, suggesting that the ability to commit ex-ante increases firm values. Consistent with the discussion above, the net effect on value is small, since the ability to preempt entry generates winners and losers ex-post. The median increase in value is roughly 1% for markets in the 5th and 6th deciles.

From the point of view of firm value, the main effect of preemption appears to be the generation of wasteful investments, and as a result, we find large effects of commitment on the discounted value of entry costs. For medium-level profitability markets, the median change in the discounted sum of fixed costs is roughly 5%. Since preemption incentives are weak for low and high profitability markets, the distributions of differences go to zero for the top and bottom deciles.

6.3. Discussion on measuring preemption

Previous literature has adopted alternative methods to measure preemption. Our counterfactual commitment equilibrium is the same concept used in Chicu (2013). In contrast, Zheng (2016) measures preemption in a duopoly game by investigating whether a player ("Red firm" in the paper) has a profitable deviation in the presence of a one-shot disturbance. Specifically, in each period, she assumes new rival entrants are blocked from entering the market and investigates the player's entry decision at those locations actual rival entry. The discrepancy between the factual and the counterfactual strategy profiles suggests the degree to which a player's strategy is affected by its rivals' strategy.

7. Conclusion

In this paper, we empirically examine the prevalence of entry deterrence strategies and their impact on the dynamics of new industries using the inception and evolution of the U.S. drive-in theater market between 1945 and 1957. We argue that the strategic entry deterrence effect of entering early is only relevant in markets of intermediate size, leading to a non-monotonic relationship between market size and the probability of observing early entry. Our analysis based on a comprehensive cross-section of county markets in the U.S. provides robust empirical support for this prediction. Furthermore, our structural estimation of the parameters of a dynamic entry game allows us to quantify the strength of the preemption incentive. Our counterfactual analyses show that strategic motives can increase the number of early entrants by as much as 50 percent higher in middle-size markets but they do not have an effect on the overall number of entrants in the long run. However, the increase in early entry comes at the expense of higher overall entry costs incurred in a market.

Our findings shed light on the effect of strategic incentives on the industry structure of new technologies and markets. While early adoption driven by preemptive motives may appear to be beneficial for enhancing consumer access to new technologies, it may lead to monopoly power and market concentration before the market structure stabilizes. While the relative importance of the costs and benefits associated with entry preemption may vary depending on the context, we find that our results are robust across alternative parameterizations. Additionally, the non-monotonic relationship between a market size proxy and the occurrence of early entry is a useful tool for detecting preemptive entry behaviors, and aligns with a dynamic entry game wherein potential entrants can expedite their entry to preempt rival entry.

Our hope is that our work will be useful for future studies on how strategic behavior shapes widely accepted facts besides industry structure, such as the dynamics of price, quantity, capacity, and R&D investments. With suitable assumptions, the extension of our method to other contexts would be straightforward and relevant to entry regulation policy design and antitrust enforcement.

References

Victor Aguirregabiria and Pedro Mira. Sequential estimation of dynamic discrete games. *Econometrica*, 75(1):1–53, 2007.

C. Lanier Benkard. A dynamic analysis of the market for wide-bodied commercial aircraft. *The Review of Economic Studies*, 71(3):581–611, 2004.

B. Douglas Bernheim. Strategic deterrence of sequential entry into an industry. *The RAND Journal of Economics*, 15(1):1–11, 1984.

Steven T Berry. Estimation of a model of entry in the airline industry. *Econometrica: Journal of the Econometric Society*, pages 889–917, 1992.

Timothy F Bresnahan and Peter C Reiss. Entry and competition in concentrated markets. *Journal of political economy*, 99(5):977–1009, 1991.

Jeremy Bulow, John Geanakoplos, and Paul Klemperer. Holding idle capacity to deter entry. *The Economic Journal*, 95(377):178–182, 1985.

Joan Calzada and Tommaso M Valletti. Network competition and entry deterrence. *The Economic Journal*, 118(531):1223–1244, 2008.

Myong-Hun Chang. Flexible manufacturing, uncertain consumer tastes, and strategic entry deterrence. *The Journal of Industrial Economics*, pages 77–90, 1993.

Judith A. Chevalier. Do lbo supermarkets charge more? an empirical analysis of the effects of lbos on supermarket pricing. *Journal of Finance*, 50(4):1095–1112, 1995.

