Sunk Cost and Entrant's Choice of Capacity

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Job Market Paper

January, 2023

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Abstract

This paper studies how sunk entry costs influence firm entry and the entrant's scale of operation in oligopolistic industries. When the scale is infeasible to adjust after entry, sunk costs shape market outcomes by altering both the number of competitors and the industry's scale distribution. Exploiting a land-use and construction regulatory reform, I empirically assess these channels in competition between South Korean cinema chains. I estimate a dynamic oligopoly model of chain-theater entry and exit. The model features that chains decide the scale of the new theater at entry and bear sunk costs varying with their scale choice. I find that (i) the chain's screen-level profits decline in both the same-chain and rival-chain screens; (ii) the sunk costs for larger-scale theaters decrease more than for smaller-scale theaters following the reform. A counterfactual analysis establishes that the industry has more larger-scale theaters by 27.8 percent than it would if sunk costs remained unchanged. Despite the expansion of larger-scale theaters, the industry suffers a 5.6 percent loss of net profits due to intensified competition and increased expenses on fixed operating costs. In contrast, a model without theater scale choice spuriously predicts a 27.3 percent add to the industry's net profits as it obscures the shift in the distribution toward a larger scale.

Keywords: *market structure, dynamic oligopoly, entry and exit, entry scale, sunk entry cost, movie industry*

JEL Codes: *C73, L13, L25, L51, L82*

* Department of Economics, Pennsylvania State University, jxh938@psu.edu. I gratefully acknowledge the guidance and support of my dissertation committee: Mark Roberts, Paul Grieco, and Joris Pinkse. I also benefited from invaluable conversations and suggestions from Gaurab Aryal, Marc Henry, Vijay Krishna, Jangwoo Lee, Conor Ryan, Karl Schurter, and Kensuke Suzuki. I thank seminar participants at Pennsylvania State University, the 17th EGSC at Washington University in St. Louis, and National Taiwan University for their comments. All errors are, of course, my own.

I Introduction

In many industries, entrants exhibit considerable heterogeneity in the scale of operation. Nevertheless, a vast literature on discrete entry typically focuses on the decision to enter a market, and the entrant's choice over the scale has not received much empirical attention. This decision is particularly relevant for industries where an adjustment in market supply primarily occurs on the firm-size (scale) margin.[1] Despite the prevalence and importance of these industries, empirical studies on the determinants of the entrant's scale choice and their economic implications remain scarce.

Although various factors affect the optimal scale of operation, the cost structure can be a central determinant of entry scale (Collard-Wexler (2013)).[2] The entry cost structure is of greater importance when post-entry scale adjustments incur prohibitively high costs. In this environment, entrants make the entry and scale decision simultaneously. Accordingly, entry barriers shape both the number of firms and the industry's scale distribution. Understanding how sunk entry costs vary with entry scale and the change in the entry costs following entry promotion measures can thus be essential when analyzing such regulatory actions implemented by regulators.[3]

This paper empirically studies the entrant's scale decision when sunk entry costs vary with entry scale, with a particular focus on the economic implications of a regulatory action which can alter the entry environment. As an empirical case study, I consider the South Korean cinema industry from 2010 to 2018, where three big chains (CGV, Lotte Cinema, and Megabox) operated multiple movie theaters with various scales (i.e., screens) across local markets.[4]

The South Korean cinema industry is an attractive laboratory to study the entrant's

[1]Examples include hotels (the number of rooms), nursing homes (the number of patient beds), and dialysis centers (the number of dialysis stations).

[2]Specifically, Collard-Wexler (2013) finds that the initial size of a concrete plant is primarily dictated by the magnitude of entry and size-adjustment costs, while market demand fluctuations have a limited role in shaping the initial size of a plant.

[3]Regulators can lower an entry barrier through direct subsidies or by removing an artificial entry barrier. For instance, Chinese governments subsidize the entry of Chinese shipyards. The Federal government encourages health practitioners to enter the under-provisioned area through Health Professional Shortage Area (HPSA) program. Michael Bloomberg reformed the zoning regulations in New York City, which could act as a removal of an artificial entry barrier.

[4]Three big chains are the major players in the industry. The three chains made up 97.6% and 96.9% of theaters and screens in 2014 (KOFIC (2014)): CGV (43.8% and 45.2% of theaters and screens), Lotte Cinema (34.7% and 33.3%), and Megabox (21.5% and 21.5%).

scale choice and the scale-dependent entry costs. The chains choose the screens of a new theater opening upon entry, given that post-entry screen adjustments are generally impractical. Sunk costs for opening a theater vary with the number of equipped screens. For instance, opening a theater with more screens is more costly due to increased expenses on capacity investments and a multi-story commercial building. Lastly, the 2014 land-use and construction regulatory reform measures and the subsequent Amendments to the Building Act provide me with a regulatory regime shift that my dataset spans. This structural break allows me to explore how sunk entry costs for different scale theaters have changed after the shift, which can serve as a data-driven guidepost for a policy counterfactual simulation.

This paper begins by demonstrating that the screen distribution has shifted toward mid-plex theaters, defined as theaters with 5-7 screens, following the regulatory regime shift. This descriptive analysis indicates that the industry, on average, has 0.2 more (9% more) mid-plex theaters per market than the other scales, namely mini-plex (4 or less screens) and mega-plex (8 or more screens), after the regime shift. The pattern is not explained by both observed market-level demand shifters as well as chain-market fixed effects, suggesting that the regulatory action might favor mid-plex theaters with a significant entry-cost advantage. Such a structural break at the point of the regime shift thus illustrates the need to allow the sunk entry costs to vary with the theater opening's screen counts.

To measure the scale-dependent sunk entry costs and their changes in response to the regulartory regime shift, I develop a dynamic model of chain-store (theater) entry and discrete entry scale choices (screen counts). A key feature of the model is that it allows sunk entry costs to vary with different scaled theaters. Specifically, the model features a sunk entry cost schedule over each screen count, thereby admitting both economies and diseconomies of entry scale. Given that only three chains exist, and demand for moviegoing is geographically localized, the chains' theater scale choices are specified as a dynamic game independently played across geographic markets. Every period, oligopolistic chains choose the scale of a theater opening, taking the market configuration as a given state and weigh the benefit of the scale of opening against the sunk entry costs. The chains' actions subsequently alter the market configuration in the next period.

I estimate the model using a geography-level panel of 131 municipalities from 2010H1 to 2018H2. The data tracks both the stock of different-scaled movie theaters as well as the flows of different-scaled movie theater openings and closures. In the estimation, I address a high-dimensional state space by using the two-step conditional choice probability (CCP) approach (Hotz, Miller, Sanders, and Smith (1994) and Bajari, Benkard, and Levin (2007)).[5] I start by estimating the chain's equilibrium theater-scale choice policy function. I then find the vector of model parameters at which alternative policy functions are not profitable deviations from the estimated policy function. Following the literature convention (Rust and Rothwell (1995), Ryan (2012), and Kalouptsidi (2018)), I assume the immediate transition from an old equilibrium to a new equilibrium and recover the early- and late-regime sunk entry cost parameters separately.

The central finding from the estimation is that sunk entry costs decrease following the regulatory regime shift, and the resulting reductions in the sunk costs are higher for larger-scaled movie theaters, suggesting that the regulatory action appealed to a larger-scale theater opening. In particular, the reductions in total sunk costs for mini-, mid-, and mega-plex theaters are estimated to be 14%, 32%, and 25%, respectively. However, in terms of the average *per-screen* entry costs, the reduction for mid-plex theaters is more substantial, shifting the minimum efficient entry scale from the mega-plex scale to the mid-plex scale. These disproportionate changes in *per-screen* entry costs reflect a salient increase in the number of mid-plex theaters.

Using the estimated model, I quantify the economic implications of such a disproportionate reduction in the average *per-screen* sunk entry costs via a counterfactual simulation. In particular, I simulate counterfactual chain's response as if the sunk entry cost structure remained unchanged. I compare the resulting market outcomes, such as screen distribution and industry net profit, with those implied by the baseline parameter estimates.

The counterfactual simulation reveals that the disproportionate reduction in the average per-screen entry costs, in conjunction with strategic interactions among the chains, decreases industry profit by 5.60%. In particular, more theaters and screens engender tougher post-entry competitions, substantially decreasing per-screen variable profits. Thus, the industry's total variable profit merely remains unchanged (-0.26%) despite

[5] In practice, despite the coarsening of data, the total number of possible states is 1,259,712. Thus, a full-solution approach like the Nested Fixed Point (NFXP) is impractical in my setting.

more screens in the industry. In addition, the chains are willing to open larger-scale theaters as the sunk cost schedule creates a greater cost advantage for mid-plex theaters. Hence, the industry has more screens than it would have if there was no change in the sunk cost reduction, increasing the industry's expenditures on the fixed costs of operating screens by 14.59% and thereby leading to a loss of industry operating profit. Furthermore, as the chains open movie theaters more frequently in response to lower sunk costs, the realized payments on the sunk entry costs decrease only by 12.53%, which is not sufficient to compensate for the loss of the industry's operating profits. Thus, altogethers engender a loss of industry net profit.

The primary contribution of this paper is illustrating that a standard model without the chain's theater scale decision fails to uncover the resulting increases in industry's expenditures on fixed operating costs. A restricted model that only focuses on changes in the number of movie theaters in a market cannot capture the shift of the industry's screen distribution toward mid-plex scales. This miss leads to under-predictions over the industry's resource uses on fixed operating costs and over-predictions over the savings from the reduced sunk entry costs. Thus, the predicted loss of the industry's operating profit is small to be compensated by savings from the reduced sunk entry costs. Accordingly, the restricted model predicts that the reduced sunk entry costs can increase industry net profits by 27.3%.

Although this paper offers a case study of the South Korean theater industry, the finding that a simple extension of the strategy space leads to a qualitatively different counterfactual can be relevant for other applied settings. In particular, an applied setting where the entrant's scale choice is important, and the regulators are interested in promoting entry would be relevant. U.S. examples may include the special nursing home industry (the number of patient beds as a unit of capacity).

I organize the rest of this paper as follows: The next subsection reviews the related studies and discusses the main departure of this paper. Section II describes the South Korean movie theater chain industry, data, and the observed patterns. Section III presents the empirical industry model, and Section IV gives the estimation strategy. Section V reports the empirical results of the model and model fit. The counterfactual simulations are constructed in Section VI. Section VII concludes.

I.I Related Literature

My analysis belongs to ample empirical literature on discrete entry. A vast majority of works in this literature study the effect of market size, competition, entry barriers, and other factors on firm profitability with a focus on the extensive margin decision of whether or not to enter. Static analyses include Bresnahan and Reiss (1990), Bresnahan and Reiss (1991), Berry (1992), Mazzeo (2002), Seim (2006), Grieco (2014); dynamic analyses include Pakes, Ostrovsky, and Berry (2007), Aguirregabiria and Mira (2007), Pesendorfer and Schmidt-Dengler (2008). [6] One of a few exceptions is Aradillas-López and Gandhi (2016) who illustrate the identification of a static entry game with an ordered action space. I contribute to the literature by extending the spirit of Aradillas-López and Gandhi (2016) toward a dynamic game and by empirically studying the importance of the intensive margin. Specifically, I embed an ordered action space to a standard dynamic game of chain-store entry where the store entry decision is binary (Igami and Yang (2016), Arcidiacono, Bayer, Blevins, and Ellickson (2016), and Aguirregabiria and Magesan (2020)); empirically analyze how the industry's scale distribution shapes the long-run market outcomes. Since the model's features are standard in the literature and also noticeable in many modern industries, the economic channel identified by this paper can apply to other empirical settings.

By leveraging the de-regulatory reform to conduct an empirical analysis, this paper contributes to the literature on the impacts of regulatory actions on market structure and outcomes in a dynamic setting. Notable examples include the entry cost effects of the environmental regulation and land-use regulation ((Ryan (2012)) and Suzuki (2013), respectively), and entry subsidy in health service sectors (Dunne, Klimek, Roberts, and Xu (2013)). This paper complements this literature in two dimensions. First, I analyze the policy impact using a model of entry and the entrant's choice of capacity. Thus, the quantified policy impact depends not on the number of competitors but also on the scale distribution, which could affect the qualitative implication of a policy of interest. Second, while previous studies tend to focus on the welfare costs of regulations, this paper illustrates the implicit costs of deregulations in a concentrated industry, which stems from strategic interactions.

[6] For further studies, refer to Berry and Reiss (2007) who provide a substantial review on static entry games. For a review on dynamic games, see Aguirregabiria, Collard-Wexler, and Ryan (2021).

Additionally, the particular application of this paper relates to the literature on the cinema industry. Specifically, empirical studies of the entry and exit of movie theaters thematically share the same focus as this paper. Empirical studies in this literature focus on each of several determinants of market structure in the movie theater industry: cannibalization between the same-chain movie theaters (Davis (2006a)), spatial competition (Davis (2006b)), strategic exits of mono-screen movie theaters (Takahashi (2015)), and preemptive entry and entry costs of drive-in movie theaters (Gil, Houde, Sun, and Takahashi (2021)). I build on this literature and develop a dynamic oligopoly model unifying these determinants. This unifying framework allows researchers to analyze each role, enriching the understanding of the turnover patterns of movie theaters in the industry.

II Industry and Data

II.I South Korean Movie Theater Industry

Chains: This paper focuses on the South Korean movie theater industry from 2010 to 2018. The industry is characterized as an archetypical chain-store industry. The South Korean movie theater industry was fragmented, consisting of many independent theaters with one or two screens. According to KOFIC 2000, 83% of movie theaters had one or two screens. Even in Seoul, the capital city of South Korea, 72% of movie theaters had less than three screens.[7]

This industry structure has changed since 1998. CGV, the first multiplex theater chain in the industry, opened its first multiplex theater in Seoul in 1998. The other two chain firms, Lotte Cinema and Megabox, were established in 1999, and they opened their first multiplex theaters in Daejeon and Seoul, respectively. After the advent of chain theaters, many small-sized independent theaters were quickly replaced by chain-affiliated multiplex theaters. By 2010, the chain-affiliated multiplex theaters made up 76%, 92%, and 97% of theaters, screens, and total box office revenue (KOFIC (2010)). These shares have slowly increased over the sample period, and the chain-affiliated multiplex theaters made up 79%, 95%, and 99% of theaters, screens, and box office revenues in 2017 (KOFIC (2017)). The industry today has the characteristic of oligopolistic industry where

[7] https://www.kofic.or.kr/kofic/business/board/selectBoardDetail.do?boardNumber=2 (downloaded in July 2022).

a few firms have multiple outlets across geographic markets.

Local Oligopoly: Although the three chains own most of the industry's theaters and screens, individual movie theaters tend to compete locally because of localized demand (Davis (2006b)). Similar to the pattern in the U.S. data, I found that most municipalities are served by fewer than five movie theaters, perhaps reflecting the unwillingness of consumers to travel to further theaters (Table 1).

A notable feature of the South Korean cinema industry is that the ticket prices do not reflect the local market competitiveness similar to the U.S. industry. Figure 1 shows that the average ticket price does not vary substantially with the number of existing movie theaters within a local market (municipality).

