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

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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

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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 misallocation of resources by incentivizing firms to overinvest 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 behaviors 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. Therefore, 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 size of strategic investments 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 committing to invest, for instance, in excess capacity or advertising.

We show that this insight can hold true in a game of entry preemption. We first build on Ellison and Ellison (2011)'s insight to derive a testable hypothesis for detecting preemptive entry motive—there exists a non-monotonic relationship between market size and the probability of early entry (i.e., strategic investment). 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 in implementing this identification strategy is to find a relevant and exogenous shifter of market size that does not directly impact the cost of entering a new market. 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 further formalized in Fang and Yang (2023), suggesting 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, as well as the number of days a theater can operate. In our statistical test for preemptive entry, we use the percentage of days with warm weather in a county as a shifter of market size. The rationale behind this choice 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 colder regions are less profitable than those in warmer regions. Crucially, this variable is proportional to the potential revenue of a theater (through the number of potential active days) but does not directly impact willingness-to-pay or average operating costs, conditional on other market characteristics. We show that the data exhibit sufficient variation across markets in the fraction of warm days to identify the effect of market size on entry separately from other shifters of profitability.

We find robust empirical evidence supporting the preemption hypothesis as an explanation for the differences in entry patterns of drive-in theaters across U.S. counties between 1945 and 1957. In particular, we show that the probability of market entry before 1950 is a non-monotonic function of the share of warm days. This result is robust to alternative measures of preemption and market size shifters. We also find that the long-run number of theaters is strictly increasing in the share of warm days, consistent with our assumption that variable profits are monotonically increasing in the number of warm days.

We use this reduced-form evidence to motivate a dynamic stochastic game in which variable profits and entry costs improve over time in a predictable manner. This improvement may stem from improvements in product quality (e.g., availability of movies and sound/picture quality), or reduction in the sunk cost of acquiring equipment. This leads to a non-stationary Markov-perfect entry game, which 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) increased 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 start by calculating steady-state monopoly profit—the unobserved theoretical market size—for all markets in our sample. 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 on and contributes to the strategic investment literature. Our work is closest to Ellison and Ellison (2011)'s analysis of strategic R&D and advertising investments in the pharmaceutical industry, Schmidt-Dengler (2006)'s model of MRI technology adoption by hospitals, Takahashi (2015)'s analysis of the war of attrition between classic movie theaters, as well as Igami and Yang (2016)'s and Fang and Yang (2021)'s analyses of the entry of fast-food restaurants.[2] Related tests of strategic investments have been proposed in various contexts such as hospitals (Dafny, 2005), airlines (Goolsbee and Syverson, 2008; Gil and Kim, 2021); supermarkets (West, 1981; Cotterill and Haller, 1992), the pharmaceutical industry (Hünermund et al., 2014), and telecommunications (Goldfarb and Xiao, 2011; Seamans, 2012). Our paper contributes to this literature in a number of ways. First, we build on the insights of Ellison and Ellison (2011) on testing for strategic preemptive entry and improve their test by using a novel shifter of market size, namely, the share of warm weather days in a year. We use this exogenous variation to identify the parameters of a dynamic entry game and quantify entry preemption in a transparent way. Third, following Schmidt-Dengler (2006) and Igami (2017), our model and counterfactual 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 firm entry and exit. 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 counterfactual analysis. The existence and uniqueness of this MPE follow from the single-direction Markov transition property described in Besanko et al. (2010).

[2]In addition to the aforementioned papers, the earlier theoretical literature on strategic investments includes Salop (1979); Bernheim (1984); Chang (1993); Waldman (1987); Gilbert and Vives (1986).

The rest of the paper is organized as follows. In Section 2, we detail the birth and background of the U.S. drive-in theater industry, and describe the data for our empirical analysis. In Section 3, we summarize the theoretical basis for the non-monotonic relationship between market size and early entry from a simple two-period duopoly game. We also present reduced-form evidence of preemptive entry through the non-monotonicity of the relationship between market size and the 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 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 AM or FM radio on often high-fidelity stereos installed in 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 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 attendance 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

[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.

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

1947 to 1960, and county-level weather data from NOAA Satellite and Information Service.[5]

We drop large counties where markets are segmented and drive-in theaters in different segments do not directly compete against each other.[6] The resulting dataset is a balanced 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 degrees Celsius and below 35 degrees 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 counties 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,

[5] See Appendix A.2 for a thorough description of our data collection and sources.