Mark Chicu. Dynamic investment and deterrence in the us cement industry. *Available at SSRN 2589580*, 2013.

Ronald W Cotterill and Lawrence E Haller. Barrier and queue effects: A study of leading us supermarket chain entry patterns. *The Journal of Industrial Economics*, pages 427–440, 1992.

Leemore S Dafny. Games hospitals play: Entry deterrence in hospital procedure markets. *Journal of Economics & Management Strategy*, 14(3):513–542, 2005.

Ulrich Doraszelski and Kenneth L Judd. Avoiding the curse of dimensionality in dynamic stochastic games. *Quantitative Economics*, 3(1):53–93, 2012.

Ulrich Doraszelski and Mark Satterthwaite. Computable markov-perfect industry dynamics. *The RAND Journal of Economics*, 41(2):215–243, 2010.

Jonathan T Elliott. Investment, emissions, and reliability in electricity markets. Technical report, Working Paper, 2022.

Glenn Ellison and Sara Fisher Ellison. Strategic entry deterrence and the behavior of pharmaceutical incumbents prior to patent expiration. *American Economic Journal: Microeconomics*, 3(1):1–36, 2011.

Limin Fang and Nathan Yang. Measuring preemptive entry in dynamic oligopoly games. *Working Paper*, 2021.

Limin Fang and Nathan Yang. Non-monotonicity in retail entry. *Available at SSRN 4061296*, 2023.

Drew Fudenberg and Jean Tirole. Preemption and rent equalization in the adoption of new technology. *The Review of Economic Studies*, 52(3):383–401, 1985.

Drew Fudenberg and Jean Tirole. Pricing a network good to deter entry. *Journal of Industrial Economics*, 48(4):373–390, 2003.

Ricard Gil. Does vertical integration decrease prices? evidence from the paramount antitrust case of 1948. *American Economic Journal: Economic Policy*, 7(2):162–191, 2015.

Ricard Gil and Myongjin Kim. Does competition increase quality? evidence from the us airline industry. *International Journal of Industrial Organization*, 77:102742, 2021.

Richard Gilbert and Xavier Vives. Entry deterrence and the free rider problem. *The Review of Economic Studies*, 53(1):71–83, 1986.

Avi Goldfarb and Mo Xiao. Who thinks about the competition? managerial ability and strategic entry in us local telephone markets *. *The American Economic Review*, 101(7): 3130–3161, 2011.

Austan Goolsbee Goolsbee and Chad Syverson Syverson. How do incumbents respond to the threat of entry? evidence from the major airlines. *Quarterly Journal of Economics*, 123(4): 1611–1633, 2008.

Paul Hünermund, Philipp Schmidt-Dengler, and Yuya Takahashi. Entry and shakeout in dynamic oligopoly. *Research Papers in Economics*, 2014.

Mitsuru Igami. Estimating the innovator's dilemma: Structural analysis of creative destruction in the hard disk drive industry, 1981–1998. *Journal of Political Economy*, 125(3): 798–847, 2017.

Mitsuru Igami and Nathan Yang. Unobserved heterogeneity in dynamic games: Cannibalization and preemptive entry of hamburger chains in canada. *Quantitative Economics*, 7(2): 483–521, 2016.

Marvin B. Lieberman. The learning curve, diffusion, and competitive strategy. *Strategic Management Journal*, 8(5):441–452, 1987.

Mario J Miranda and Paul L Fackler. *Applied computational economics and finance*. MIT press, 2004.

Martin Pesendorfer and Philipp Schmidt-Dengler. Asymptotic least squares estimators for dynamic games. *The Review of Economic Studies*, 75(3):901–928, 2008.

Carson Reeling, Valentin Verdier, and Frank Lupi. Valuing goods allocated via dynamic lottery. *Journal of the Association of Environmental and Resource Economists*, 7(4):721–749, 2020.

John Rust. Optimal replacement of gmc bus engines: An empirical model of harold zurcher. *Econometrica: Journal of the Econometric Society*, pages 999–1033, 1987.

Steven C Salop. Strategic entry deterrence. *The American Economic Review*, 69(2):335–338, 1979.

Richard Schmalensee. Advertising and entry deterrence: an exploratory model. *Journal of political Economy*, 91(4):636–653, 1983.

Philipp Schmidt-Dengler. The timing of new technology adoption: The case of mri. *Research Papers in Economics*, 2006.