Theater Size: The size (scale) of a theater in my data is measured by the number of screens. The theater scale can be affected by entry barriers. The number of screens for a new theater is determined upon entry, and it is fixed over the life cycle of the theater in most cases. This irreversible nature implies that the chain's theater size decision can carry much weight in entry decisions. Hence, entry barriers are of great importance in shaping the chain's theater size decision. Second, screen counts of a theater opening and closure are important strategic decisions for the chains. All the movie theaters provide arguably homogenous services, and ticket prices are nearly fixed, thus a movie theater differentiates itself from its local competitors by serving a variety of movies or screening a popular movie in multiple timeslots (Rao and Hartmann (2015), Orhun, Venkataraman, and Chintagunta (2016), and Yang, Anderson, and Gordon (2021)). In this light, a theater with more screens may thus easily outperforms smaller competitors (i.e., steal a greater portion of businesses from smaller competitors). These features motivate a dynamic entry model that accommodates both the decision to open a theater and the choices over screen counts.

Sunk Costs and Regulatory Regime Shift: Opening a movie theater is an expensive investment in terms of accounting costs. According to a business report in 2018, the nominal capital expenditure (CAPex) for opening a 6-screen movie theater is 4.2 billion

Korean Won (approximately \$3.9 million).[8] In addition to monetary sunk opening costs, the chains should comply with strict guidelines about a cinema auditorium when opening a movie theater.[9] The guidelines mainly regulate a projection angle and the minimum distance between an installed screen and the first row of auditorium seating. To meet these requirements, the height of the ceiling in auditoriums tends to be higher than the counterparts of typical service businesses. Given that each auditorium accommodates one screen, the chains should build either a wider or multi-story commercial building when opening a theater with multiple auditoriums (i.e., a multiplex theater).

One complicating but attractive feature of the South Korean theater industry is that the industry underwent a series of nationwide land use regulatory reform measures and follow-up Amendments. In February and September 2014, to revitalize the urbanization of disadvantaged areas, the Ministry of Land, Infrastructure and Transport announced two nationwide plans, *The Introduction of Areas under Minimal Siting Restrictions* and *Urban and Building Regulatory Reform Measures*, which primarily include plans to place more lenient administrative processes and abolish duplicated restrictions on building location and construction. After the announcement of the measures, there were subsequent changes in enforcement decrees and rules, primarily focusing on abolishing or revising stringent zoning and construction regulations. Among the follow-up regulatory actions, two primary regulatory actions could affect sunk entry costs of opening a movie theater: the Amendment to Enforcement Decree of the Building Act in November 2014 and the Amendment to the Building Act in May 2015.

The Ministry of Land, Infrastructure and Transport passed The Amendment to the Enforcement Decree of the Building Act. Since this Amendment, the Ministry has reduced the required paper works by 60% and expedited auditing processes. This regulatory action may have provided the chain firms with room to open a movie theater much easier as the chains do not have to undergo stringent administrative processes, thereby paying less bureaucratic costs associated with opening a new movie theater.

The Amendment to the Building Act in May 2015, which abolished Article 60.3, may have also changed the entry environment of the industry substantially. Article 60.3 was a setback regulation from road width. It limited the shape of buildings near roads in an

[8] https://www.thebell.co.kr/free/content/ArticleView.asp?key=20170714010002794000l669&lcode=00 (lastly accessed in September 2021).

[9] Article 8, Enforcement Rule Of The Promotion Of The Motion Pictures And Video Products Act.

urban area, thereby limiting the maximum height of a building. In the 2014 *Urban and Building Regulatory Reform Measures*, the Ministry of Land and Transportation appointed the abolishment of Article 60.3 as it had long been regarded as a primary source of inefficient building construction as well as an impediment to construction investment in urban areas. The National Assembly immediately passed the Amendment in May 2015 to boost construction investments and thus stimulate the economy. This Amendment led to considerable changes in urban structure, particularly increasing the height of commercial properties in an urban area substantially (Kim, Yoo, and Cho (2017) and Kim, Cho, and Yoo (2020)).

In this light, the regulatory regime shift may provide the theater chains with room for opening a theater with more screens much easier, suggesting that it might alter the theater opening and screen count choice behaviors. To reflect the regime shift, the empirical analysis of this paper will estimate the sunk entry cost schedule over different-sized theaters separately for periods before and after it. The analysis then will use the estimated changes in the entry cost schedule as a guidepost for a counterfactual exercise.

II.II Data

The data consist of a panel of geographic markets in South Korea observed from 2010 to 2018. I combine a series of publicly available administrative datasets to construct a panel dataset that contains the stock of chain-affiliated theaters owned and the flows of entry-exit of chain-affiliated theaters in each market.

Theater-level data. The initial data source is web-crawled from an online database archive (Korea Box Office Information System; KOBIS) administered by the Korean Film Council (KOFIC, www.kobis.or.kr). The KOFIC dataset contains the universe of movie theaters in South Korea between 2010 and 2018 at the level of the theater-screen-day-schedule. KOFIC also provides key theaters' characteristics: theater names, chain affiliations (CGV, Lotte Cinema, Megabox), opening/closure dates, number of screens (size), and geo-coordinates.

Selection of theaters. I first select a set of theaters by applying the following filters:

(1) eliminating art houses that exhibited only independent or art movies and (2) eliminating movie theaters that located at the airport, apartment complexes, and the theme park. The first filter reflects the fact that art houses and commercial theaters exhibit a completely different set of movies: the commercial theaters tend to focus on showing blockbusters. So, the art houses could not be close substitutes for commercial theaters. The second filter is adopted because multiplex theaters in those locations target specific customer groups (airport or theme park visitors and residents of an apartment complex). After applying this filter, there are 543 commercial theaters that had operated during the sample period. Using the information on chain affiliation, I eliminate 99 fringe theaters that are not affiliated to the three chains. This selection reflects two institutional details of the South Korean exhibition industry. First, 50 fringe theaters were in municipalities where the chain-affiliated theaters have never entered, so they cannot be substitutes for chain-affiliated theaters. Second, though the remaining 49 fringe theaters were located close to chain-affiliated theaters, they did not have significant box office revenue.[10]. Thus, fringe theaters in the same geographic market do not appear to affect the profitability of chain-affiliated theaters and do not have significant impacts on the three chains' entry and exit decisions.

Market definition and characteristics. I consider a municipality (*si-gun-gu* in Korean) as a single local market because additional data, such as population and GDP per capita, are available at the municipality-level. The municipality-level population is from the Korean Ministry of the Interior and Safety, which records at the monthly frequency. For each municipality, I keep the population in January and July of each year to make this information coincide with the KOFIC dataset. The municipality-level real GDP is from the Korean Statistical Information Service, which records at the annual frequency. Municipalities' real GDPs are expressed in 2011 Korean Wons, and I divide them by the municipality's population in July to construct the municipality's real GDP per capita. To capture the market-time level variations in fixed operating and sunk entry costs, I collect the municipality-level property values of commercial area from the Ministry of Land and Transportation. The property values of commercial area are also expressed in 2011 Korean Wons.

[10]Chain-affiliated movie theaters make up 97% of total box office revenue (KOFIC (2014))

Among 272 municipalities, I focus on 131 municipalities where 444 chain-affiliated theaters had ever located. Table 2 reports the summary statistics on the characteristics of these 131 municipalities. Over the sample periods, the average population has remained unchanged. Although the average has not changed, the 95 percentile has declined by 26%. This time series pattern reflects the decline in Korean population. Meanwhile, GDP per capita and commercial property values have increased by 16% and 3.3%, respectively. At a point in time, there are substantial differences in market characteristics across the municipalities. For instance, in 2010 H1, commercial property values range from 1.77 million Korean Wons to 7.33 million Korean Wons, suggesting the possibility that the costs of operating a theater and opening a new theater are heterogeneous across the local markets.

Measures of theater entry and exit. Following Dunne et al. (2013), a new theater opening (entry) at period t is a theater that first appears in a market in period $t+1$. Similarly, a theater closure (exit) at period t is a theater that disappears in a market in period $t+1$. Opening a new multiplex theater is an expensive investment that takes time to build, so I use the data at the half-yearly frequency rather than the daily frequency.

II.III Descriptive Patterns

This section documents empirical patterns of market structure and turnover in the South Korean theater industry. I first explore the relationships between the patterns of turnover and the market characteristics. I then focus on the changes in theater opening and size decisions after the regulatory regime shift.

Table 3 divides market-time observations into four quartiles based on population and reports the corresponding market structure and turnover. I observe that markets with larger population have more theaters and more theater openings. As population increases, the number of active theaters grows from 1.17 to 3.56, and the average number of theater openings increases from 0.08 to 0.149. The fourth column indicates that the size of theater openings increases with the market size. For instance, in the smallest group of markets, the average number of screens per entry is 5.86, whereas the counterpart of the largest group of the markets is 6.84.

Table 4 reports the distributions of theater openings and closures before and after the regulatory regime shift. The distributions uncover two points. First, theater entry increases from 3.14% (=0.99 + 1.68 + 0.48) to 4.25% (= 1.09 + 2.76 + 0.40) following the regime shift, indicating the presence of high entry barriers associated with opening a new theater or low expected profit after entry. Second, the industry has experienced higher turnover rates in the later sample periods, which partly suggests a reduction in entry barriers. A lower entry barrier encourages entry of theaters, and it also increases the threat of potential entering theaters. Thus, a lower entry barrier increases both entry and exit rates.

Table 4 also decomposes the theater openings and closures into three categories based on their scale (screens). The numbers inform the importance of accommodating decisions to choose the theater opening's size when evaluating the economic implications of lowering sunk entry costs. For instance, in the later regime, chains tended to open more middle-scale movie theaters (1.68% to 2.76%), while they tended to close small-scale movie theaters (0.03% to 0.15%). The observation in Table 4 is not an artifact of the coarsening of theater scales. Figure 2 displays the histogram of annualized entry rates by screen counts under the early- and late-regime periods. Following the regulatory regime shift, the entry rates for theaters with less than four screens have decreased, while those for theaters with more than five screens have mildly increased, echoing the patterns in Table 4. An analysis with extensive margin entry-exit decisions alone, which is common in the literature, fails to capture the change in scale choice behaviors and could spuriously measure the overall market-structure effect of sunk entry costs.

The disproportionate changes in the size of theater openings translate into the expansion of mid-plex theaters. Table 5 reports the half-annual transition rates for market structure, which is described by the number of mini-, mid-, and mega-plex theaters for periods before and after the reforms. There is considerable persistence in the market structure under both regimes, reflecting the huge sunk costs of opening a new theater. In addition, the transition rates for periods after the reforms are less persistent, in line with the way that sunk entry costs have declined following the reform. Lastly, in line with Table 4, the transition rates toward the market structure with a mid-plex theater (i.e., $n_{mid} = 1+$), have increased following the reforms, suggesting the disproportionate impacts of the reforms on the industry's sunk cost structure.

Figure 3 maps the mini-, mid-, and mega-plex theaters in Seoul metropolitan area (*Seoul, Incheon, and Gyeonggi-do*) in 2012 and 2018 which are three years before and after the regulatory regime shift. Two key patterns stand out from the comparison of the two maps. First, there are more movie theaters in Seoul metropolitan area as more dot points appear on the map in 2018 than in 2012. This finding indicates that the reforms may act to reduce sunk entry costs. Second and more importantly, most of the new dot points are colored green, suggesting that most of the new theater openings were mid-plex theaters. This pattern echoes the finding in Table 4 that the chains open more mid-plex theaters after the reforms.[11]

The empirical pattern suggests that the chains began to open midplex theaters more than others after the reforms, thereby changing the entire market structure (i.e., the number of theaters and screen distribution). However, it is not sufficient to gauge the magnitude of a reduction in sunk entry costs and the resulting economic implication, such as changes in industry net profits. In addition, the pattern is insufficient to study the importance of accommodating the chain's choice of the size of a theater opening. To do so, I construct a model to identify how the cost structures changed in the later regime and examine the impact of the changes in the entry cost structures on industry net profits.

Before introducing a structural model, it is noteworthy to illustrate data features that the model should accommodate. First, population and the size of a theater opening are positively correlated. The industry model of this paper will capture this feature by specifying *per-screen* profit as a function of population, so a theater with more screens can be more profitable in markets with larger population than less populated markets. Second, the turnover rates have increased after the reforms, suggesting a reduction in the sunk entry costs. To map this pattern to the entry cost estimates, the model will be a dynamic model which sharply distinguishes between the sunk entry costs and fixed operating costs. Lastly, chains adjust their size decisions following the regulatory regime shift, partly indicating that the reforms decrease the sunk entry costs but disproportionately affect the entry costs for midplex theaters. In that light, the model will admit a flexible specification of an entry cost schedule over the size of a theater opening.

[11] A potential concern is that the shift of the screen distribution is driven by demand shocks or aggregate time trends. Appendix A addresses these by conducting a variant of an event study.

III Industry Model

This section introduces a dynamic game of chain-store entry and exit in which three oligopolistic chains decide whether to open a new theater and choose how many screens to be constructed for the theater opening. The model will allow me to recover the chains' operating profits at the screen level and the magnitude of a reduction in the sunk entry cost due to land-use and construction regulatory regime shift. These quantities will be subsequently employed in counterfactual simulations to quantify the welfare implications of the reduced sunk entry costs.

I model the chain's theater entry decision and screen counts choice as a dynamic game which is independently played in local markets. The modeling choice reflects two considerations. First, the data spans the regulatory regime shift, which might have changed the sunk entry cost. So, to appropriately address this, a structural model has to be a dynamic model which sharply distinguishes between sunk and fixed costs. Second, a model without strategic interaction among chains is not a relevant structure to study the welfare implication of lower entry barriers. In the presence of strategic interaction, a new theater can steal its competitors' business rather than expanding the market, opening the possibility that industry operating profits decrease. Thus, the economic implication of lower entry barriers becomes an empirically open question, while a single-agent model assumes away this channel and automatically produces the benefit of lower entry barriers.

III.I Environment

Setting: Time is discrete with an infinite horizon, $t = 1, 2, 3, \ldots, \infty$, corresponding to six months. In the model, three cinema chains $i = 1, 2, 3$ operate multiple theaters in independent local markets $m = 1, 2, 3, \ldots, M$. Theaters differ by the number of equipped screens $j = 1, 2, \ldots, J$. In local market m, chain i decides to open or close a theater, and if it does, it chooses the number of screens of the theater opening or closure, d_{imt}. Once the number of screens is determined, the chains cannot expand or shrink it in later periods. The chains discount the future by a common discount factor β.

Market state: The industry model describes the competition among the three theater chains within a local market (municipality), which is fully characterized by market states.

The market states include the chain's state variables, market demand/cost shifters, and market-specific profitability. The chain's state is a vector of the chain's theaters across the number of equipped screens. The market demand and cost shifters include population, GDP per capita, and commercial property value per meter square. The state vector in market m and period t is defined by

$$s_{mt} = (\underbrace{\{n^1_{1mt}, \ldots, n^J_{imt}\}}_{\equiv \vec{n}_{1mt}}, \{n^1_{2mt}, \ldots, n^J_{2mt}\}, \{n^1_{3mt}, \ldots, n^J_{3mt}\}, z_{1mt}, z_{2mt}, R_{mt}, \mu_m), \quad (1)$$

where n^j_{imt} represents the number of chain i's j-screen theaters in market m and period t. z_{1mt}, z_{2mt}, and R_{mt} represent population, GDP per capita, and commercial property value per meter square in market m and period t. μ_m is the market-specific profitability, which is observed by chains, but not by researchers.