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

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 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.

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

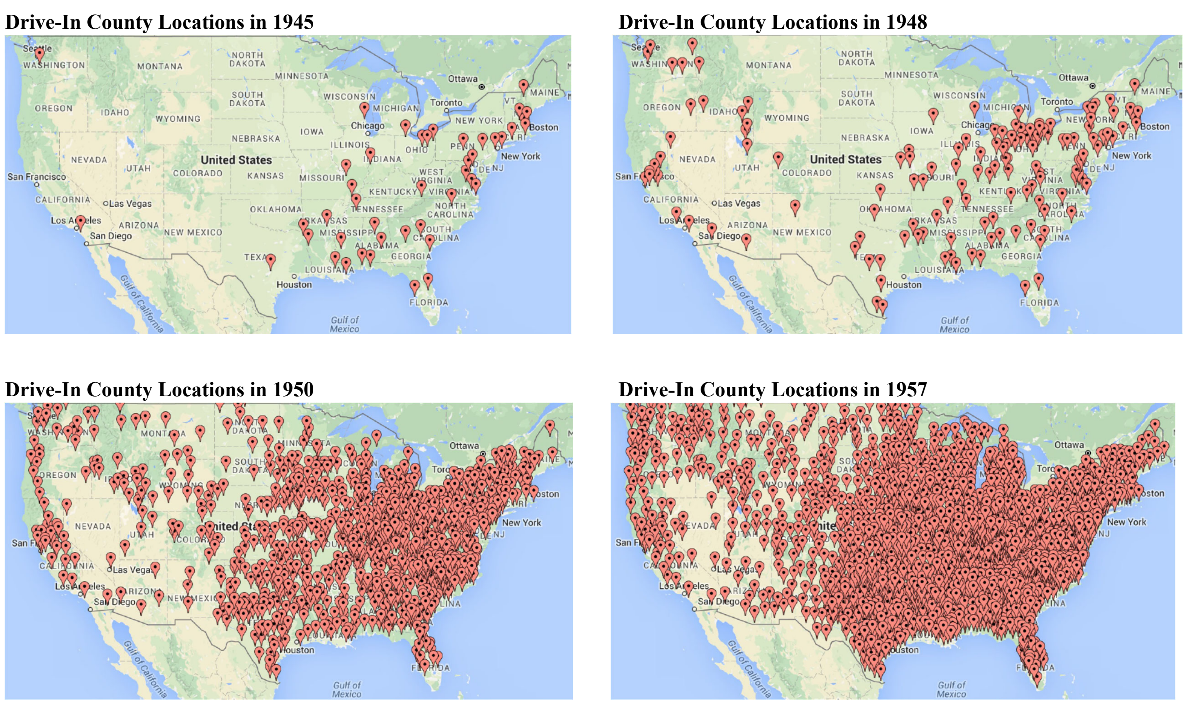


Figure 1: Diffusion graph of drive-in movie theaters at the county level for 1945, 1948, 1950 and 1957

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.

3. Reduced-Form Evidence

3.1. The relation between early entry and market size

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. We do so in Appendix B.1 by analyzing a simple two-period duopoly game in which firms benefit from entering late because of a reduction in the sunk entry cost. We extend that model into a multi-player, multi-period dynamic entry game in Section 4.

The two-period duopoly game in Appendix B.1 yields the following predictions. In a world with a decreasing fixed cost of entry, a firm would unambiguously benefit from delaying entry, all else equal, when its entry decision does not affect the other potential entrant's entry decisions. When this is not the case and firms are forward-looking, they should take into account the impact of their entry decisions in the first period on the future entry decision of the other player.

To understand the extent to which strategic entry incentives affect the timing of firm entry, it is important to categorize markets into small, intermediate and large sizes. The probability of any entry is zero in very small markets in which the monopoly and duopoly profits are smaller than the entry costs in both periods. When the market is large enough to accommodate two players in the second stage, firms cannot credibly commit to deterring entry by entering in the first period. However, in markets of intermediate size (i.e., where the second-period entry cost is smaller than the monopoly profit but greater than the duopoly profit), a firm benefits from strategically entering in period 1: when its rival does not enter in the first period and observes its entry before period 2, the rival will not enter in period

2 because the duopoly profit cannot cover the entry cost. Consequently, the probability of early entry is zero in small and large markets, but positive in intermediate markets. If firms behave strategically, this creates a non-monotonic relationship between market size and the probability of entering early. This is the entry preemption hypothesis that we test in the next section.