Robert C. Seamans. Fighting city hall: Entry deterrence and technology upgrades in cable tv markets. *Management Science*, 58(3):461–475, 2012.

Yuya Takahashi. Estimating a war of attrition: The case of the us movie theater industry. *The American Economic Review*, 105(7):2204–2241, 2015.

Michael Waldman. Noncooperative entry deterrence, uncertainty, and the free rider problem. *The Review of Economic Studies*, 54(2):301–310, 1987.

Douglas S. West. Testing for market preemption using sequential location data: Reply. *The Bell Journal of Economics*, 12(1):129–143, 1981.

Chenyu Yang. Vertical structure and innovation: A study of the soc and smartphone industries. *The RAND Journal of Economics*, 51(3):739–785, 2020.

Fanyin Zheng. Spatial competition and preemptive entry in the discount retail industry. *Columbia Business School Research Paper*, (16-37), 2016.

Appendix A. Further details on institutional detail and data collection

A.1. History of the drive-in theater industry

The first ever known drive-in opened its doors to the public 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 this and similar experiments in Texas, it was Richard Hollingshead from Camden, New Jersey, who applied for a drive-in patent on August 6, 1932, and consequently given U.S. Patent 1909537 on May 16, 1933. Hollingshead's drive-in opened on Admiral Wilson Boulevard in Pennsauken, New Jersey, on June 6, 1933, offering 400 slots and a 40 by 50 feet (12 by 15 meter) screen. Although Hollingshead's drive-in only operated for three years, the business concept caught on in New Jersey and other states such as Pennsylvania, California, Massachusetts, Ohio, Rhode Island, Florida, Maine, Maryland, Michigan, New York, Texas and Virginia.

Fixed costs of entry steadily decreased over time between 1933 to their final demise in the 1970s. On the one hand, the patent earned by Richard Hollingshead in 1933 was invalidated in 1950 by the Delaware District Court (by the end of its life). On the other hand, better and cheaper technology steadily appeared over time in combination with constant learning-by-doing that industry practitioners easily transmitted across contemporaneous and future exhibitors. Thus, it is straightforward to conclude that entry costs decreased over time in the drive-in theatrical industry.

Finally, the increase in competition from home entertainment (namely, from color television and VCRs), the 1970s oil crisis and wide adoption of daylight saving time as well as the 1980s real estate interest rate hikes, attendance to movie theaters declined sharply and made it harder for drive-ins to operate profitably. By the late 1980s, less than two hundred drive-ins were in operation in the U.S. and Canada.

Appendix B. An illustrative theoretical framework

B.1. An entry game

Here, we provide a simple model of entry with preemption gains that builds on work of Ellison and Ellison (2011). Consider a game of entry with two potential entrants where time is discrete: $t = 1, 2, \ldots$. For simplicity, we assume that players can make an entry decision only in these 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. Players perfectly observe entry after players' decisions in period 1. In the second period, players who have not entered the market in the previous period decide whether to enter or not. From the third period on, players make no entry decisions and the period payoffs of the two players stay constant.[20]

For the sake of simplicity, we make assumptions on the per-period payoffs and entry costs that grant no stand-alone incentive to early entry. In particular, we assume zero payoffs in the first period and a second-period payoff that depends on the number of entrants and is common across players; the monopoly profit is M, while the duopoly profit D, with $D < M$. In addition, upon entry, a player incurs one-shot entry cost, ϕ_t. This entry cost ϕ_t is a common (across players) and deterministic entry cost that satisfies $\phi_1 = \phi$, and $\phi_2 = 0$. Players maximize their expected payoff, and we ignore discounting again for simplicity purposes.

In this setting, we solve for the mixed strategy equilibrium under complete information by specifying $\sigma_t(k)$ as the probability that a player enters in period t when k players have already entered. We consider three distinct cases: small markets ($D < M < 0$), intermediate size markets ($D < 0 < M$), and large markets ($0 < D < M$). The first case of a small market is easy to solve and uninteresting in that $\sigma_t = 0$ because there is no incentive to enter ever. The third case of large markets is also easy to solve and uninteresting in that $\sigma_2(0) = \sigma_2(1) = 1$. Anticipating the certain entry of competition in the second period, both firms will choose to avoid paying the entry cost ϕ and wait for the second period. Hence, we have $\sigma_1 = 0$ because there is no point in rushing into the market in $t = 1$.