The number of j-screen theaters operated by chain i depends on the chain's expansion-subtraction decision d_{imt}. Accordingly,

$$n^{(j)}_{imt+1} = n^{(j)}_{imt} + \mathbb{I}_{\{d_{imt}=j\}} - \mathbb{I}_{\{d_{imt}=-j\}} \qquad \text{for } j = 1, 2, \ldots, J\ . \quad (2)$$

This transition equation indicates that the three chains can expand or shrink the total number of own screens in a market only through opening or closing a movie theater. This restriction is indeed in line with the fact that downsizing an existing theater is extremely rare in the data. In addition, due to this restriction, a set of possible actions will depend on the chain's state $\vec{n}_{imt}$.

While the chain's state evolves deterministically, other exogenous market state variables (population, GDP per capita, and commercial property values) evolve according to a μ_m-specific first-order Markov process

$$F_{\mu_m}(z_{1mt+1}, z_{2mt+1}, R_{mt+1} | z_{1mt}, z_{2mt}, R_{mt}). \quad (3)$$

Timeline:

1. At the beginning of period t, each chain observes the market state s_{mt} and makes operating profits based on the current payoff-relevant market state.

2. The chains simultaneously draw a privately observed cost shock ε_{imt} from the pub-

licly known distribution G. The chains form beliefs over their rival's decisions and then decide to open or close a movie theater and choose the number of screens for the opening or closure d_{imt}.

3. The chains pay the sunk entry costs if they decide to open a theater (i.e., $d_{imt} > 0$).

4. The dynamic decisions $(d_{1mt}, d_{2mt}, d_{3mt})$ are realized at the end of period t, and the market structure $(\vec{n}_{1mt}, \vec{n}_{2mt}, \vec{n}_{3mt})$ is updated to $(\vec{n}_{1mt+1}, \vec{n}_{2mt+1}, \vec{n}_{3mt+1})$ according to (2). The exogenous market state variables are updated according to (3).

Operating profit: Empirical studies on the dynamic chain-store oligopoly tend to specify the reduced-form *per-store* operating profit (Igami and Yang (2016), Arcidiacono et al. (2016), and Aguirregabiria and Magesan (2020)). This approach, however, assumes that the competitive effect of a store is equal regardless of the store size. To capture the size-dependent competitive effects, I instead express the operating profit in terms of *per-screen* operating profit while employing the reduced-form specification following the literature standard.

Specifically, chain i in market m and period t makes operating profit, which is given by

$$\pi_i(s_{mt}) = k_{imt} \times (-\phi_i^{FC}(\mu_m) - \phi_R^{FC} R_{mt} + \gamma_1 k_{imt} + \gamma_2 k_{-imt} + z_{mt}' \lambda), \tag{4}$$

where k_{imt} is the total number of own screens $k_{imt} = \sum_j j \times n_{imt}^j$; k_{-imt} is the total number of rival chains' screens $k_{-imt} = \sum_j j \times n_{-imt}^j$. The terms in bracket in equation (4) represent the average profit *per screen*.

$\phi_i^{FC}(\mu_m)$ is a composite of fixed operating cost and a baseline profit. A positive value of $\phi_i^{FC}(\mu_m)$ can be interpreted that a fixed operating cost overrides a baseline profit, and vice versa. Since market-specific profitability μ_m affects the baseline profit, ϕ_i depends on μ_m. For instance, higher μ_m (i.e., the higher baseline profitability) will be reflected on a lower value of $\phi_i(\mu_m)$. Commercial property value R_{mt} also constitutes a fixed operating cost as it influences the rental rate of commercial space in a local market. The equation (4) admits the differential competitive effects of same-chain and rival-chain screens, allowing me to distinguish between cannibalization and the business-stealing effect. Here, γ_1 captures profit cannibalization effects among same-chain screens, and γ_2 measures the competitive effect of rival screens. λ captures the effects of demand and cost shifters on the average profit per screen.

Equation (4) illustrates the trade-off between fixed operating costs and higher variable gross profits. If chain i owns a theater with many screens, it will gain higher variable profits $k_{imt} \times z'_{mt}\lambda$. In contrast, owning a theater with many screens will incur higher operating costs $k_{imt} \times (\phi_i(\mu_m) + \phi_R R_{mt})$.

In addition to the mechanical trade-off between fixed operating costs and higher variable profits, the strategic trade-off between cannibalization and business stealing also arises in equation (4). On the one hand, chains can steal higher market shares of incumbent theaters by opening a theater with many screens, which is captured by γ_2. However, this strategic benefit comes at the cost of harming the existing same-chain theaters γ_1.

Sunk costs for theater opening: After the post-entry competition, chain i draws a privately observed cost shock ε_{imt} and decides to open a new theater. The industry model of this paper admits a flexible sunk entry cost schedule. Chain i may pay less in sunk entry costs *per screen* by constructing a movie theater with many screens (economies of entry scale). However, economies of entry scale may have limits, thereby the sunk entry costs *per screen* begin to increase as the number of added screens pass the minimum efficient entry scale (diseconomies of entry scale). To accommodate these possibilities, the sunk entry cost for entry size decision d_{imt} is given by

$$C(d_{imt}, R_{mt}, \varepsilon_{imt}) = \phi^{EC}_{d_{imt}} R_{mt} \mathbb{I}_{\{d_{imt}>0\}} + \varepsilon_{imt} d_{imt}. \tag{5}$$

Here, there are J total sunk entry cost schedule parameters $(\phi^{EC}_1, \ldots, \phi^{EC}_J)$. Equation (5) implies that the exit cost (or scrap value) is assumed to be zero, given that the entry, exit, and fixed costs of a dynamic model cannot be jointly identified. [12] Chains should pay higher sunk entry costs in markets with higher commercial property values. Thus, the entry cost depends on commercial property value R_{mt}, and this allows the sunk entry costs to differ across regional markets. A privately known cost shock ε_{imt} is assumed to

[12]Under the normalization that the exit cost is zero, the estimates $\hat{\phi}^{FC}_d$ and $\hat{\phi}^{EC}_d$ will actually represent composites of the costs and the scrap value, namely ϕ^{SV}_d. More specifically, $\hat{\phi}^{FC}_d$ and $\hat{\phi}^{EC}_d$ can be interpreted as $\phi^{FC}_d + (1-\beta)\phi^{SV}_d$ and $\phi^{EC}_d - \phi^{SV}_d$, respectively. See Table 3 in Aguirregabiria and Suzuki (2014).

be independently and identically distributed according to the normal distribution with mean zero and standard deviation $\nu \times R_{mt}$.

Collecting the operating profits and sunk entry costs for theater and screen openings, the per-period payoff function is specified as net profit:

$$\zeta_i(s_{mt}, d_{imt}, \varepsilon_{imt}) = \pi_i(s_{mt}) - C(d_{imt}, R_{mt}, \varepsilon_{imt}). \tag{6}$$

III.II Dynamic Optimization and Equilibrium

Like most other dynamic oligopoly models, it is hard to track all the possible Nash equilibria of the model described in the previous subsection. In light of this, I analyze the chain's dynamic decision to add/subtract movie screens with a focus on pure Markovian strategies and stationary Markov Perfect Nash Equilibria (MPNEs) in the spirit of Ericson and Pakes (1995) and Maskin and Tirole (2001). In an MPNE, chians' strategies for the theater size only rely on a vector of current payoff-relevant state variables and a private cost shock.

Throughout this subsection, market and time subscripts, m and t, are suppressed, and superscript $'$ will refer to the future period in order to simplify the exposition.

Value Function: Chain i observes public state $s = (\vec{n}_i, \vec{n}_{-i}, z_1, z_2, R, \mu)$ and private cost shock ε_i. Then, chain i forms belief over the rival chains' actions d_{-i} and decides whether to open or close a theater and the number of screens for the theater opening or closure d_i in order to maximize the present value of future net profits. The corresponding Bellman equation is given by

$$\begin{aligned} V_i(s, \varepsilon_i) = \pi_i(s) + \max_{d_i \in D(\vec{n}_i)} \Bigg[& -\phi^{EC}_{d_i} d_i \mathbb{I}_{\{d_i>0\}} R - d_i \times \varepsilon_i \\ & + \beta \sum_{\vec{n}'_{-i}} \sum_{z'_1, z'_2, R'} EV_i(\vec{n}'_i(\vec{n}_i, d_i), \vec{n}'_{-i}, z'_1, z'_2, R', \mu) \Psi_i(\vec{n}'_{-i}|s) F_\mu(z'_1, z'_2, R'|z_1, z_2, R) \Bigg], \end{aligned} \tag{7}$$

where

$$EV_i(\vec{n}'_i(\vec{n}_i, d_i), \vec{n}'_{-i}, z'_1, z'_2, R', \mu) = \int_{\varepsilon'} V_i(\vec{n}'_i(\vec{n}_i, d_i), \vec{n}'_{-i}, z'_1, z'_2, R', \mu, \varepsilon') dG(\varepsilon'_i) \tag{8}$$

Here, $V_i(s, \varepsilon_i)$ is the chain i's value function at state s and ε_i. $EV_i(\vec{n}_i'(\vec{n}_i, d_i), \vec{n}_{-i}', z_1', z_2', R', \mu)$ is the chain i's *ex-ante* value function, the chain's valuation before observing ε_i. $\vec{n}_i'(n_i, d_i)$ is chain i's own state in the next period determined by equation (2). $\Psi_i(\vec{n}_{-i}'|s)$ is the chain i's belief over rival chains' states in the next period. $D(\vec{n}_i)$ is the set of feasible actions. For instance, if chain i owns 4-screen and 6-screen theaters, the chain could only close either 4-screen or 6-screen theater from the market. Thus, the corresponding $D(\vec{n}_i)$ is $\{-6, -4, 0, 1, \ldots, J\}$.

Following Nishiwaki (2016) and Caoui (2022), I consider a monotone strategy with respect to private information: the optimal policy function is expressed in terms of the cutoff strategy; the corresponding cutoff points are characterized by differences between two choice-specific value functions.[13]

I first define the chain i's choice-specific value function of taking action d_i

$$W_i(d_i|s) \equiv \beta \sum_{\vec{n}_{-i}'} \sum_{z_1', z_2', R'} EV_i(\vec{n}_i'(\vec{n}_i, d_i), \vec{n}_{-i}', z_1', z_2', R', \mu) \Psi_i(\vec{n}_{-i}'|s) F_\mu(z_1', z_2', R'|z_1, z_2, R).$$

To derive a cutoff point, consider $d_i + 1, d_i, d_i - 1 \in D(\vec{n}_i)$. Let $\bar{\varepsilon}_{d_i, d_i - 1}$ be the cutoff point at which actions d_i and $d_i - 1$ are indifferent. Thus,

$$\begin{aligned} & W_i(d_i - 1|s) - \phi_{d_i-1}^{EC} R - (d_i - 1)\bar{\varepsilon}_{d_i, d_i-1} R = W_i(d_i|s) - \phi_{d_i}^{EC} R - d_i \bar{\varepsilon}_{d_i, d_i-1} R \\ & \Rightarrow \bar{\varepsilon}_{d_i, d_i-1}(s) = \frac{W_i(d_i|s) - W_i(d_i - 1|s)}{R} - \frac{\phi_{d_i-1}^{EC}}{d_i - 1} - d_i\left(\frac{\phi_{d_i}^{EC}}{d_i} - \frac{\phi_{d_i-1}^{EC}}{d_i - 1}\right) \end{aligned} \tag{9}$$

The cutoff point at which actions $d_i + 1$ and d_i are indifferent is characterized analogously

$$\bar{\varepsilon}_{d_i+1, d_i}(s) = \frac{W_i(d_i + 1|s) - W_i(d_i|s)}{R} - \frac{\phi_{d_i}^{EC}}{d_i} - (d_i + 1)\left(\frac{\phi_{d_i+1}^{EC}}{d_i + 1} - \frac{\phi_{d_i}^{EC}}{d_i}\right). \tag{10}$$

Thus, chain i in state s with realized private cost shock ε_i open a d_i-screen theater if

$$\bar{\varepsilon}_{d_i+1, d_i}(s) < \varepsilon_i < \bar{\varepsilon}_{d_i, d_i-1}(s). \tag{11}$$

Cutoff points (9) and (10), and decision rule (11) show the role of economies (disec-

[13] The conditions under which a monotone strategy Markov Perfect Equilibrium exists are satisfied in my model. Specifically, the payoff function (6) satisfies the *decreasing difference* restriction. See Srisuma (2013).

onomies) of entry scale in shaping the chain's choice of the number of screens upon theater entry. For instance, if there are entry scale economies from $d_i - 1$ to d_i (i.e., $\frac{\phi^{EC}_{d_i}}{d_i} < \frac{\phi^{EC}_{d_i-1}}{d_i-1}$), chain i would enjoy an additional margin, $-d_i(\frac{\phi^{EC}_{d_i}}{d_i} - \frac{\phi^{EC}_{d_i-1}}{d_i-1})$, from choosing d_i against $d_i - 1$. This additional margin is reflected on a larger value of $\bar{\varepsilon}_{d_i,d_i-1}(s)$ (Equation (9)), increasing the likelihood that chain i to choose d_i (Equation (11)). The opposite case (diseconomies of entry scale) can be established analogously.

Taken together, the optimal decision rule for the new theater's screen counts is given by

$$d_i = \begin{cases} J & \text{if } \varepsilon_i < \bar{\varepsilon}_{J,\max J-1}(s) \\ \underline{d}_i < d < J & \text{if } \bar{\varepsilon}_{d+1,d}(s) < \varepsilon_i < \bar{\varepsilon}_{d,d-1}(s) \\ \underline{d}_i & \text{if } \varepsilon_i > \bar{\varepsilon}_{\underline{d}_i+1,\underline{d}_i}(s) \end{cases}, \tag{12}$$

where $\underline{d}_i = \min D(\vec{n}_i)$. Note that the maximum number of screens to be subtracted depends on the chain's configuration since shrinking the total number of screens can only occur through closing an existing theater. For instance, if chain i owns 3-screen and 4-screen theaters in a market, $\underline{d}_i = -4$.

Assuming that ε_i is drawn from a Normal distribution with standard deviation νR, the chain i's optimal decision rule can be expressed as conditional choice probabilities (CCPs) $P_i(d_i|s)$:

$$P_i(d_i|s) = \begin{cases} \Phi(\frac{\bar{\varepsilon}_{J,J-1}(s)}{\nu R}), & \text{if } \ d_i = J \\ \Phi(\frac{\bar{\varepsilon}_{d,d-1}(s)}{\nu R}) - \Phi(\frac{\bar{\varepsilon}_{d+1,d}(s)}{\nu R}) & \text{if } \ \underline{d}_i < d_i < J \\ 1 - \Phi(\frac{\bar{\varepsilon}_{\underline{d}_i+1,\underline{d}_i}(s)}{\nu R}), & \text{if } \ d_i = \underline{d}_i, \end{cases} \tag{13}$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function.