3.2. Market size

A key challenge in implementing the preemption test described in Section 3.1 is to find a relevant and exogenous shifter 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.[7] 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.

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, differences in temperature across counties offer a more direct and transparent proxy for market size. Because drive-in theaters operate outdoors, weather affects the number of days theaters can profitably operate. 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 days). Consequently, after accounting for other variables influencing profit and entry cost, it is reasonable to assume that per-period profits are monotonically increasing in 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

[7] 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.

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 aimed at capturing the non-monotonic relationship between the probability of early entry and 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 the average predicted probabilities. The non-monotonic relationship between market size and early entry is present in this figure.

A potential concern regarding the analysis in column (1) of Table 3 is that a linear and quadratic term of market size may not adequately control for highly non-linear effects of market size that could be correlated with early entry. To address this concern, the specification in column (2) of Table 3 divides our sample of counties into quintiles based on 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 the 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 probability relative to the fourth quintile but higher than

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 of 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.

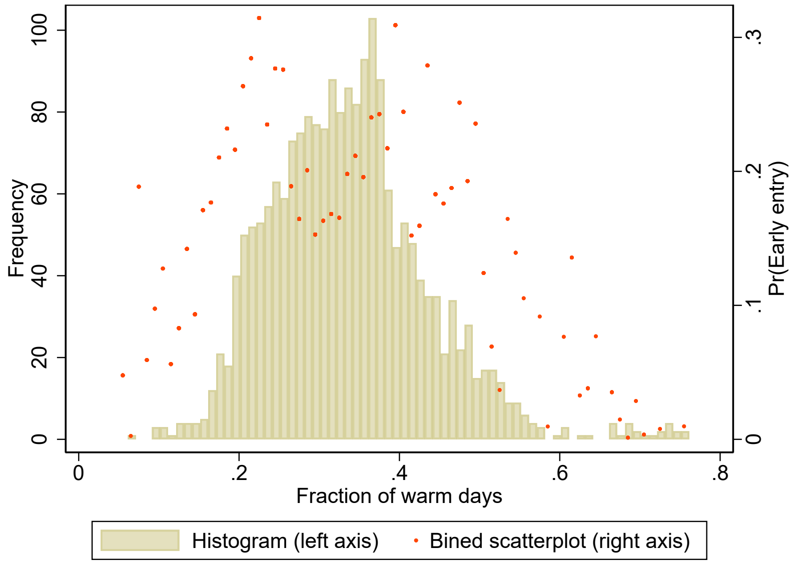


Figure 2: The relationship between early entry probability and the fraction of warm days

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.

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 of the fraction of warm days.[8] 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 a different dependent variable measuring the number of years observed before entry since 1945 (the first year of our data). Once this dependent variable is created, we employ the same strategy as in columns (1) and (2) and run OLS regressions that include the fraction of warm days, population and their squared variables, as well as other demographic controls 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 expectations. First, we include both population and population squared terms in the regressions, and the

[8]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 hypothesis testing.

coefficient estimates on both terms are significant across all specifications. However, the inflection points of the estimated quadratic functions of population 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 included to proxy for entry costs, are negatively correlated with early entry.

In a nutshell, we find evidence of non-monotonic relationships between market size (measured by the fraction of warm days) and (1) the probability of entry prior to 1950 and (2) 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 the fraction of warm days 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. An alternative interpretation of the results in Section 3.3 is that 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), which would invalidate our proxy for market size.

Table 4 examines the relationship between the terminal period number of drive-in theaters 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. 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 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. We therefore conclude that the fraction of warm days is a valid proxy for market size.

3.5. Robustness checks

We present the results of three robustness checks in Appendix C.

3.5.1. Alternative measures of early entry

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 dependent variables. In Panel A, only the fraction of warm days is included. In Panel B, we also 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.

3.5.2. Alternative definitions of warm days

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

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.

(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.

3.5.3. The statistical test in Ellison and Ellison (2011)

Finally, we conduct the statistical test in Ellison and Ellison (2011). 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 varies 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.

4. An empirical model of entry and technology diffusion

In this section, we generalize our analysis of preemptive entry by developing and estimating a finite-horizon entry game with incomplete information. 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, $t = 1, ..., \infty$, with entry happening in the first T periods (i.e., market structure is fixed after period T). 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 $n_{i,t+1}$;[9] (iii) non-entering potential entrants and entrants draw an independently and identically distributed type-1 extreme valued private 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 $\pi_{it}(n_{i,t+1})$;[10] (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 $t = T+1, ..., \infty$.