The interesting case for our purpose of study is the case of intermediate size markets where $D < 0 < M$. In this scenario, in period $t = 2$, it is easy to show that $\sigma_2(1) = 0$ because no

[20] The assumption that players do not exit is supported by the observation that the frequency in our data that exits are observed is very low.

firm would join an incumbent in the second period if $D < 0$. Calculating $\sigma_2(0)$ is also simple in this context. In equilibrium, $\sigma_2(0)$ must be such that the expected payoff of entering in the second period equals the certain payoff of not entering such that,

$$\sigma_2(0)D + (1 - \sigma_2(0))M = 0,$$

and therefore,

$$\sigma_2(0) = M/(M - D).$$

Anticipating this result in $t = 1$, the equilibrium σ_1 must be such that the expected payoff of entering in the first period equals the expected payoff of holding off to the second period. This is equivalent to the following expression,

$$\sigma_1 D + (1 - \sigma_1)M - \phi = (1 - \sigma_1)[\sigma_2(0)D + (1 - \sigma_2(0))M],$$

and as a result,

$$\sigma_1 = (M - \phi)/(M - D).$$

It is then easy to show that σ_1 will be non-monotonic in market size. Let us show through an example the existence of non-monotonicity between the probability of entry and market size. Let us call x market size, and assume $M = x - 0.5, D = x/3 - 0.5$, and $\phi = 0.3$. See Figure B1 for an illustration of how the probability of entry in period 1 σ_1 is increasing from $x = 0.8$ to $x = 1.4$, and decreasing from $x = 1.4$ to $x = 1.5$. See also that the probability of entry in the first period $\sigma_1 = 0$ for smaller and larger markets as predicted.

B.2. Discussions on market size

The demand seasonality in the drive-in theater industry provides us with a clean setting where the fraction of warm days can be used as a proxy for market size. While the fraction of warm days is plausibly exogenous to the unobservable characteristics in drive-in theater market development, we provide additional evidence in this subsection that the fraction of warm days is stable over time and commonly known to potential entrants.

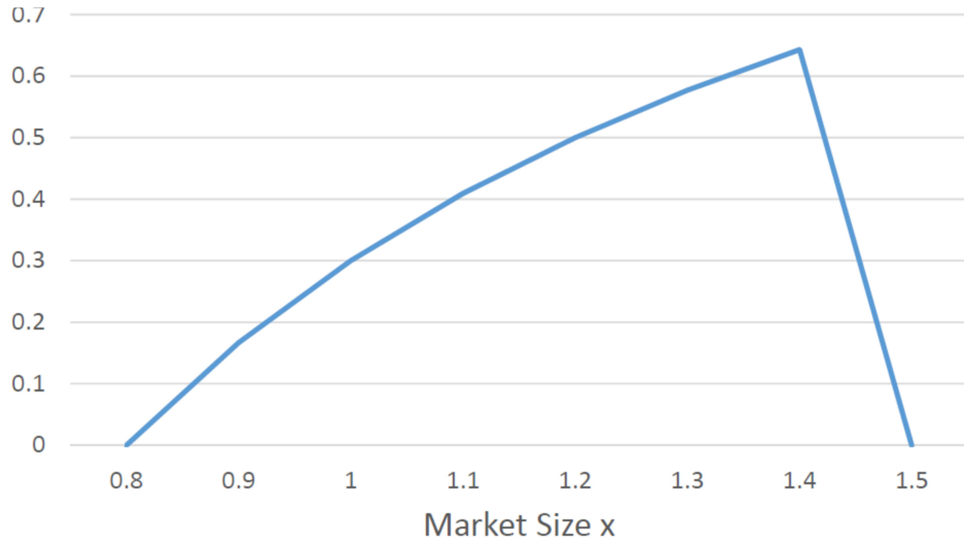


Figure B1: Early entry probability is non-monotonic in market size x (assume $M = x - 0.5$, $D = x/3 - 0.5$, $\phi = 0.3$)

B.2.1. The fraction of warm days is commonly known to potential entrants

Although the methods of information dissemination were not as advanced as today, numerous sources have documented that weather information was commonly known to the public in the 1940s United States. For example, the US Department of Commerce provided a review of the collection and dissemination of weather information provided by the National Weather Service in the 1940s.[21] The Weather Bureau collaborated with local telephone, television, and radio companies to enhance public access to weather forecasts in US cities through recorded forecasts accessible via phone, TV, and radio. Besides, weather information can also be accessed from the book *Old Farmer's Almanac*.