Markov Perfect Nash Equilibrium: A Markov-perfect Nash equilibrium constitutes the chains' screen adding/subtracting strategy profile and beliefs (σ^*, Ψ^*) such that

1. Given belief Ψ^*, $\sigma^*_i(s, \varepsilon_i)$ is optimal at all states

$$V_i(s, \varepsilon_i; \sigma^*_i, \sigma^*_{-i}) \geq V_i(s, \varepsilon_i; \tilde{\sigma}_i, \sigma^*_{-i}), \qquad \forall s, i, \tilde{\sigma}_i.$$

2. Belief Ψ_i^* is consistent with conditional choice probabilities (13)

$$\Psi_i^*(x'_{-i}|s) = \prod_{l \neq i} P_l^*(\sigma_l^*|s).$$

The existence of an MPNE of the game follows from Doraszelski and Satterthwaite (2010) and Srisuma (2013).

IV Estimation

This section describes the estimation of the industry model in Section III. The key objects of interest are the competitive effects of the same-chain screens and rival-chain screens, γ_1 and γ_2, and two different sunk entry costs schedules, $(\phi_1^{EC}, \ldots, \phi_J^{EC})$, under the early- and late-regimes.

Solving the model repeatedly for any candidate of the structural parameters is impractical, hindering a nested-fixed point algorithm for the estimation. [14] I circumvent the issue regarding a high-dimensional state-space by following two-step approach proposed by Bajari et al. (2007). The approach allows me to estimate the structural parameters without solving the model. The estimation of the structural parameters is divided into two stages. In the first stage, I estimate the chain's equilibrium conditional choice probabilities (13) for the number of screens for a theater opening or closure before and after the regulatory regime shift. These estimates are complete descriptions of how chains will choose the size of their theater opening or closure in a geographic market. In the second stage, I search the structural parameters at which the estimated CCPs weakly dominate possible alternative strategies.

To recognize the impact of the regulatory regime shift, I allow the fixed operating costs (or baseline profit) and the sunk entry costs to differ before and after 2014. Identifying changes in the fixed operating and sunk entry costs relies on two key assumptions. First, following the spirit of Rust and Rothwell (1995), Ryan (2012), and Kalouptsidi (2018), I assume that the regulatory regime shift were unexpected; firms believed that the reforms would be permanent; and they immediately switch from the old equilibrium

[14] For instance, assuming the maximum number of screens to be added is 10 (i.e., $J = 10$), and chains can open at most one theater for each size, the total number of states is 1,073,741,824.

to the new one. Thus, the identification of the cost impact of the regime shift relies on a comparison between the firms' behaviors before and after the regime shift.[15] Second, I assume that the other profit function parameters, such as competitive effects of the same-chain and rival-chain screens and the effect of the demand shifters, have remained unchanged after the regime shift. Given that the goal of the reforms is to relax land-use regulations involved in opening a new business, the reforms most likely affected the sunk entry costs, while retaining the nature of competition among theaters.

I also allow the fixed operating costs (or baseline profit) to differ before and after the regulatory regime shift because of the following reason. In response to the relaxation of land-use regulations, other service businesses would have entered a local market, which could increase the baseline profit of a theater. This change would be reflected in a decrease in the fixed operating costs in the model of this paper. Thus, assuming fixed costs to be the same before and after the regime shift would obscure positive spillover effects on the entry of theaters, which translates into a considerable reduction in sunk entry costs, biasing the counterfactual predictions.

IV.I First Stage: Estimating Conditional Choice Probabilities

In the first stage, I estimate an ordered probit regression of the size (screen) of a theater opening or closure which is implied by equation (13). Similar to Caoui (2022), I coarsen the size of a theater opening or closure into three scale categories to bypass the high-dimensionality of state space. Specifically, theaters with four screens or less are assumed to be 3-screen theaters, and theaters with five, six, or seven screens are treated as 6-screen theaters. Theaters with eight screens or more are set to be 9-screen theaters. Such a coarsening is sufficient to study the importance of intensive margin entry decisions while controlling the size of the state space.[16]

I approximate cutoff point $\bar{\varepsilon}_{d_i,d_i-1}(s)$ as a function of the number of same-chain screens, the number of rival-chain screens, population, GDP per capita, commercial property value

[15] Of course, firms might have slowly adjusted their behaviors after the regulatory reforms due to uncertainty about their rivals' behaviors. In this regards, accommodating the learning process regarding the competitors' new strategies might be appealing, such as Doraszelski, Lewis, and Pakes (2018) who estimate the learning processes of firms in the UK frequency response market after the deregulation. However, the periods that my dataset spans are too short to pursue this avenue.

[16] Indeed, the coarsening reduces the number of possible market configurations substantially from 1,073,741,824 to 19,683.

per m^2, and market dummies. The first five variables are the payoff-relevant state variables, while market dummies are introduced to capture the unobserved market-specific profitability μ_m. To capture the impact of the regulatory regime shift on the chain's theater opening/closure's size decisions, I allow for cutpoints in an ordered probit regression to differ across the chains and before and after 2014H2. Thus, the probability of observing chain i adding or subtracting a j-screen theater at state s_{mt} and in policy regime $r \in \{before, after\}$ is given by

$$\begin{aligned} P(d_{imt} = j|s_{imt}, r) &= P(\kappa_{irj-1} < d^*_{imt} + u_{imt} < \kappa_{irj}) \\ &= \Phi(\kappa_{irj} - d^*_{imt}) - \Phi(\kappa_{irj-1} - d^*_{imt}), \end{aligned} \tag{14}$$

where κ_{irj} is a chain i's cutpoint at policy regime r corresponding to opening j-screen theater (if $j > 0$) or closing j-screen theater (if $j < 0$), and u_{imt} is drawn from standard normal. As discussed, I specify the latent variable d^*_{imt} as

$$d^*_{imt} = \alpha_1 k_{imt} + \alpha_2 k_{-imt} + z_{mt}\alpha_3 + \alpha_4 R_{mt} + \delta_m, \tag{15}$$

where k_{imt} and k_{-imt} are the total numbers of own and rival screens in market m at point in time t; δ_m is market dummies. The main parameters of interest are α_1, α_2 and the collection of cutpoints κ_{irj}.

α_1 and α_2 in equation (15) are informative about the strategic interactions among the chains. If there is strong business stealing, the entry of rival chain's screens reduces the profitability of chain i's theater, so chain i is unwilling to open a theater or would like to close the existing theater. This effect turns in a decrease in latent variable d^*_{imt}. Thus, one would expect $\alpha_2 < 0$. An analogous argument can be made for α_1. When cannibalization among same-chain theaters exists, the entry of same-chain screens reduces the profit of the other same-chain theater, so α_1 is expected to be negative.

The estimates of cutpoints will inform the fixed operating costs and sunk entry costs. As well documented by Dunne et al. (2013), the fixed operating costs govern the decision to close a theater (exit), while the sunk entry costs shape the decision to open a theater (entry). All else equal, a higher cutpoint for $j > 0$ translates into a decrease in the probability of observing chain i opening a theater as $P(d_{imt} > 0|s_{imt}, r) = 1 - \Phi(\kappa_{ir0} -$

d^*_{imt}). Hence, a higher cutoff will suggest higher sunk entry costs. Similarly, a higher cutpoint $j < 0$ would reflect the higher fixed operating costs since it implies an increase in the probability of a theater closure ($P(d_{imt} < 0|s_{imt}, r) = \Phi(\kappa_{ir,-3} - d^*_{imt})$). In addition, the differences between cutpoints further reflect how the sunk entry costs vary with the size of a theater opening. As shown in equation (14), the larger difference between κ_{irj} and κ_{irj-1} implies that chain i is more likely to open a j-screen theater than a theater with a different number of screens, making the sunk entry cost estimates for a j-screen theater smaller than those for other theaters.

I estimate (14) via the method of maximum likelihood using a panel at the firm-market-time level. Note that firms cannot have a negative number of j-screen theaters, thereby making the feasible action space depend on own configurations. For instance, if firm i has only owned a 3-screen theater in m, the set of possible choices $D(\vec{n}_i)$ would not contain -9 and -6. When constructing the likelihood function, such a state-dependency is taken into account.

Coarsening of Data: Before proceeding to the second stage, I discretize the data to facilitate the structural estimation. First, I discretize estimated market dummies into three categories based on their 33rd and 66th percentiles in order to control market-level profitability μ_m. Accordingly, 131 markets are grouped into the three categories, and the fixed operating costs (or baseline profits) are separately estimated for each category. Second, for each market category, I divide population, GDP per capita, and commercial property values into their respective quartiles. Thus, for each market-type category, markets will fall into 64 possible combinations ($4 \times 4 \times 4$). Using a bin estimator, I separately estimate transition matrices for population, GDP per capita, and commercial property values. That is, $F(z'_1, z'_2, R'|z_1, z_2, R) = F_{z_1}(z'_1|z_1)F_{z_2}(z'_2|z_2)F_R(R'|R)$. The transition matrices are also estimated separately for time periods before and after the regime shift. Since the regulatory regime shift may also alter the dynamics of exogenous market state variables, particularly commercial property values. Estimating the transitions separately for periods before and after the regime shift may capture such a change.

IV.II Second Stage: Recovering the structural parameters

Although the estimated CCPs characterize how chains choose the size of theater opening and closure in any state before and after the regime shift, they are not sufficient to study how chains adjust their decisions in response to an exogenous reduction in the sunk entry costs and measure the welfare implications. Doing so requires the estimates of the operating profits and sunk entry costs.

The industry model is characterized by a vector of the structural parameters $\Theta = (\vec{\phi}^{FC}, \gamma_1, \gamma_2, \lambda, \vec{\phi}^{EC}, \nu)$, where $\vec{\phi}^{FC}$ and $\vec{\phi}^{EC}$ are vectors of fixed and sunk cost parameters. Solving for equation (7) at every guess of Θ is computationally impractical due to a high-dimensional state space. In the spirit of Hotz et al. (1994) and Bajari et al. (2007), I sidestep this computational challenge. Specifically, I approximate the *ex-ante* value function $EV_i(s_m; \sigma_i, \sigma_{-i})$ via Monte Carlo simulation.

Note that the *ex-ante* value function (8) is the discounted sum of flows of per-period payoffs:

$$EV_i(s_m; \sigma_i, \sigma_{-i}, \Theta) = \mathbb{E}\left[\sum_{\tau=0}^{\infty} \beta^\tau \zeta_i(s_{m\tau}, d_{im\tau}, \varepsilon_{im\tau}; \Theta) | s_{m0} = s_m, \sigma_i, \sigma_{-i}\right], \tag{16}$$

where $\mathbb{E}$ are taken conditional on own and rivals' strategies σ_i and σ_{-i}.

Given initial state s, I can simulate NS paths of firms' actions, industry states, and the corresponding per-period payoffs forward using $\hat{\sigma}$ and the estimated transition matrices $\hat{F}_\mu(z'|z)$. For each simulated path, I can calculate the discounted sum of flows of per-period payoffs and then approximate (16) by averaging the NS discounted sums:[17]

$$\hat{EV}_i(s_m; \hat{\sigma}_i, \hat{\sigma}_{-i}, \Theta) = \frac{1}{NS} \sum_{ns=1}^{NS} \left[\sum_{\tau=0}^{T} \beta^\tau \zeta_i(ns; s_{m\tau}, d_{im\tau}, \varepsilon_{im\tau}; \Theta) | s_{m0} = s_m, \hat{\sigma}_i, \hat{\sigma}_{-i}\right]. \tag{17}$$

Following Srisuma (2013), I construct a set of alternative strategies by perturbing the estimated equilibrium cutoffs using the first stage estimates of CCPs. To do so, I first derive the normalized cutoffs by inverting equation (13) in the spirit of Hotz and Miller

[17] Following Bajari et al. (2007) and subsequent empirical applications, I leverage the fact that payoff function $\zeta_i(s, d_i, \varepsilon_i)$ is linear in vector of parameters Θ to avoid repeated calculations of (17) when iterating Θ.

(1993):

$$P(d_{imt} \leq d | s_{mt}) = 1 - \Phi(\frac{\bar{\varepsilon}_{d+1,d}(s_{mt})}{\nu R}), \qquad \text{for } d < \max D_i(\vec{n}_{imt}). \tag{18}$$

Since the left-hand side of equation (18) is obtained from the first stage estimates of CCPs, I obtain the normalized cutoff values which is given by

$$\frac{\bar{\varepsilon}_{d+1,d}(s_{mt})}{\nu R} = \Phi^{-1}(1 - P(d_{imt} \leq d | s_{mt})). \tag{19}$$

I construct NP perturbed normalized cutoff values (19) by adding small random numbers: $\Phi^{-1}(1 - \hat{P}(d_{imt} \leq d | s_{imt}) + \xi_i$, where ξ_i is drawn from a normal distribution with zero mean and 0.1 standard deviation. For each perturbation $np = 1, 2, \ldots, NP$, I use a perturbed cutoff values to compute perturbed CCPs $\tilde{\sigma}_{i,np}$. I use the perturbed CCPs to calculate the alternative *ex-ante* value function $\hat{EV}_i(s_m; \tilde{\sigma}_{i,np}, \hat{\sigma}_{-i}, \Theta)$ as equation (17). For perturbation np, the penalty of deviating from an equilibrium is given by

$$g_{i,np}(s_m; \Theta) = \hat{EV}_i(s_m; \hat{\sigma}_i, \hat{\sigma}_{-i}, \Theta) - \hat{EV}_i(s_m; \tilde{\sigma}_{i,np}, \hat{\sigma}_{-i}, \Theta). \tag{20}$$

Since chains face different fixed and sunk entry costs and play the different strategies for periods before and after the regulatory regime shift, I do the jobs described above separately for the estimated MPNE cutoffs for periods before and after the regime shift as Ryan (2012). Thus, $g_{i,np}(s_m; \Theta)$ is essentially policy-regime specific: $g_{i,np,r}(s_m; \Theta_r)$, where r is the index of regulatory regime.

For each regime, I search for a vector of the structural parameters at which the observed strategies weakly dominate the perturbed strategies. Thus, the estimated vector of the structural parameters $\hat{\Theta}_r$ is the minimizer of the following objective function. [18]

$$Q_r(\Theta_r) = \frac{1}{M \times I \times NP} \sum_{m,i,np} (\min\{0, g_{i,np,r}(s_m; \Theta)\})^2. \tag{21}$$

[18] I can also jointly estimate the pre- and post-reforms parameters by minimizing the following objective function:

$$Q(\Theta_1, \Theta_2) = \frac{1}{M \times I \times NP \times 2} \sum_{m,i,np,r} (\min\{0, g_{i,np,r}(s_m; \Theta_r)\})^2.$$

The estimation results are qualitatively similar, but the estimated reduction in the sunk entry costs resulting from the regime shift is unreasonably large (a reduction of 40%).

Implementation and Calibration: I use $NS = 2,000$ and $T = 80$ to approximate the ex-ante value function (17). I draw 500 perturbed strategies ($NP = 500$) to construct objective function (21).

Since the data contain only the market structure and the theater entry-exit patterns along with their size, the estimated structural parameters will be expressed in units of standard deviation. To interpret the parameters in money units, I calibrate the sunk entry cost parameter for a 6-screen theater in the early-regime periods, $\phi^{EC}_{6,1}$, to 1,800 million KRW. In doing so, the sunk entry cost in the municipality of *Gyeong-ju* can be 3.6 billion KRW, in line with an engineering estimate quoted from a business report.

I choose half-year discount factor β to 0.963, matching the average annual real interest rates of 7.8% in South Korea from 2010 to 2018.[19]

V Empirical Results

V.I CCP Estimates

Table 6 presents estimated coefficients of the policy function for the screens of a theater opening or closure (14). Column (1) in Table 6 reports the result of an estimation that has market dummies, while Column (2) does not.