We now discuss three modeling features in our model setup. 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 without observing rivals' private payoff shocks and before payoff-relevant states are realized. Therefore, these decisions are made based on beliefs about how $n_{i,t+1}$ will evolve and the distribution of payoff shocks.

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

[10] 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 $\sigma_i = \{\sigma_{it}(n)\}_{n=0,\dots,N;t=2,\dots,T} \cup \{\sigma_{i1}(0)\}$ as the strategy profile of potential entrants in market i.[11] 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 $\sigma_{it}(n_{it})$:

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

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

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

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.

[11] $\sigma_{i1}(n)$ 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:

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

where δ 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 and γ is 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:

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

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 $\sigma^* = \{\sigma^*_{it}(n)\}_{n=1,\dots,N;t=2,\dots,T} \cup \{\sigma^*_{i,1}(0)\}$ 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 $\sigma^* = \{\sigma^*_{it}(n)\}_{n=1,\dots,N;t=2,\dots,T} \cup \{\sigma^*_{i,1}(0)\}$ is a fixed-point to the following best-response entry probability mapping:

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

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 $(W^{\sigma*}_{iT}(n_{iT}), V^{\sigma*}_{iT}(n_{iT}))$ 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, $W^{\sigma^*}_{i,T}(n_{iT})$ and the option value as a potential entrant, $V^{\sigma*}_{iT}(n_{iT})$. Using the same argument, there exists a unique Bayesian Nash equilibrium in period $T-1$, as well as in all periods $t < T-1$, and 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 Besanko et al. (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 analysis

5.1. Parameterization and functional form assumptions

5.1.1. 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.

5.1.2. Profits

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

$$\pi_{it}(n) = M_i \frac{\log(1+\exp(x_i\beta_x + \beta_t \log t + u_i))}{(1+n)^{\theta}}, \qquad (7)$$
$$u_i \overset{iid}{\sim} N(0, \sigma_u^2),$$

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,[12] 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.[13] 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.[14] The functional form of its denominator nests the Cournot profit function if $\theta = 2$.[15] Under this specification, differences in monopoly profits across market-period pairs are monotonically increasing in market size M_i and in the term $(x_i\beta_x + \beta_t \log t + u_i)$.

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

[13] A positive value for β_t is 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.

[14] 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.

[15] 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 $\pi^*_{it} = (a_{it} - c_{it})^2/(b(1+n_{i,t+1})^2)$.

5.1.3. 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.

5.2. Estimation and identification

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 5.1.1, 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., $N(0, \sigma^2_u)$)

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

The log-likelihood function of the sample is

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

We estimate the model parameters via maximum likelihood.[16] For computing the integral in equation (11), we use the Gauss-Hermite quadrature method.[17] The full sample utilized in our reduced-form analysis is used for estimating the structural model in this section. We set the discount factor δ to 0.9, and fix the number of potential entrants at 7, corresponding to the maximum number of firms observed in the dataset.

Although we do not have a formal identification proof, it is useful to consider the relationship between the model parameters and moments from the data. The model generates two types of endogenous outcomes that differ across markets: the long-run market structure (approximated by the number of firms in $T = 6$), and the speed of diffusion of theaters over time. The parameters β_x and γ_z are identified from the correlation between these two outcomes and county characteristics (x_i, z_i). The remaining parameters include the competition parameter θ, the speed of technological progress (γ_t, β_t), and the importance of unobserved heterogeneity σ_u.

Absent preemption incentives, the rate of technological progress (γ_t, β_t) is proportional to the speed of diffusion of theaters. For instance, the observed growth of theaters over time in large markets (where preemption incentives are muted) can be used to identify the technology parameters. Differences in this rate across markets with observed differences in profit and entry cost covariates (x_i, z_i) identify the relative importance of γ_t and 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. 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.

[16] 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.

[17] 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).

Standard identification arguments borrowed from the static entry literature, which examines the determinants of long-run market structure, can be used to identify the competition parameters. For instance, as in Bresnahan and Reiss (1991), one can use changes in the entry thresholds across different market structures to measure the extent to which variable profits decline more than proportionally with the number of firms. In our setting, the long-run number of firms in each market is unaffected by the preemption incentive, and can therefore be used to measure the correlation between the number of entrants and market size. Moreover, as in the dynamic entry game literature, the competition parameter is identified by measuring the effect of the number of incumbents on the probability of entry.