Our archival data suggests that there were 5,004 weather stations in 1950 with full coverage of the 50 states and the District of Columbia.

B.2.2. The fraction of warm days is stable over time

Our raw data consists of county-year level fraction of warm days M_{it}. In this part, we show that the total variation in fraction of warm days

$$\frac{1}{mT}\sum_i \sum_t (M_{it} - \bar{M})^2, \text{ with } \bar{M} = \frac{1}{mT}\sum_i \sum_t M_{it},$$

[21]Source: https://2010-2014.commerce.gov/blog/2012/04/02/back-1940s.html.

m the number of counties and T number of periods, is mostly cross-county variation

$$\frac{1}{m}\sum_i (M_{it} - \bar{M}_i)^2, \text{ with } \bar{M}_i = \frac{1}{T}\sum_t M_{it},$$

rather than within-county variation

$$\frac{1}{T}\sum_t (M_{it} - \bar{M}_i)^2.$$

Note that the total variation in fraction of warm days can be decomposed as

$$\begin{aligned}
&\frac{1}{mT}\sum_i\sum_t (M_{it} - \bar{M})^2 \\
=&\frac{1}{mT}\sum_i\sum_t (M_{it} - \bar{M}_i + \bar{M}_i - \bar{M})^2 \\
=&\frac{1}{mT}\sum_i\sum_t (M_{it} - \bar{M}_i)^2 + \frac{1}{mT}\sum_i\sum_t (\bar{M}_i - \bar{M})^2 \\
&+ \frac{2}{mT}\sum_i\sum_t (M_{it} - \bar{M}_i)(\bar{M}_i - \bar{M}) \\
=&\frac{1}{mT}\sum_i\sum_t (M_{it} - \bar{M}_i)^2 + \frac{1}{mT}\sum_i\sum_t (\bar{M}_i - \bar{M})^2 \qquad (17) \\
=&\frac{1}{m}\sum_i \frac{1}{T}\sum_t (M_{it} - \bar{M}_i)^2 + \frac{1}{m}\sum_i (\bar{M}_i - \bar{M})^2
\end{aligned}$$

That is, the total variation in M_{it} can be decomposed into average within-county variation $\frac{1}{m}\sum_i \frac{1}{T}\sum_t (M_{it} - \bar{M}_i)^2$ and cross-county variation $\frac{1}{m}\sum_i (\bar{M}_i - \bar{M})^2$.[22] In our sample, 89.74% variation in the total variation in M_{it} is cross counties, and 10.26% variation is within county. The square root of the within-county variation is 2% (or 7 warm days a year).

B.2.3. Market size does not correlate with population growth

While we control for population and other market characteristics in our reduced-form test for entry preemption, the non-monotonicity between market size (fraction of warm days) and early entry might not be entirely driven by entry preemption if markets exhibit differential prospects (e.g., population growth).

To address this concern, we first present evidence that population is very stable over time: the twelve-year cumulative population growth rate is 5%. When we conduct a variance decom-

[22] The equality in (17) holds because $\frac{2}{mT}\sum_i (M_{it} - \bar{M}_i)(\bar{M}_i - \bar{M}) = \frac{2}{mT}\sum_i (\bar{M}_i - \bar{M})\sum_t (M_{it} - \bar{M}_i) = \frac{2}{mT}\sum_i (\bar{M}_i - \bar{M}) \times 0 = 0$.

position exercise similar to the previous section, the results suggest that 98.2% of county-year level variation in population is across counties, and 1.8% is within-county.

Moreover, cross-county population differences are highly persistent and not correlated with the fraction of warm days. The correlation coefficient between population in 1945 and population growth is 0.683, while the correlation between the fraction of warm days and population growth is only -0.073. We further run two univariate regressions of population growth on the fraction of warm days and population in 1945. The results suggest that the fraction of warm days explains 0.51% variation in population growth and population in 1945 explains 46.64%.