The results suggest that the presence of competing theaters (screens) lowers a propensity to open a theater. The competitive effect of own screens is -0.1013; the effect of rival chains' screens is -0.0739. The magnitude of the effect of same chain theaters is slightly larger than the rival chains' counterpart, despite the difference not being statistically significant. Yet, this finding suggests cannibalization among theaters within the same chain would be a concern for a chain-store firms in the South Korean movie theater industry.

Contrasting the estimates in Column (1) with those in Column (2), I observe introducing market dummies, which control for the unobserved market-specific profitability μ_m, is crucial to obtaining correct estimates for the competitive effect. Since chains may prefer to open a theater in markets with higher μ_m, markets with higher μ_m can attract more theaters and screens. Thus, chains appear to enter markets with more rivals without

[19] $0.963 \approx (\frac{1}{1+0.078})^2$.

control for the unobserved market-specific profitability (Igami and Yang (2016)). Indeed, without the market dummies, the effect of the number of rival-chain screens on the entry and size decisions is positive. In addition, the effect of same-chain screens substantially increases from -0.1013 to -0.0260. Overall, the absence of market dummies spuriously suggests that a chain favors the presence of competing theaters and is less concerned about cannibalization. These biased estimates will result in an incorrect prediction of the welfare implications of the reduced sunk entry costs.

Addressing market-specific the unobserved market-specific profitability is also vital to accurately measure the effect of commercial property values on the chain's theater opening decisions, which is informative about the fixed cost of operating screens. Since markets with higher μ_m would attract several service establishments, they are more likely to have a higher demand for commercial space, leading to higher commercial property values. Thus, without control for the unobserved market profitability, the CCP estimates suggest an implausible pattern that the chains do not respond to changes in property values (Column (2) in Table 6). In contrast, I obtain the significantly negative effect of property values on the chain's decision after including market dummies (Column (1) in Table 6).

Table 7 presents estimated cutpoints of theater entry-exit policy function (14). For the exposition purpose, I report only the estimated cutpoints when chain firms do not have any theater in a local market at a point in time (i.e., $\vec{n}_{imt} = \{0, 0, 0\}$).

The result shows that the cutpoints for all the chain firms have decreased after the regime shift, suggesting a possible reduction in sunk entry costs. For instance, the cutpoints for an entry of a CGV's 3-,6-, and 9-screen theaters decrease from 3.1500, 3.2563, and 3.7141 to 2.6105, 2.6788, and 3.3317, respectively. Such a decrease implies that moving CGV from the early-regime periods to the late-regime periods increases the probability of observing an entering CGV theater.

In addition, the cutpoints do not decrease uniformly: the difference between the first two cutpoints decreases from 0.1063 to 0.0683, whereas the difference between the last two cutpoints increases from 0.4573 to 0.6563. The probability of observing an entering 3-screen CGV theater increases in the first difference, while the probability of observing an entering 6-screen CGV theater increases in the second difference. Thus, the estimation result implies that conditioning on opening, the probability of observing a 3-screen theater opening decreases and that of observing a 6-screen theater opening increases when moving CGV from the early-regime periods to the later-regime periods.

Note that all the parameter estimates are expressed in units of one standard deviation of the Normal distribution. To interpret the results as changes in the probabilities of entry, I calculate the corresponding probabilities at the median of all the other explanatory variables and tabulate them in Table 8. In line with the summary statistic in Table 4, the chains open a theater more frequently in the late-regime. For instance, the probability of CGV not opening a theater decreases from 98% to 93.85%. Similar patterns stand out for the other two chains. Put differently, the probabilities of CGV, Lotte Cinema, and Megabox opening a theater increase by 4.28 percentage points, 2.15 percentage points, and 4.97 percentage points, respectively. The reforms also alter the chains' decisions to choose the size of a theater opening. The probability of observing an entry of CGV's 3-screen theater has increased only by 75%, from 0.44% to 0.79%. In contrast, I find that the conditional probability of observing an entry of CGV's 6-screen theater has increased by 400%, from 1.03% to 4.18%. A similar pattern also holds for the other two chain firms. Overall, the estimation results highlight the chain's theater size decisions.

Goodness of the fit of the CCP: Before proceeding to estimating the model parameters, I assess the overall performance of the estimated policy functions for theater opening's screen counts (CCPs) in matching the industry dynamics. Since the technique of Bajari et al. (2007) relies on the value functions simulated by the CCPs, the accuracy of the CCPs is crucial in obtaining the correct model parameters (Collard-Wexler (2013)).

I take the initial period's configuration of 131 markets as given and simulate the market structures from 2010H2 to 2014H2 using the CCPs and transition matrices for the pre-reform periods. Taking the simulated market structure in 2014H2 as given, I then simulate the market structures from 2015H1 ot 2018H2 using the CCPs and transition matrices for the post-reform periods. Table 9 compares the moments of raw data with the simulated counterparts.

The estimated CCPs predict the distribution of theater size (Panel A) and the market structure (Panel B) precisely. Although the model underpredicts the share of 9-screen theaters, the deviations are small. The calculated CCPs do a good job of predicting the correlations between demand shifters and the market structure, though they overpredict the correlation between a population and the total number of theaters in a market (Panel C).

The CCPs do not fit the correlation between commercial property values and market structure (Panel C). For instance, the correlation between the number of theaters and property values is 0.2 in the realized data, while the simulated counterpart is only 0.0359. However, this discrepancy between the realized and simulated data may not harm the structural estimates and counterfactual outcomes. The high correlation in the realized data may reflect the positive correlation between unobserved market-level profitability and commercial property values, as discussed in Section V.I. In contrast, the CCPs accurately obtain the negative effect of property values on the chain's theater opening decision by including market dummies (Table 6), so the simulated data produce a much weaker correlation between commercial property values and market structure. Overall, the discrepancy between the realized and simulated data indicates that the CCPs obtain the plausible relationship between the chain's theater opening decision and commercial property values rather than evidence of the poor predictive performance of the CCPs.

In Appendix B, I further examine the performance of the estimated CCPs in describing the industry dynamics. The CCPs closely match the trend in theater counts and their average number of screens. In addition, the CCPs replicate the considerable persistence of screen transition.

V.II Model Parameters

Variable profit parameters: Table 10 displays estimates of variable profit function per screen. In line with the policy function estimates in Table 6, both same-chain and rival-chain screens reduce the profit of an incumbent theater by a equal amount. For instance, the entry of a same-chain theater with six screens will reduce a incumbent same-chain theater's profit by 22.8 million KRW (6×3.8). A rival-chain theater with six screens has the similar competitive effect by decreasing the incumbent's per-screen profit by 20.88 million KRW (6×3.48). The parameter estimates further suggest the size-dependent business effects, which govern strategic motives of the three theater chains. By opening 3-screen, 6-screen, and 9-screen theaters in a local market, a chain can steal business of rival chains by 10.44, 20.88, and 31.32 million KRW.

More screens do not necessarily translate into the higher chain's variable profits because of profit cannibalization. Figure 4 plots the chain's variable profit function in a median market with median population and GDP per capita over the numbers of own screens and rival screens. Indeed, the variable profit function is concave in the number of screens. In addition, as rival screens increase, the chain's variable profits decrease, capturing the business-stealing effect. The figure thus suggests that the industry's variable profits can diminish, even though there are more theaters/screens due to tougher within- and between-chain competition.

Fixed operating cost parameters: The estimates of the fixed operating cost (or baseline profit) parameters before and after 2014 are tabulated in the first and second panels in Table 11. There is considerable heterogeneity $\phi_i^{FC}(\mu_m)$ across chains and market types, reflecting the dispersion in market profitability. Furthermore, the positive sign of ϕ_R^{FC} suggests that the chains will pay higher fixed operating costs in markets with higher commercial property values. This finding is consistent with the fact that the rental rates of commercial buildings, which could account for considerable parts of operating fixed costs, tend to increase as commercial property values increase.

Fixed operating cost (or baseline profit) parameters have decreased (increased) after 2014. These results suggest that the 2014 land-use regulatory reforms might have a positive effect on the underlying profitability, perhaps reflecting the positive spillover effect from the entry of other service businesses after the reforms. For instance, the per-screen fixed operating cost parameter for Megabox in market category 1 decreases by 46% from 69.64 million KRW to 47.75 million KRW; the baseline profit for CGV in market category 3 increases by 54% from 34.19 million KRW to 52.63 million KRW. Although the percentage changes in the fixed cost operating parameters after the reforms are substantial, changes in magnitudes are small compared to the per-screen entry cost parameter for 6-screen (300 million KRW). For instance, the per-screen fixed cost operating parameter for Megabox in market category 1 decreases by only 7.2% of the per-screen entry cost parameter for 6-screen ((69.64-47.75)/300). This change thus may not be large enough to rationalize the increases in the theater entry, suggesting a considerable reduction in the sunk entry costs.

Sunk entry cost parameters: The last panel in Table 11 displays the sunk entry cost parameters for early- and late-regimes. In periods before the regime shift, the sunk entry cost structure exhibits economies of scale: the average *per-screen* entry cost declines as a chain opens a larger-scaled theater. Thus, a 9-screen is the minimum efficient entry scale before the reforms. After the shift, the average *per-screen* entry costs for 3-, 6-, and 9-screen theaters decreases by 14% (84 million KRW), 32% (97 million KRW), and 25% (67 million KRW) respectively, and thus a 6-screen becomes the minimum efficient entry scale. This disproportionate shift increases the relative benefit of opening a 6-screen theater to other scales, which is characterized in equations (9) and (10), leading the chains to open a theater more frequently and more likely to choose the scale of 6-screen when opening a theater.

The disproportionate changes in the *per-screen* sunk entry cost schedule do not imply that the *total* sunk entry costs for 6-screen theaters decrease more than those for other scales. After the reforms, the total sunk entry costs for 3-, 6-, and 9-screen theaters have declined from 1,572M KRW, 1,800M KRW, and 2,583M KRW to 1,317M KRW, 1,217M KRW, and 1,982M KRW, respectively. These decreases indicate that the reforms actually have decreased the total sunk entry costs for 6- and 9-screen theaters equally by 600M KRW, even though 6-screen In contrast, the total sunk entry costs for 3-screen theaters have decreased by smaller amounts of 250M KRW. One possible explanation for the cost advantage for larger-scaled theaters is that the Amendment to the Building Act indeed relaxed restrictions on the maximum height of a building, thereby benefiting chains with cheaper economic costs for constructing a larger commercial property.

Assessing the relevance of the model and calibration: Using the estimated parameters of the variable profit function and fixed operating costs, I can calculate the operating margins of each chain and compare them with the actual margins in the chains' financial statement. In doing so, I can assess the relevance of the structural model and calibration. Figure 5 plots the realized annual operating margins for CGV and the predicted counterparts implied by the structural parameter estimates and the estimated CCPs. According to the financial statement of CGV from 2010 to 2018, the average operating profit margin at CGV is 8.4%. The average CCP-predicted operating profit margins over the same periods is 7.10%. Furthermore, as shown in Figure 5, the model predicts the downward trend in operating profit margins. Given that the estimated profits are inferred without exploiting any direct observation of theater-level revenues or operating profits, these findings support the validity of the model and calibration.

VI Counterfactual Analysis

This section explores the economic implications of the reduction in the *per-screen* sunk entry costs resulting from the land-use regulatory reforms. Following the literature standard (Ryan (2012), Dunne et al. (2013), and Kalouptsidi (2018)), I employ the estimated reduction in the sunk cost parameters (Table 11) as a guideline for a policy counterfactual.

The exercise in this section narrowly focuses on how the reduced sunk entry costs, in conjunction with strategic interactions among the chains, influence the chain's behaviors and industry net profits rather than measuring the overall impacts of the reforms. To do so, fixed operating costs, variable profit function, and transition matrices are held fixed at the post-reform estimates, and I solve the dynamic model with the pre-reform entry cost schedule. That is, I re-solve the model with $\vec{\phi}^{EC'} = (1.16\phi^{EC}_{3,2}, 1.47\phi^{EC}_{6,2}, 1.33\phi^{EC}_{9,2})$ for a counterfactual MPNE policy functions for each market type.[20] I then use the calculated counterfactual MPNE policy function to simulate the market structure dynamics 2,000 times and average them for each municipality. I compare the resulting dynamics to those implied by the estimated CCPs for periods after the reforms following Arcidiacono et al. (2016). Specifically, I measure the effects as $\Delta Q = \frac{Q(\vec{\phi}^{EC}_2) - Q(\vec{\phi}^{EC'})}{Q(\vec{\phi}^{EC'})}$, where $Q(.)$ is a counterfactual market structure: the number of all movie theaters, 3-screen, 6-screen, and 9-screen movie theaters in the industry.

[20]Specifically, following Igami and Yang (2016), I parameterize the MPNE CCPs and iterate the parameters until the implied CCPs for the three chains are mutually best responses to each other in the spirit of Pakes and McGuire (1994). As discussed in Igami and Yang (2016), a dynamic oligopoly model of chain-store entry can possess multiple equilibria. However, without using a state-of-art algorithm, finding the possible equilibria is infeasible. In addition, this task is beyond the scope of this paper. The reported results in this section are based on an MPNE that the proposed algorithm has encountered. The results thus only suggest the existence of an MPNE in which the main qualitative message in this section arises and do not guarantee the non-existence of other equilibria. An analogous argument of Suzuki (2013) can be applied to my setting to address a concern about the presence of an equilibrium whose qualitative implications are considerably different from my finding. Since the chains' theater size decisions are strategic substitutes, the industry's total numbers of mini-, mid-, and mega-plex theaters might be similar across equilibria, which implies a similar effect on industry profits and costs.

Table 12 tabulates counterfactual changes in market composition for years 1, 3, 5, and 7. I particularly focus on changes in the number of theaters and proportions of 3-screen, 6-screen, and 9-screen theaters. The top panel shows that the reduced sunk entry costs raise the number of theaters in the industry. The number of theaters increases by 7.51% immediately. In addition, the number of theaters gradually increases over time. After seven years, the number of theaters is higher by 21.04%.

A key finding is that the reduction in sunk entry costs shifts the theater size distribution toward mid-plex scales. This is mainly driven by the fact that 6-screen becomes the minimum entry scale after the reforms. Thus, the chains open more 6-screen movie theaters, resulting in a substantial increase in the proportions of 6-screen theaters and a reduction in the proportions of other theaters. The last three panels in Table 12 show that the number of 6-screen and 9-screen theaters in the industry are higher by 52.93% and 3.58% after seven years, respectively. In contrast, the number of 3-screen theaters in the industry decreases by 20.29% in response to the changes in sunk cost schedules. As opening a 6-screen theater becomes cheaper, chains might find it is more profitable to close an existing 3-screen theater and open a new 6-screen theater.

I further investigate how these changes in industry composition translate into industry performance. Note that having knowledge of the parameter values and the corresponding MPNE policy functions, the NPVs of variable profit and costs are easily computed through forward-simulation. In this counterfactual exercise, I calculate changes in industry performance as the aggregate differences between counterfactual quantities under the two different cost structures:

$$\Delta\Pi = \frac{\sum_i \sum_m \left(\Pi_i(s_m; \vec{\phi}_2^{EC}) - \Pi_i(s_m; \vec{\phi}^{EC'}) \right)}{\sum_i \sum_m \Pi_i(s_m; \vec{\phi}^{EC'})},$$

where $\Pi_i(s_m; \vec{\phi}^{EC'})$ and $\Pi_i(s_m; \vec{\phi}_2^{EC})$ are counterfactual quantities evaluated at market state s_m under pre-reform and post-reform cost structures, respectively: NPV of net profit (chain value), NPV of variable profit, NPV of fixed costs, NPV of sunk costs.