The importance of preemption, measured by the non-monotonic relationship between market size and the probability of observing an early entry, imposes additional restrictions on the competition and technological progress parameters. Conditional on (γ_t, β_t), the preemption incentive is stronger in markets with tougher competition (i.e., $\theta > 0$). Similarly, absent technological progress, firms cannot credibly deter entry by entering early.

Finally, the importance of unobserved heterogeneity is identified using the panel dimension of our data, particularly the degree of persistence of firms' entry decisions over time. For instance, unobserved heterogeneity lowers the correlation between the probability of entry and the duration since the last entry. This is because, conditional on observed characteristics, markets with longer spells of no entry are adversely selected (low u_i), and therefore are less likely to generate new entrants. However, with technological progress and conditional on u_i, the entry probability is an increasing function of the number of years since the last entry because the market becomes more profitable over time. As a result, failure to account for unobserved heterogeneity will lead to attenuation bias in the rate of technological progress.[18] Similarly, the fact that markets with more incumbents are *positively selected* biases upwards the correlation between the number of incumbents and the probability of entry, and therefore understates the effect of competition on profits.

An important assumption for the identification of the parameters is the existence of a common and predictable diffusion pattern for the new technology measured by β_t and γ_t. If the rate of technological progress varied across markets, the probability of early entry could not be used as a measure of preemptive entry, which would invalidate the previous identification

[18] In the extreme case of no technology progress, all firms will enter in the first period and early entry probability monotonically increases in market size.

argument. Nevertheless, we maintain that this assumption largely because it 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. This is mostly driven by the increasing availability of movies distributed nationwide that could be screened in drive-in theaters.

5.3. 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.

First, as the number of incumbents increases, variable profits decline at a lower rate than that in a Cournot model, but faster than under perfect competition or monopoly. Recall that under perfect competition and monopoly conduct models, the variable profits decline with n at a constant rate ($\theta = 1$). Specifications (3) and (4) lead to estimates of θ that are close to 1, highlighting the importance of accounting for two sources of technological progress when measuring the competitive conduct parameter. This is because the competitiveness of the market and technology jointly determine the predicted speed of diffusion of drive-in theaters by varying the preemption incentive.

The parameter estimates for β_x and γ_z are mostly consistent across specifications (at least qualitatively). Average daily variable profit increases with population size, median income, share of urban 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, we find that there is a rising time trend in variable profit ($\beta_t > 0$).

The parameter estimates in the entry cost function 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.

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 largest impact on the model fit. Setting $\sigma_u = 0$ cuts in half our estimate of the effect of technological progress on variable profits (as discussed above), and reduces slightly the competition parameter (although the difference is not statistically significant).

5.4. Goodness of fit

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. Column (6) summarizes the moments in the observed sample.

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 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.

Panels A and B summarize the predicted market structures in each period. Panel A reports the number of incumbents (note that all markets were empty before 1945, so $n_{i1} = 0$), and 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 the first two periods. Additionally, the model tends to under-predict the share of empty markets in early periods, with the unconstrained baseline model (column (1)) and

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: $N = 2,713$. 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).

the model with Cournot restrictions (column (2)) performing the best.

The importance of unobserved heterogeneity across markets σ_u and the competition parameter θ are related to the degree of serial correlation in the number of entrants within each market (conditional on time trends). In particular, because of selection, unobserved heterogeneity biases upward the correlation between entry ($e_{it} \equiv \Delta n_{i,t+1}$) and the number of incumbents n_{it}. We report the regression coefficient obtained by regressing the number of entrants in each period on the number of incumbents, controlling for county characteristics and period fixed-effects.[19] The point estimate obtained in the observed sample is -0.06. Estimating this regression using the dataset generated from the Cournot model or the specification without unobserved heterogeneity overstates this reduced-form parameter (-0.142 in column (2) and -0.17 in column (5)). The other three specifications are closest to the observed moment, consistent with the presence of unobserved heterogeneity. The fact that the Cournot model with unobserved heterogeneity (specification 2) leads to a more negative estimate of β^{OLS} is also consistent with our finding that variable profits decline with n at a slower rate than Cournot, but at a faster rate than perfect competition or monopoly.