Appendix C. Robustness Checks on the Reduced-Form Results

C.1. Alternative definitions of early entry

Table C1: Entry in different years

Panel A: Linear function

	Dependent variable: entry before							
	1949	1950	1951	1952	1953	1954	1955	1956
Fraction warm days	0.271	2.102**	1.757***	1.736***	3.298***	2.585***	3.219***	2.603**
	(0.756)	(0.837)	(0.647)	(0.585)	(0.536)	(0.717)	(0.801)	(1.169)
N	1,996	1,996	1,996	1,996	1,996	1,996	1,996	1,996
Psudo R^2	0.194	0.225	0.218	0.228	0.248	0.206	0.164	0.158

Panel B: Quadratic function

	Dependent variable: entry before							
	1949	1950	1951	1952	1953	1954	1955	1956
Fraction warm days	9.395**	12.729***	9.596***	6.422***	6.946***	6.775***	5.164**	-1.742
	(4.247)	(3.812)	(2.579)	(2.252)	(2.059)	(2.256)	(2.563)	(4.369)
(Fraction warm days)^2	-12.683**	-13.601***	-9.766***	-5.818**	-4.649*	-5.387**	-2.688	6.475
	(5.703)	(4.468)	(3.346)	(2.568)	(2.488)	(2.466)	(2.783)	(5.731)
N	1,996	1,996	1,996	1,996	1,996	1,996	1,996	1,996
Psudo R^2	0.201	0.238	0.226	0.231	0.250	0.209	0.165	0.160
M^*	0.37	0.468	0.491	0.552	0.747	0.629	0.961	0.134
	(0.041)	(0.032)	(0.059)	(0.078)	(0.196)	(0.103)	(0.54)	(0.227)
Sample	Max # drive-ins > 0							

Notes: This table reports coefficient estimates of the probit model where the dependent variables are dummy variables indicating drive-in entry before 1949, 1949, ..., 1956. All specifications control for the same covariates as in column (1) of Table 3. The estimating sample is a cross-section of 1,996 counties that had at least one drive-in theater between 1945 and 1957. Standard errors clustered at the state level are reported in parentheses.

C.2. Alternative market size measures

Table C2: Alternative market size measures

	Warm day definition: max daily temperature				
	$> 25°C$	$25°C - 30°C$	$25°C - 35°C$	$> 20°C$	$20°C - 35°C$
	(1)	(2)	(3)	(4)	(5)
Fraction warm days	10.015***	28.809***	12.729***	12.422***	15.608***
	(3.026)	(10.578)	(3.812)	(3.875)	(4.726)
(Fraction warm days)^2	-10.267***	-55.815**	-13.601***	-9.526***	-12.345***
	(3.365)	(21.706)	(4.468)	(3.130)	(3.931)
N	1,996	1,996	1,996	1,996	1,996
Psudo R^2	0.235	0.230	0.238	0.235	0.237
M^*	0.488 (0.032)	0.258 (0.013)	0.468 (0.032)	0.652 (0.03)	0.632 (0.028)
mean(M)	0.373	0.184	0.331	0.531	0.488
Sample	Max # drive-ins > 0				

Notes: This table reports coefficient estimates of the probit model where, in each coloumn (1)–(5), warm days used for constructing the market size proxy are defined as maximum daily temperature (1) $> 25°C$, (2) $25°C - 30°C$, (3) $25°C - 35°C$, (4) $> 25°C$, and (5) $25°C - 35°C$. The means of the fraction of warm days under different definitions are reported. All specifications control for the same covariates as in column (1) of Table 3. The estimating sample is a cross-section of 1,996 counties that had at least one drive-in theater between 1945 and 1957. Standard errors clustered at the state level are reported in parentheses.

C.3. Implementing non-monotonicity test by Ellison and Ellison (2011)

1. Initialization.

   (a) Denote $\boldsymbol{x} = (x, \boldsymbol{x}^{(2)})$ as the explanatory variable matrix, where x is the standardized variable used in the monotonicity test.

   (b) Create the weighting matrix W used in the EE statistic.

   - $w_{ii} = 0$ so only covariance between observations affect the statistic.
   - $w_{ij} = \left(1 - \frac{(x_i - x_j)^2}{h_w^2}\right) \times 1(|x_i - x_j| < h_w)$ for $i \neq j$.
   - Normalize w_{ij} so that column sum is 1.

   (c) Create the weighting matrx Ω used in partialling out $\boldsymbol{x}^{(2)}$ from x

   - $\omega_{ij} = \left(1 - \frac{(x_i - x_j)^2}{h_\omega^2}\right) \times 1(|x_i - x_j| < h_\omega)\ \forall i, j$.
   - Normalize w_{ij} so that column sum is 1.