Table 13 reports the impact of a disproportionate reduction in the average *per-screen* entry costs on chain value and the NPV of variable profit, fixed operating costs, and sunk entry costs. As displayed in the first panel, the lower sunk entry costs reduce the total chain values by 5.60% (77.35 billion KRW). The loss of industry net profits primarily comes from tougher competition. The second panel shows industry variable profit does not change, suggesting that additional theaters make their profit primarily by stealing business from incumbents, not expanding the market. As shown in Figure 4, more screens can result in a reduction in the industry variable profits. Thus, the shift of the theater size distribution toward mid- and mega-plex scales translates into less variable profits at the industry level.

No surprisingly, the third panel of Table 13 shows that a substantial increase in theaters, particularly 6-screen theaters, incur much higher fixed operating costs by 14.59% (367.26 billion KRW), reducing industry operating profits substantially. In addition, as shown in the last panel, even though the three chains pay less sunk entry costs, the total expenses on the sunk costs decreases only by 12.53% (95.68 billion KRW) as the chains open larger-sized movie theaters in response to the disproportionate reduction in the sunk costs. These savings thus are not sufficient to compensate for the substantial decreases in operating profits, resulting in a reduction in net profits. Overall, the reduced sunk entry costs engender competition externalities in the industry.

Although industry net profits decrease substantially, not all three chains experience the loss of their net profits. Following the reduction in sunk entry costs, the net profit of Megabox increased by 16% (57.31 billion KRW) at the expense of the other two chains. Since Megabox had the smallest market share of theaters and screens in 2015H1, the reduction in sunk entry costs provides it with an opportunity for expansion. Specifically, Megabox has a larger pool of business stealing while being less concerned about profit cannibalization. Indeed, as shown in the second panel in Table 13, the other two chains make much fewer variable profits due to tougher competition, and their loss is transferred to the variable profits of Megbox. Thus, there is almost no change in total industry variable profits. Megabox expands its business more rapidly, paying more expenses on fixed operating and sunk entry costs. Thus, the industry's payments on fixed costs increase, and those on sunk costs do not decrease as much to compensate for increases in fixed costs.

Are the resulting welfare penalty to the chains indeed socially undesirable? Despite a considerable loss of industry net profits, consumers may derive welfare gains from more movie theaters in the market. For example, new movie theaters provide consumers with easier access to the theaters, and thus the consumer demand for moviegoing can increase, improving consumer welfare. However, the aggregate trend in demand for moviegoing in South Korea suggests that such a welfare-enhancing channel may not be the case. Figure 6 shows that the number of movie attendees began to grow more slowly after 2014, indicating that the consumer welfare gains from easier access to movie theaters are expected to be limited in the current empirical setting.

Abstracting away the chain's theater scale decision influences how researchers interpret the impacts of the reduced sunk entry costs. Table 14 displays the industry outcomes under the model without the chain's theater scale decision.[21] When researchers ignore the theater scale decision, they miss the shift of the industry screen distribution toward mid-plex scales. Such a miss in turn results in (i) under-predictions over increases in fixed operating costs and (ii) over-predictions over savings from the reduced sunk entry costs as researchers predict the increases by merely comparing the number of theaters. The third panel in Table 14 indeed confirms this conjecture: the restricted model predicts a mild increase of 2.77% (120.83 billion KRW) in industry fixed operating costs, which is 66% lower than those predicted by the baseline model. In addition, the restricted model predicts that the inudstry saves 23.1% of resource uses on sunk entry costs (-169.95 billion KRW) due to the reduction in sunk entry costs. Thus, additional resource uses on fixed operating costs are outweighed by the savings from the reduced sunk entry costs, resulting in increases of 27.3% in industry net profit.

VII Conclusion

Despite the prominence of industries where entrants are heterogeneous in the scale of operation, studies on the entrant's scale decision are limited. This paper has empirically investigated the implications of such a size decision upon entry with a focus on the role of scale-dependent sunk entry costs. In particular, I studied how the entrant's scale decision, in conjunction with lower sunk costs, shapes market structure and the industry's profit and expenditures.

Employing the South Korean cinema industry as an empirical case, I have estimated the dynamic game in which sunk entry costs vary with the scale, the number of screens,

[21]The estimation results of the restricted model are reported in Appendix C.

of theater openings. I found that sunk entry costs shape the optimal scale of a theater opening since post-entry screen adjustments are almost infeasible. Regarding the 2014 land-use regulatory reform measure and the following amendments as a reduction in sunk entry costs, I have recognized the regulatory regime shift favored mid-plex theaters with a greater *per-screen* sunk-cost advantage, expanding the number of mid-size theaters, which were defined as theaters with 5-7 screens, across South Korea. Simulation exercise has established that the shift of screen distribution toward mid-plex scales engenders a substantial increase in fixed operating costs. In contrast, I have found that the model without the scale decisions did not capture the shift of screen distribution, underpredicting an increase in fixed operating costs.

Tables and Figures

Table 1: Summary of Market Structure

# of theaters	# of municipality-semester obs.	Percent
0	265	11.24%
1	721	30.58%
2	631	26.76%
3	302	12.81%
4	204	8.65%
5	120	5.09%
6 or more	115	4.88%
Total	2,358	100%

Note. The unit of measurement is market-halfyear.

Table 2: Summary Statistics on Market Characteristics of 131 Municipalities

	No. Obs.	Mean	Std. Dev	5 percentile	95 percentile
	2010 H1				
Population (thousand)	131	335.203	248.343	83.134	999.289
GDP per capita (thousand KRW)	131	31.334	38.813	9.269	77.692
Commercial property value per m^2 (million KRW)	131	2.969	1.772	1.2836	7.3311
	2018 H2				
Population (thousand)	131	348.765	211.162	82.724	733.861
GDP per capita (thousand KRW)	131	36.514	40.040	10.436	92.266
Commercial property value per m^2 (million KRW)	131	3.0689	1.8475	1.2982	7.3533

Note. Cross-sections of 131 municipalities in 2010 H1 and 2018H2. GDP per capita and commercial property values are expressed in 2011 million Korean Wons.

Table 3: Market Structure and Turnover by Market Size (Population)

Market	Structure		Turnover			
Size^a	theaters	screens per theater^b	entries	screens per entry^c	exits	screens per exit^d
1	1.1780	5.7495	0.0805	5.8690	0.0233	6.3846
2	1.4904	7.5654	0.0844	6.4348	0.0395	7.1818
3	2.3746	7.5413	0.1178	7.0238	0.0308	7.9412
4	3.5586	7.5318	0.1485	6.8442	0.0376	6.7500

Note 1. ^{a} based on thousands of people. Size 1 is a group of market-semester observations with population lying in $[43.315, 195.256)$; Size 2 is a group of observations with population lying in $[195.256, 311.608)$; Size 3 is a group of observations with population lying in $[311.608, 444.282)$; and Size 4 is a group of observations with population lying in $[444.282, 1203.285]$.
Note 2. $^{b\ c\ d}$ calculated using municipalities with positive numbers of theaters, entries, and exits, respectively.

Table 4: Entry and Exit of Theaters (% Of the Sample)

	2010H1-2014H2	2015H1-2018H2
Entry of megaplex (screens more than 8)	0.99%	1.09%
Entry of midplex (screens between 5 and 7)	1.68%	2.76%
Entry of miniplex (screens less than 4)	0.48%	0.40%
Unchanged	95.93%	94.51%
Exit of miniplex (screens less than 4)	0.03%	0.15%
Exit of midplex (screens between 5 and 7)	0.53%	0.51%
Exit of megaplex (screens more than 8)	0.38%	0.58%

Note. The unit of measurement is firm-market-halfyear.

Table 5: Market Structure Transition Rates for Periods before and after the Reforms (%)

		Market Strcuture in $t+1$							
Market Structure in t		$n_{mini}=0$, $n_{mid}=0$, $n_{mega}=0$	$n_{mini}=1+$, $n_{mid}=0$, $n_{mega}=0$	$n_{mini}=0$, $n_{mid}=1+$, $n_{mega}=0$	$n_{mini}=0$, $n_{mid}=0$, $n_{mega}=1+$	$n_{mini}=1+$, $n_{mid}=1+$, $n_{mega}=0$	$n_{mini}=1+$, $n_{mid}=0$, $n_{mega}=1+$	$n_{mini}=0$, $n_{mid}=1+$, $n_{mega}=1+$	$n_{mini}=1+$, $n_{mid}=1+$, $n_{mega}=1+$
$n_{mini}=0$, $n_{mini}=0$, $n_{mini}=0$	Before	97.06	0.93	1.55	0.46	–	–	–	–
	After	90.37	2.96	5.93	0.74	–	–	–	–
$n_{mini}=1+$, $n_{mini}=0$, $n_{mini}=0$	Before	–	98.75	–	–	–	1.25	–	–
	After	–	98.25	–	–	0.87	0.87	–	–
$n_{mini}=0$, $n_{mini}=1+$, $n_{mini}=0$	Before	–	–	99.66	–	0.11	–	0.23	–
	After	–	–	99.62	–	0.13	–	0.25	–
$n_{mini}=0$, $n_{mini}=0$, $n_{mini}=1+$	Before	–	–	–	98.36	–	0.10	1.54	–
	After	–	–	–	98.13	–	–	1.68	0.19
$n_{mini}=1+$, $n_{mini}=1+$, $n_{mini}=0$	Before	–	–	–	–	96.88	–	–	3.13
	After	–	–	–	–	100.00	–	–	–
$n_{mini}=1+$, $n_{mini}=0$, $n_{mini}=1+$	Before	–	–	–	–	–	97.50	–	2.50
	After	–	–	–	–	–	96.67	–	3.33
$n_{mini}=0$, $n_{mini}=1+$, $n_{mini}=1+$	Before	–	–	0.12	0.24	–	–	98.80	0.84
	After	–	–	–	0.22	–	–	99.78	–
$n_{mini}=1+$, $n_{mini}=1+$, $n_{mini}=1+$	Before	–	–	–	–	–	–	–	100.00
	After	–	–	–	–	–	–	–	100.00

Note 1. Market structure is described by the numbers of theaters of scale categories (Miniplex, Midplex, Megaplex).
Note 2. The unit of measurement is market-halfyear.

Table 6: Ordered Probit on Intensive Marginal Theater Entry-Exit Decision: Coefficients

Covariates	(1)	(2)
# own chain screens	-0.1013^{***}	-0.0260^{***}
	(0.0129)	(0.0094)
# rival chain screens	-0.0739^{***}	0.0022
	(0.0082)	(0.0034)
population (thousand people)	0.0084^{***}	0.0008^{***}
	(0.0014)	(0.0001)
GDP per capita (thousand KRW)	0.0057	0.0013
	(0.0048)	(0.0007)
Property value per m^2 (million KRW)	-0.3692^{*}	-0.0250
	(0.2067)	(0.0160)
Market Dummies	✓	
Log likelihood	-1456.33	-1551.38
Observations	6,681	

Note. Estimated using a strongly balanced panel of the chain-market-time level. Standard errors are in parenthesis. Asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All units are expressed in one standard deviation of the standard Normal distribution.

Table 7: Ordered Probit on Intensive Marginal Theater Entry-Exit Decision: Cutpoints

Cutpoints	2010H1-2014H2	2015H1-2018H2
	CGV	
κ_3	3.1500	2.6105
κ_6	3.2563	2.6788
κ_9	3.7141	3.3317
	Lotte Cinema	
κ_3	3.0476	2.7593
κ_6	3.1540	2.8276
κ_9	3.6118	3.4805
	Megabox	
κ_3	3.4949	2.6464
κ_6	3.6012	2.7148
κ_9	4.0590	3.3676
Log likelihood	-1456.33	
Observations	6,681	

Note. Estimated cutoffs for $\vec{n}_{imt} = (0,0,0)$ are reported. $\vec{n}_{imt}$ is a vector of own state, which collects the number of theaters by size: $\vec{n}_{imt} = (n^{(3)}_{imt}, n^{(6)}_{imt}, n^{(9)}_{imt})$. Estimated cutpoints for other own states are suppressed for the expositional purpose. All units are expressed in one standard deviation of the standard Normal distribution.

Table 8: Predicted Probabilities at Median of Explanatory Variables

Predicted Probs.	2010H1-2014H2	2015H1-2018H2
	CGV	
$P(d=0\|s)$	0.9813	0.9385
$P(d=3\|s)$	0.0044	0.0079
$P(d=6\|s)$	0.0103	0.0418
$P(d=9\|s)$	0.0041	0.0118
	Lotte Cinema	
$P(d=0\|s)$	0.9761	0.9546
$P(d=3\|s)$	0.0054	0.0062
$P(d=6\|s)$	0.0130	0.0313
$P(d=9\|s)$	0.0055	0.0079
	Megabox	
$P(d=0\|s)$	0.9924	0.9427
$P(d=3\|s)$	0.0020	0.0074
$P(d=6\|s)$	0.0043	0.0391
$P(d=9\|s)$	0.0014	0.0107

Note. Predicted probabilities for $\vec{n}_{imt} = (0,0,0)$ at the median of explanatory variables are tabulated.

Table 9: Goodness-of-Fit: Conditional Choice Probabilities

Moments	Real Data (2010H1-2018H2)	Simulated Data Using CCPs
	Panel A. Chain-Level Moments	
Share of 3-screen theaters: CGV	8.23%	9.76%
Share of 6-screen theaters: CGV	37.82%	39.87%
Share of 9-screen theaters: CGV	53.95%	50.37%
Share of 3-screen theaters: Lotte Cinema	9.03%	8.31%
Share of 6-screen theaters: Lotte Cinema	48.35%	45.18%
Share of 9-screen theaters: Lotte Cinema	42.62%	46.52%
Share of 3-screen theaters: Megabox	7.65%	7.31%
Share of 6-screen theaters: Megabox	41.38%	42.64%
Share of 9-screen theaters: Megabox	50.96%	50.06%
	Panel B. Market-Level Moments	
# Theaters per Market (All)	2.150	2.208
# Theaters per Market (Category 1)	2.321	2.442
# Theaters per Market (Category 2)	1.841	1.860
# Theaters per Market (Category 3)	2.282	2.315
	Panel C. Correlations	
Avg Screen per Theater & Population	0.3521	0.3270
Avg Screen per Theater & GDP	-0.0258	-0.0349
Avg Screen per Theater & Property value	0.3359	0.0585
# Theater & Population	0.5528	0.7503
# Theater & GDP	0.0642	0.0078
# Theater & Property value	0.2003	0.0359
	Panel D. Profitability	
Avg annual operating margins: CGV	8.448%	7.1022%

Note. Data are simulated using computed CCPs and market type-specific demand process D^{μ}. The predicted moments are obtained by averaging 500 simulations.