Additionally, we replicate our reduced-form tests for entry preemption using data simulated from our model. In particular, we regress the probability of experiencing at least one entry before the end of periods $t = 1, 2$, and 3 on the fraction of warm days and its square, as well as the control variables used in all specifications presented in Table 3. Based on the coefficient estimates, we compute the market sizes that maximize the probability of entry before the end of periods $t = 1, 2, 3$, denoted by M_t^* in Panel D. Although all models underpredict the degree of preemption in early periods, as suggested by a larger M_1^* and M_2^* compared to their data counterparts, the baseline full model has the best fit for M_3^*. Importantly, the model without unobserved heterogeneity predicts the lowest level of preemption (highest inflection point), due to the attenuation effect of omitting unobserved heterogeneity on the estimated competition and technology progress.

[19] The regression model is: $e_{it} = \alpha + \beta^{OLS} n_{it} + \tau_t + (x_i, z_i)'\lambda + \epsilon_{it}$.

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						
$\hat{\beta}^{OLS}$	-0.115	-0.142	-0.102	-0.096	-0.17	-0.062
Panel D: preemption tests						
M_1^*	0.618	0.615	0.616	0.654	0.683	0.449
M_2^*	0.608	0.604	0.609	0.551	0.712	0.492
M_3^*	0.587	0.472	0.6	0.514	0.666	0.586

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. We simulate the equilibrium under commitment (Fudenberg and Tirole, 1985) while keeping the preference, competition, and technology parameters the same as in column (1) of Table 5.[20] 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,[21] 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}.[22]

Using equations (12) and (13), we can define the best-response entry probability mapping

[20] 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 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 with actual rival entry.

[21] 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.

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

with commitment as follows:

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

Definition 2 formally defines the equilibrium of this game.

Definition 2. A strategy profile $\sigma^c = \{\sigma_{it}^c\}_{t=1,...,T}$ 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:

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

The algorithm used to solve for σ^c is described in 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:

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

where $f(u)$ is the prior probability density function of $u_i \sim N(0, \sigma_u^2)$, $\mathcal{L}_i(\boldsymbol{\Theta})$ 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).[23] Together with variable profit and entry cost covariates (x_i, z_i) and the estimated structural parameters $\hat{\boldsymbol{\Theta}} = (\hat{\theta}, \hat{\beta}_x, \hat{\beta}_t, \hat{\gamma}_z, \hat{\gamma}_t, \hat{\sigma}_u)$ 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.

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

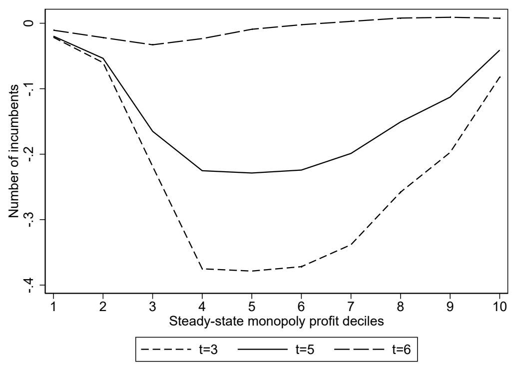
To illustrate the relationship between preemption, market structure, and the value of a potential entrant, we group markets in terms of profitability as measured by the profit of a monopolist in the steady state $\pi_{iT}(n_{i,T+1} = 1) = M_i \times \log(1+\exp(x_i\hat{\beta}_x + \hat{\beta}_t \log T + \bar{u}_i)) \times 2^{-\hat{\theta}}$. 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 $\bar{u}_i$). The profit of a monopolist summarizes this heterogeneity in a single index.[24] 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.

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

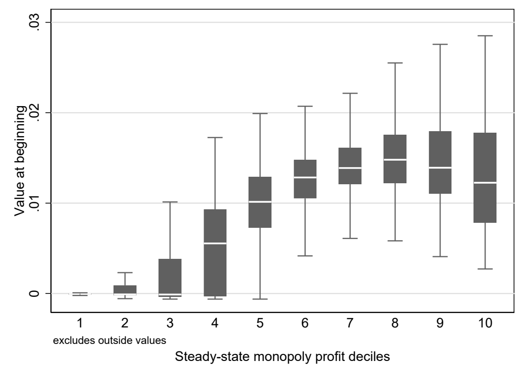
The first thing to note is that the commitment and Markov equilibria generate roughly the same number of firms in the final stage (i.e., the median of $E\left(n_{i,T}^{\text{Commit}}\right) - E\left(n_{i,T}^{\text{MPE}}\right)$ at $T = 6$ is close to zero for all deciles). Instead, preemption affects 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