(d) Partialling out $\boldsymbol{x}^{(2)}$ from x

$$\tilde{\boldsymbol{x}}^{(2)} = (I - \Omega)\boldsymbol{x}^{(2)}, \tilde{y} = (I - \Omega)y$$
$$\tilde{\beta} = (\tilde{\boldsymbol{x}}^{(2)\prime}\tilde{\boldsymbol{x}}^{(2)})^{-1}\tilde{\boldsymbol{x}}^{(2)\prime}\tilde{y}$$
$$\dot{\tilde{y}} = y - \tilde{\boldsymbol{x}}^{(2)}\tilde{\beta}$$

2. Calculate test statistic

$$T = \frac{\hat{\epsilon}' W \hat{\epsilon} + FSC}{\sqrt{2}\hat{\sigma}^2 \sum_{ij} \bar{w}_{ij}^2}$$

where $\hat{\epsilon} = y - isotone(\dot{\tilde{y}}, x)$, $\bar{W} = (W + W')/2$, $\hat{\sigma} = \sqrt{\frac{\hat{\epsilon}'\hat{\epsilon}}{n-1}}$, $\bar{w}_{ij}$ is the (i,j)th element of $\bar{W}$, and $FSC = \hat{\sigma}^2(x'x)^{-1}x'Wx$ is a finite sample correction. Save $y^{pred} = isotone(\dot{\tilde{y}}, x) + \boldsymbol{x}^{(2)}\beta$ for inference with bootstrap.

3. Inference with bootstrap samples

   - For continuous dependent variables, use $y^{new} = y^{pred} + \text{bootstrap}(\hat{\epsilon})$
   - For discrete dependent variables, use $y^{new} = y^{pred} > u$ where $u \sim N(0, \hat{\sigma}^2)$.

   Find the percentile of T in the distribution of statistics calculated from the bootstrap samples.

Table C3 reports the p-values associated with the Ellison and Ellison (2011) test for the three dependent variables in our reduced-form analysis, as shown in Tables 3 and 4: an indicator of entry before 1950, years before the first entry, and the count of incumbents in the terminal period. The results for entry before 1950 and terminal period incumbents are consistent with our main findings: the former increases non-monotonically with market size, while the latter shows a monotonic increase. However, the non-monotonicity in years until the first entry is not statistically significant.

Table C3: Ellison and Ellison (2011) test

	(h_w, h_ω)		
	(0.1,0.1)	(0.2,0.1)	(0.5,0.5)
Entry before 1950	0.004	0.004	0
Years until first entry	0.389	0.366	0.411
Terminal period incumbents	0.922	0.933	0.906

Appendix D. Additional discussion on identification of structural parameters

We estimate the following linear probability hazard model:

$$P(n_{i,t+1} > 0 | u_i, x_i, z_i, n_{it} = 0) = \tau_t + (x_i, z_i)'\lambda + u_i + \epsilon_{it}, \tag{18}$$

where $n_{i,t+1} > 0$ represents market i experiences its first entry in period t, u_i is unobserved heterogeneity, τ_t is the period fixed effect, and (x_i, z_i) is the vector of profit and entry cost covariates. We estimate the model using four datasets. The first dataset is the actual data used in structural estimation. The other three are dataset simulated from specifications (1), (2), and (5) in Table 5, which correspond to the baseline model, the model imposed the Cournot assumption, and the model without random coefficients, respectively.

Since we do not observe u_i in equation (18), by regressing $n_{i,t+1} > 00$ on period dummies τ_t and the vector $(x_i, z_i)'$, we can estimate,

$$P(n_{i,t+1} > 0 | x_i, z_i, n_{it} = 0) = \int_u P(n_{i,t+1} > 0 | u_i, x_i, z_i, n_{it} = 0) f(u_i | x_i, z_i, n_{it} = 0) du$$

When there is unobserved heterogeneity, $f(u_i | x_i, z_i, n_{it} = 0)$ tends to screw towards low u's as t increases. That is, the markets that stay empty in later periods are those with less favorable unobserved characteristics. However, if there is no unobserved heterogeneity, we do not have such a selection effect. We plot the estimated period fixed effects in Figure D2. Clearly from the figure, the full model and the model imposing the Cournot assumption, where unobserved heterogeneity is allowed, predict a flatter evolution of hazard compared to the one predicted by the model without unobserved heterogeneity. The fixed effects from the first two models are closer to the ones estimated from the data.