Table 10: Estimates of Variable Profits per Screen (In Millions of 2011 Korean Won)

	Estimates	SEs
Competitive Effects: γ		
Cannibalization	-3.8228	0.2392
Rival competition	-3.4897	0.3130
Demand Shifters: λ		
Population (thousands)	0.3676	0.0241
GDP per capita (thousand 2011 KRW)	0.0964	0.0402

Note. The sunk entry cost parameter for a 6-screen theater is calibrated to 1,800 million KRW, which is quoted from a business report. All units of the other estimates are expressed in millions of 2011 constant KRW. Standard errors are calculated via subsampling.

Table 11: Estimates of Fixed Operating and Sunk Entry Costs (In Millions of 2011 Korean Won)

	2010H1-2014H2		2015H1-2018H2	
	Estimates	SEs	Estimates	SEs
Fixed Cost Parameters:$\phi_i^{FC}(\mu_m)$				
CGV in market category 1	53.4994	5.0688	56.2970	5.3429
CGV in market category 2	6.2942	3.4670	-12.2008	2.9616
CGV in market category 3	-34.1934	5.5993	-52.6255	6.5957
Lottecinema in market category 1	49.9761	4.6929	45.7212	4.9224
Lottecinema in market category 2	9.6216	3.6917	-7.8857	3.0319
Lottecinema in market category 3	-43.6061	4.4018	-56.2455	5.8793
Megabox in market category 1	69.6435	5.7576	47.7503	4.9274
Megabox in market category 2	15.2166	3.5697	-10.7940	3.0788
Megabox in market category 3	-26.6932	4.5031	-64.4234	6.7935
Fixed Cost Parameters:ϕ_R^{FC}				
Property Values per m^2 (million 2011 KRW)	12.7179	1.6744	15.4969	1.5118
Sunk entry cost parameters				
3-screen (ϕ_3^{EC})	1573.375	43.9893	1318.671	102.1674
6-screen (ϕ_6^{EC})	*1800.00*	N/A	1217.902	60.5988
9-screen (ϕ_9^{EC})	2587.919	44.6247	1982.5209	115.6194
standard deviation (ν)	64.6319	3.3262	-	-

Note. This table displays the sunk entry cost parameters. The sunk entry cost parameter for a 6-screen theater is calibrated to 1,800 million KRW, which is quoted from a business report. All units of the other estimates are expressed in millions of 2011 constant KRW. Standard errors are calculated via subsampling.

Table 12: Reduced Sunk Entry Costs and Industry Composition

	Year			
	1	3	5	7
Changes in the number of movie theaters				
Percent	7.51	17.95	20.33	21.04
Changes in the number of 3-screen theaters				
Percent	-1.62	-7.11	-14.24	-20.29
Changes in the number of 6-screen theaters				
Percent	12.49	34.74	45.26	52.93
Changes in the number of 9-screen theaters				
Percent	5.15	8.97	6.79	3.58

Note. The table tabulates the percent and percentage-point differences in market structure variables between baseline and counterfactual MPNEs. The first stage CCPs for periods after 2015H1 are used as the baseline MPNE following Arcidiacono et al. (2016). The predicted differences are obtained by averaging 2,000 simulations.

Table 13: Reduced Sunk Entry Costs and Industry Performance

	Percent	billions in KRW
△ NPV of net profits (Chain value)		
Industry Total	-5.60	-77.35
CGV	-16.07	-81.68
Lotte Cinema	-10.25	-52.98
Megabox	16.06	57.31
△ NPV of variable profits		
Industry Total	-0.26	-10.79
CGV	-3.39	-57.57
Lotte Cinema	-23.76	-395.61
Megabox	59.00	442.39
△ NPV of fixed operating costs		
Industry Total	14.59	367.26
CGV	11.96	134.65
Lotte Cinema	-13.58	-137.43
Megabox	97.62	370.04
△ NPV of sunk entry costs$*$		
Industry Total	-12.53	-95.68
CGV	-15.23	-42.65
Lotte Cinema	-44.81	-149.11
Megabox	63.67	96.08

Note 1. All the Net Present Values (NPV) are evaluated at the observed state in 2015H1.
Note 2. Caculated by excluding the NPV of expected scrap shocks $\mathbb{E}(\varepsilon|d < 0, s)$.

Table 14: When Screen Count Choices Are Ignored

	Percent	billions in KRW
△ NPV of net profits (Chain value)		
Industry Total	27.3	311.51
CGV	25.9	129.58
Lotte Cinema	15.3	64.96
Megabox	47.1	137.02
△ NPV of variable profits		
Industry Total	-0.00	-0.908
CGV	-4.24	-100.31
Lotte Cinema	0.71	12.78
Megabox	5.05	86.62
△ NPV of fixed operating costs		
Industry Total	2.77	120.83
CGV	-3.21	-56.22
Lotte Cinema	4.08	55.24
Megabox	9.77	121.33
△ NPV of sunk entry costs $*$		
Industry Total	-23.1	-169.95
CGV	-5.50	-11.52
Lotte Cinema	-28.9	-64.20
Megabox	-30.9	-94.23

Note 1. All the Net Present Values (NPV) are evaluated at the observed state in 2015H1.

Note 2. * Caculated by excluding the NPV of expected scrap shocks $\mathbb{E}(\varepsilon|d<0,s)$.

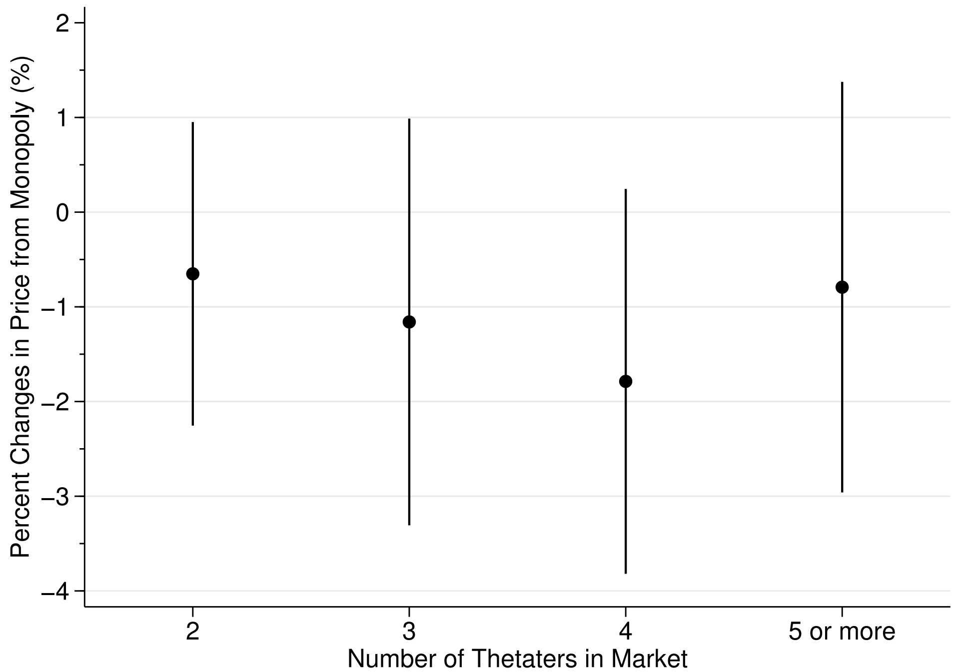

Figure 1: Average Ticket Price and Number of Theaters

Note. The figure depicts how the average ticket prices changes with the number of competing movie theaters.

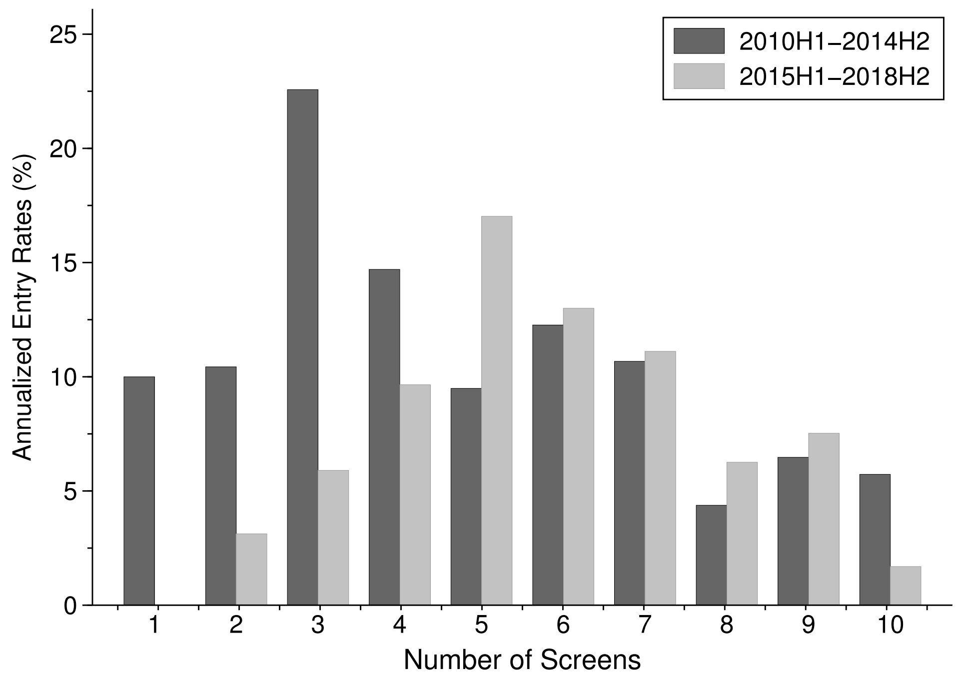

Figure 2: Annualized Theater Entry Rates by Screen Counts

Note. This figure displays the histograms of annualized theater entry rates by screen counts. The figure shows the entrant's screen count choices has shifted following the land-use and construction regulatory reforms.

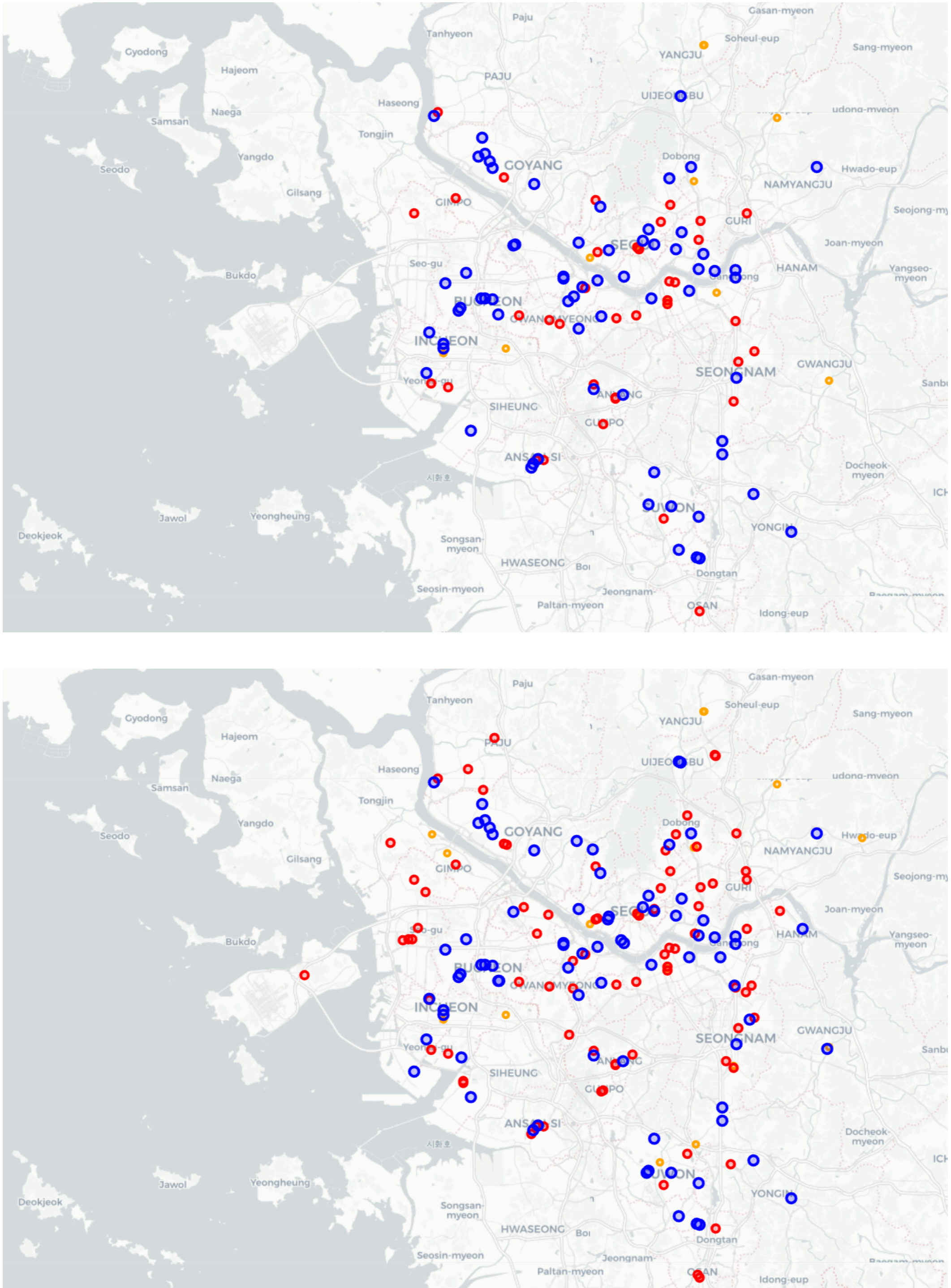

Figure 3: Theater Locations in 2012 and 2018

Note. The upper and lower figures map the theaters by size which located in Seoul metropolitan area in 2012 and 2018, respectively. The orange, red, and blue circles indicate miniplex, midplex, and megaplex theaters, respectively. The figures suggest that the industry had more theaters, particularly midplex theaters after the reforms.

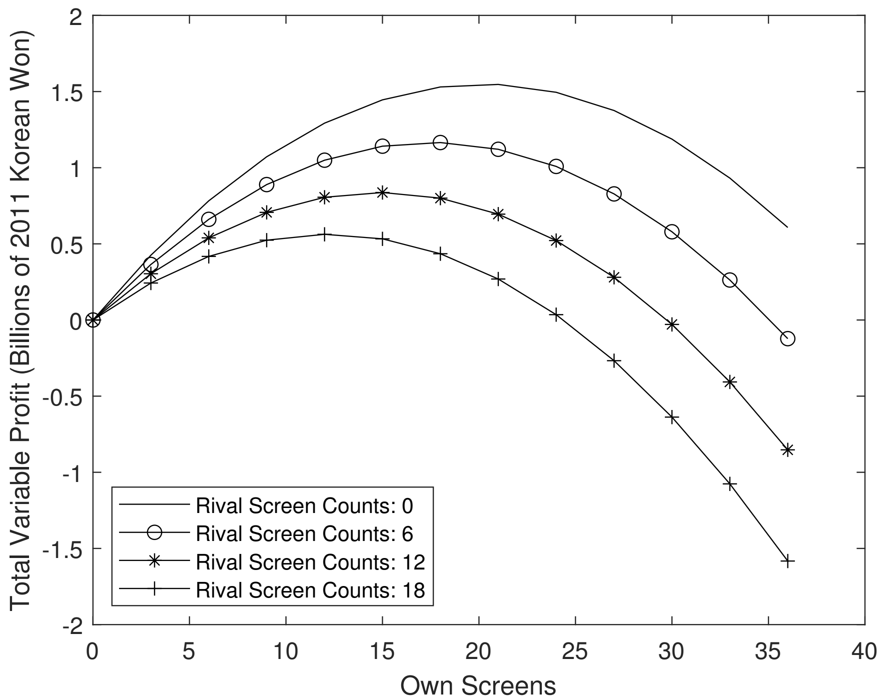

Figure 4: Chain's Variable Profits

Note. The figure displays chain's variable profits over the numbers of own screens and rival screens in a market with median population and median GDP per capita, calculated using the estimated parameters (Table 10). The variable profit function is concave in the number of own screens, suggesting that more screens do not necessarily translate into higher variable profits.