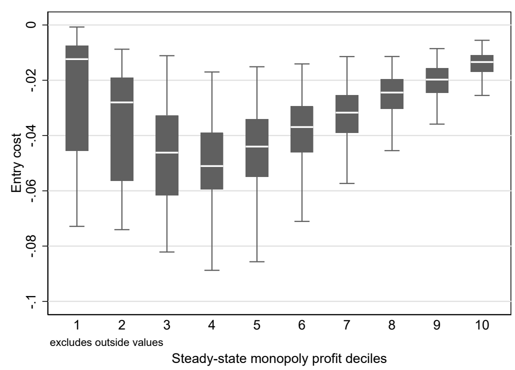
[24] As monopolistic profit is not readily observed in the data, we use the fraction of warm weather, which monotonically raises monopolistic profit in the steady state, to proxy for market size in our reduced-form test, and control other market-level characteristics that affect profit. In the counterfactual 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.



(a) Number of Incumbent



(b) V_{i1}



(c) Entry Cost

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

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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.

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%.

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.

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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 was consequently granted 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 and their final demise in the 1970s. On 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, due to 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, fewer than two hundred drive-ins were in operation in the U.S. and Canada.

A.2. Data collection

Our data are obtained from the yearly issues of the Movie Yearbook between 1945 and 1957. This Yearbook published an annual *de facto* census of theaters in the U.S. as well as a directory of U.S. theatrical firms with four or more theaters (Gil, 2015; Takahashi, 2015). Of particular relevance to our study, the Movie Yearbook also included a listing of all drive-in theaters

DRIVE-IN THEATRES
IN THE UNITED STATES

Figure A1: Data example: Movie yearbook

by city and state (refer to Figure A1). As most theaters from this period are no longer in existence or were located in cities or towns that are no longer independent municipalities, we supplemented the data with information from www.cinematreasures.org when necessary. This website provided us with approximate theater locations and allowed us to verify whether any changes in theater names occurred during the sample period. In addition to the Movie Yearbook data, we supplemented our dataset with county-level data from the "County and City Data Book" spanning from 1947 to 1960, as well as county-level weather data from NOAA Satellite and Information Service.

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 the work of Ellison and Ellison (2011). Consider a two-period game of entry with two potential entrants. 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. Entry is perfectly observed 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.

For simplicity, we make assumptions about 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 denoted as M, while the duopoly profit is denoted as D, where $D < M$. In addition, upon entry, a player incurs a one-shot entry cost, F_t. This entry cost F_t is common (across players) and deterministic, satisfying $F_1 = \phi$, and $F_2 = 0$. Players maximize their expected payoff, and we ignore discounting for simplicity.

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-sized markets ($D < 0 < M$), and large markets ($0 < D < M$).

B.1.1. Equilibrium in small and large markets

The first case of a small market is straightforward to solve and uninteresting in that $\sigma_t = 0$, indicating no incentive to enter in any period. 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, $\sigma_1 = 0$ because there is no point in rushing into the market in period $t = 1$.

B.1.2. Equilibrium in intermediate-sized markets

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

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

and therefore,

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

Anticipating this result in period $t = 1$, the equilibrium σ_1 must be such that the expected payoff of entering in the first period equals the expected payoff of holding off until the second period:

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

It is then straightforward to show that σ_1 will be non-monotonic in market size. Below we provide a numerical example. Let x denote market size such that $M = x - 0.5, D = x/3 - 0.5$, and $\phi = 0.3$. Figure B2 illustrates how σ_1 increases from $x = 0.8$ to $x = 1.4$, and decreases from $x = 1.4$ to $x = 1.5$.

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.