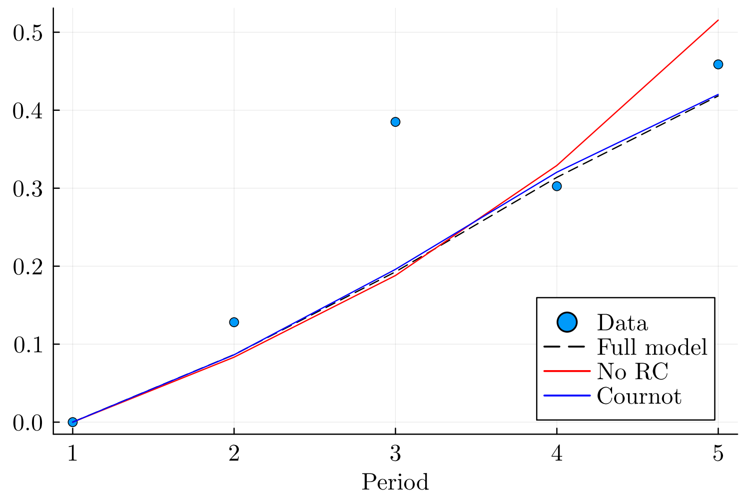


Figure D2: Period fixed effects in the estimated hazard model

Appendix E. Details on the Counterfactual Analysis

E.1. Distribution of the number of incumbents in the commitment equilibrium

In this section, we first derive the beliefs of a potential entrant on the number of incumbents at the beginning of period t, $Q^\sigma(n_{it})$. It is equal to $\Pr(n_{it} = n|n_{i,1} = 0)$, the probability of having n_{it} rivals entering before period t conditional on $n_{i,1} = 0$. Using the Law of Total Probability, we can calculate the transition probability $\Pr(n_{it}|n_{i,1} = 0)$ recursively,

$$\begin{aligned}
\Pr(n_{i,3}|n_{i,1}) &= \sum_{n_{i,2} \leq n_{i,3}} \Pr(n_{i,3}|n_{i,2}) \Pr(n_{i,2}|n_{i,1}), \\
&\dots \\
\Pr(n_{it}|n_{i,1}) &= \sum_{n_{i,t-1} \leq n_{it}} \Pr(n_{it}|n_{i,t-1}) \Pr(n_{i,t-1}|n_{i,1}), t \leq T
\end{aligned} \tag{19}$$

where $\Pr(n_{it}|n_{i,t-1}) = \mathrm{B}(N - 1 - n_{i,t-1}, n_{it} - n_{i,t-1}, \sigma^*_{i,t-1})$ is the probability of $n_{it} - n_{i,t-1}$ out of $N - 1 - n_{i,t-1}$ potential entrants entering in period $t - 1$ following their strategy $\sigma^*_{i,t-1}$.

E.2. Simulation algorithm

1. Use equilibrium in the baseline model $\sigma^0 = \sigma_{it}(n_{it})$ as an initial guess of commitment equilibrium, where n_{it} is data.
2. Given the initial guess, calculate the transition probabilities perceived by incumbents and entrants (equations (1) and (2)) and a potential entrant's belief of the number of incumbents at the beginning of each period $Q^\sigma(n_{it})$ (equation (19)).
3. Solve the model backward and get best response σ^*_{it}.
4. Repeat until σ^0 and σ^*_{it} converge.

E.3. Computing posterior expectation of the random effect

The integral in Equation (16) does not have an analytical expression. Therefore, we use Gaussian-Hermite quadrature to approximate the integral as described in footnote 15:

$$\int \frac{u f(\boldsymbol{n}_i|u)}{\mathcal{L}_i(\boldsymbol{\Theta})} f(u) du \approx \sum_{k=1}^{K} \frac{\omega_k}{\sqrt{\pi}} \frac{u_k f(\boldsymbol{n}_i|u_k)}{\mathcal{L}_i(\boldsymbol{\Theta})},$$

where u_k and ω_k are the nodes and weights of a Gaussian-Hermite quadrature, respectively, K is the number of quadrature notes, $\mathcal{L}_i(\boldsymbol{\Theta})$ is the likelihood contribution from market i defined in equation (10), and $f(\boldsymbol{n}_i|u_k)$ is the likelihood of observing entry sequence $\boldsymbol{n}_i$ in market i conditional on the unobservable variable profit intercept u_k defined in equation (9).