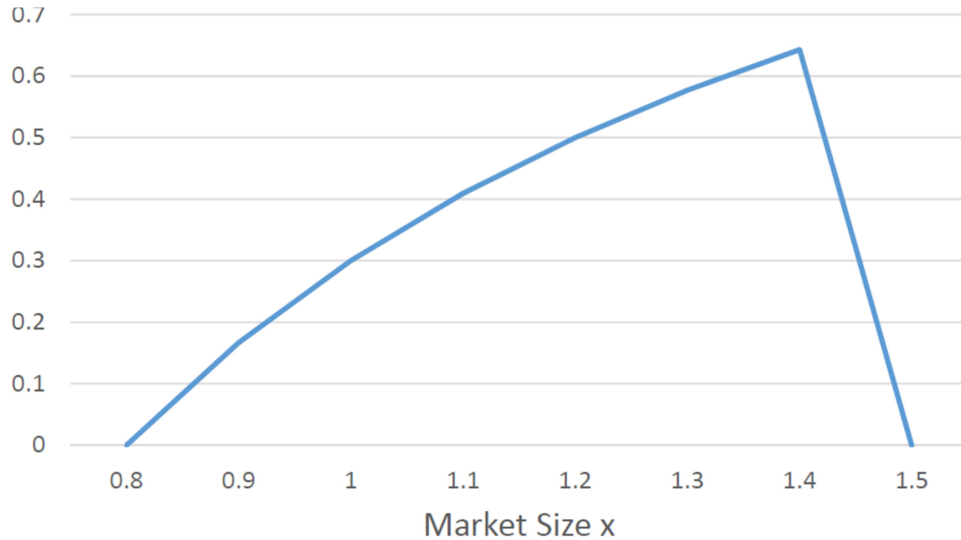

Figure B2: Early entry probability is non-monotonic in market size x

Note: This figure provides a numerical example of how the early entry probability varies with market size x in a two-period entry game with two players. We parameterize the monopoly profit as $M = x - 0.5$, the duopoly profit as $D = \frac{x}{3} - 0.5$, and the entry cost as $\phi = 0.3$.

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.[25] 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.

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

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

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

m the number of counties and T the 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 $\frac{1}{m}\sum_i(\bar{M}_i-\bar{M})^2$.[26] In our sample, 89.74% variation in the total variation in M_{it} is cross-county, and 10.26% variation is within-county. The square root of the within-county variation is 2% (or 7 warm days a year).

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

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 column (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 experiencing 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 datasets simulated from specifications (1), (2), and (5) in Table 5, which correspond to the baseline model, the model imposing the Cournot assumption, and the model without random coefficients, respectively.

Since we do not observe u_i in equation (18), by regressing $P(n_{i,t+1} > 0 | x_i, z_i, n_{it} = 0)$ 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 skew 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 D3. 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.

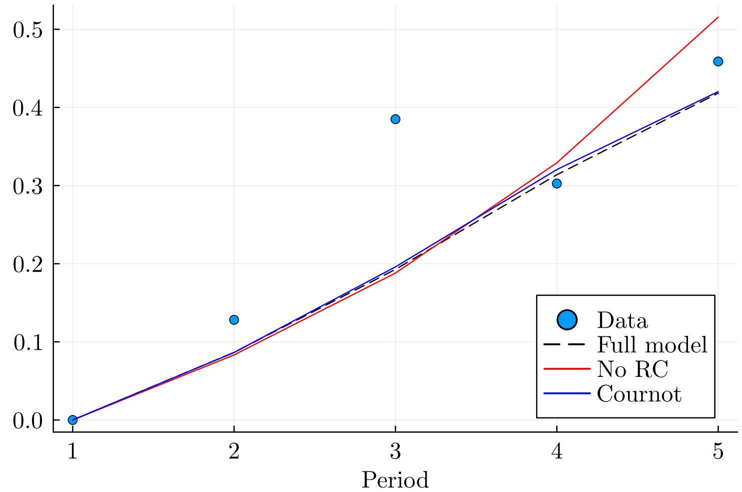

Figure D3: Period fixed effects in the estimated hazard model

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,

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

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 17:

$$
\int \frac{uf(n_{i2},...,n_{iT}|u)}{\mathcal{L}_i(\mathbf{\Theta})} f(u)du \approx \sum_{k=1}^{K} \frac{\omega_k}{\sqrt{\pi}} \frac{u_k f(n_{i2},...,n_{iT}|u_k)}{\mathcal{L}_i(\mathbf{\Theta})},
$$

where u_k and ω_k are the nodes and weights of a Gaussian-Hermite quadrature, respectively, K is the number of quadrature notes, $\mathcal{L}_i(\mathbf{\Theta})$ is the likelihood contribution from market i defined in equation (10), and $f(n_{i2}, ..., n_{iT}|u_k)$ is the likelihood of observing entry sequence $(n_{i2}, ..., n_{iT})$ in market i conditional on the unobservable variable profit intercept u_k defined in equation (9).