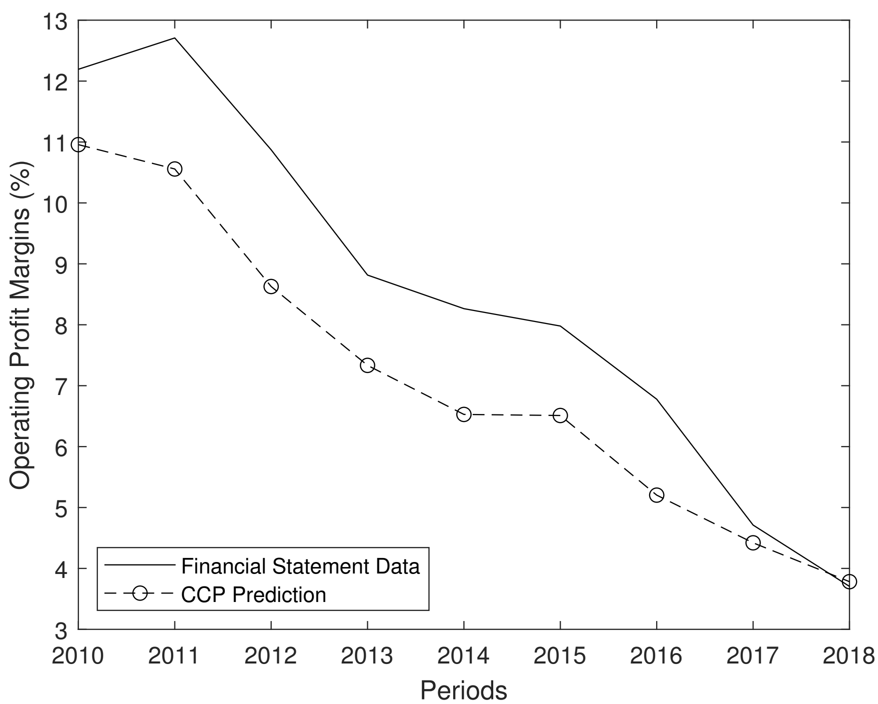

Figure 5: Trend in Operating Margins: CGV

Note. Annual operating profit margins are calculated using the estimated parameters (Tables 10 and 11) and the estimated conditional choice probabilities (Table 6). The predicted operating profit margins are obtained by averaging 500 simulations.

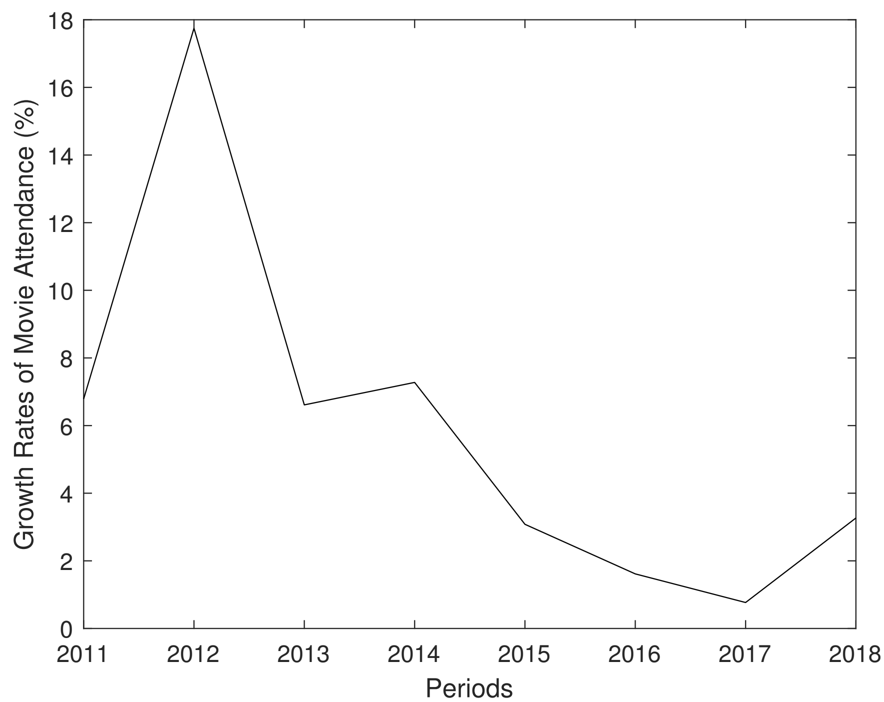

Figure 6: Growth Rates of Movie Attendance

Note. The figure depicts the time series of the annual growth rates of movie attendance.

Source. Korea Film Council.

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Appendices

A Structural Break in Market Structure Dynamics

The shift of the screen distribution toward mid-plex theaters suggests that the chains have altered their size decisions. However, this change might be driven by local market characteristics or aggregate time trends. In this appendix, I alleviate this concern by estimating the following regression:

$$n_{mt}^{(j)} = \theta_j + \theta_m + \theta_t + \sum_{k=-1}^{-8} \tau_k T_k D_j + \sum_{k=1}^{8} \tau_k T_k D_j + W_{mt-1}' \theta_w + u_{mt}^{(j)}, \tag{A.1}$$

where $j \in \{\text{others}, \text{midplex}\}$, $n_{mt}^{(j)}$ is the number of j-type theaters in market m and in period t, and θ_j, θ_m, and θ_t are market, size, and time fixed effects, respectively. D_j is an indicator of whether or not j is midplex. T_k is a dummy whether time t relative to 2014H2 is the same with k. W_{mt-1} is a vector of lagged market characteristics, including population, GDP per capita, and commercial property values. The key parameters are τ_k with $k > 0$. These coefficients capture the structural break at a point of the regime shift in the relative changes in the number of midplex theaters to the others. I omit T_0 by using it as a reference group.

Figure 7 displays the estimates of τ_k in equation (A.1) and the corresponding 95-percent confidence intervals. The early-regime coefficients are statistically indistinguishable from zero, suggesting that the numbers of midplex theaters and the other share a parallel trend before the regime shift.

The regulatory regime shift had a disproportionate impact on the size of movie theaters. Following the shift, the number of midplex theaters per market gradually increased. During the first two years, the number of midplex theaters per market increased by 0.05. However, during the last two years, that increased by 0.25. This gradual transition suggests the presence of the sunk entry costs that impedes an immediate response of the chains to the changes in the profit and cost structures.

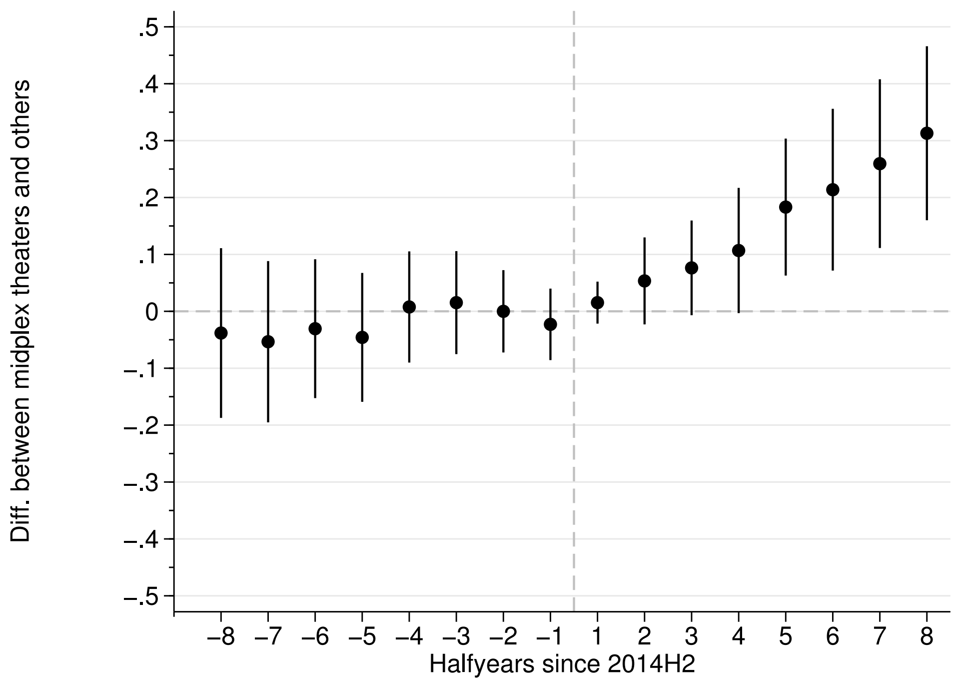

Figure 7: Effect of Regulatory Regime Shift

Note. The figure depicts the effects the land use regulatory regime shift on the number of midplex theaters. It plots the point estimates of τ_k in equation (A.1).

B CCP's Goodness of Fits

In this appendix, I report the performance of the first stage CCPs in describing the industry dynamics.

Market Structure Dynamics The estimated CCPs track the trends in theater counts and their average number of screens well. Figure 8 plots the evolution of the number of CGV, Lotte Cinema, and Megabox theaters, and Tables B.1 tabulates the time evolution of the average number of screens per theater by chains. Note that the predictions of the number of theaters are smoother than the actual trends, and the predicted average number of screens is lower than the data counterpart. Despite these discrepancies, the model MPNEs capture the main trends in the data well.

Transitions of Screens Lastly, I evaluate the performance of the model in matching the transition patterns of the number of screens. Table B.2 tabulates screen transition. The calculated MPNEs do a good job of replicating a considerable persistence of screen transition, suggesting a considerable sunk opening cost. Also, the MPNEs predict a higher transition rate from k to $k+6$ than those to $k+3$ and $k+9$. This pattern means that the sunk cost of opening a 6-screen theater is lower than those of opening 3-screen and 9-screen theaters.

The calculated MPNEs show a poor performance in matching screen transition when the number of screens is higher than 21. In particular, the MPNEs underpredict the persistence of screen transition. However, this finding is likely driven by rare observations with screens of more than 21.

Table B.1: Trends in Average Number of Screens per Theater

	CGV		Lotte Cinema		Megabox	
	Real Data	Simulated Data	Real Data	Simulated Data	Real Data	Simulated Data
2010H1	7.8041	7.4842	7.5273	7.5818	7.7885	7.6731
2010H2	7.7822	7.4469	7.4000	7.4992	7.7843	7.6064
2011H1	7.7885	7.4092	7.3770	7.4048	7.7255	7.5574
2011H2	7.7273	7.3679	7.3636	7.3362	7.6981	7.5143
2012H1	7.7431	7.3375	7.2143	7.2772	7.7321	7.4729
2012H2	7.7143	7.3059	7.0513	7.2319	7.6909	7.4345
2013H1	7.7436	7.2769	6.9639	7.1891	7.7636	7.3999
2013H2	7.7692	7.2462	6.8571	7.1480	7.6552	7.3614
2014H1	7.7845	7.2233	6.8351	7.1138	7.6491	7.3270
2014H2	7.6000	7.2018	7.0000	7.0839	7.5082	7.2906
2015H1	7.6290	7.1807	7.0481	7.0579	7.4355	7.2593
2015H2	7.6429	7.1442	6.9083	7.0291	7.1714	7.1725
2016H1	7.6349	7.1147	6.9455	7.0026	7.1081	7.1024
2016H2	7.5769	7.0860	6.9561	6.9772	7.1358	7.0540
2017H1	7.5259	7.0597	6.9569	6.9554	7.0920	7.0125
2017H2	7.5106	7.0351	6.9407	6.9355	6.9677	6.9772
2018H1	7.4257	7.0142	6.9661	6.9128	6.9565	6.9486
2018H2	7.3775	6.9934	6.9918	6.8974	6.9388	6.9210

Note. Data are simulated using the estimated CCPs and market type-specific demand process D^{μ}. The predicted evolutions are obtained by averaging 500 simulations.

Table B.2: Half-Annual Predicted Transition Rates (%)

Screens at t	Screens at $t+1$													
		0	3	6	9	12	15	18	21	24	27	30	33	36
0	Predicted	95.53	0.65	2.45	1.36	0	0	0	0	0	0	0	0	0
	Actual	96.30	0.59	2.16	0.96	0	0	0	0	0	0	0	0	0
3	Predicted	0.79	95.67	0.4q	1.8t	1.29	0	0	0	0	0	0	0	0
	Actual	0.41	96.75	0.41	1.63	0.81	0	0	0	0	0	0	0	0
6	Predicted	3.20	0.01	92.72	0.26	2.55	1.26	0	0	0	0	0	0	0
	Actual	1.83	0.00	95.25	0.27	2.01	0.64	0	0	0	0	0	0	0
9	Predicted	2.77	0.04	0.11	92.33	0.19	2.49	2.07	0	0	0	0	0	0
	Actual	1.40	0.00	0.17	94.42	0.17	2.27	1.57	0	0	0	0	0	0
12	Predicted	0	0.18	2.20	0.55	94.73	0.49	0.45	1.40	0	0	0	0	0
	Actual	0	0	3.11	0.44	94.67	0.00	0.44	1.33	0	0	0	0	0
15	Predicted	0	0	2.73	2.42	0.18	90.51	1.06	1.75	1.36	0	0	0	0
	Actual	0	0	1.71	2.05	0	93.15	1.03	1.37	0.68	0	0	0	0
18	Predicted	0	0	0	3.24	0.15	0.33	93.40	0.27	2.50	0.10	0	0	0
	Actual	0	0	0	2.03	0	0.29	95.64	0.29	1.45	0.29	0	0	0
21	Predicted	0	0	0	0	3.82	2.37	1.11	90.76	0.58	0.39 3	0.97	0	0
	Actual	0	0	0	0	0	3.57	0	96.43	0	0	0	0	0
24	Predicted	0	0	0	0	0	3.08	2.35	0.26	91.58	1.10	1.58	0.05	0
	Actual	0	0	0	0	0	3.92	1.96	0	90.20	1.96	1.96	0	0
27	Predicted	0	0	0	0	0	0	4.90	2.97	8.23	80.77	0.72	2.40	0
	Actual	0	0	0	0	0	0	0	0	16.67	66.67	0	16.67	0
30	Predicted	0	0	0	0	0	0	0	8.22	7.32	0.52	83.22	0.67	0.05
	Actual	0	0	0	0	0	0	0	0	0	0	100	0	0
33	Predicted	0	0	0	0	0	0	0	0	16.14	6.89	15.44	61.16	0.38
	Actual	0	0	0	0	0	0	0	0	0	0	0	100	0
36	Predicted	0	0	0	0	0	0	0	0	0	0	8.33	2.27	89.39
	Actual	na	na	na	na	na	na	na	na	na	na	na	na	na

Note. The unit of measurement is firm-market-halfyer. Data are simulated using the estimated CCPs and market type-specific demand process D^{μ}. The predicted moments are obtained by averaging 500 simulations.

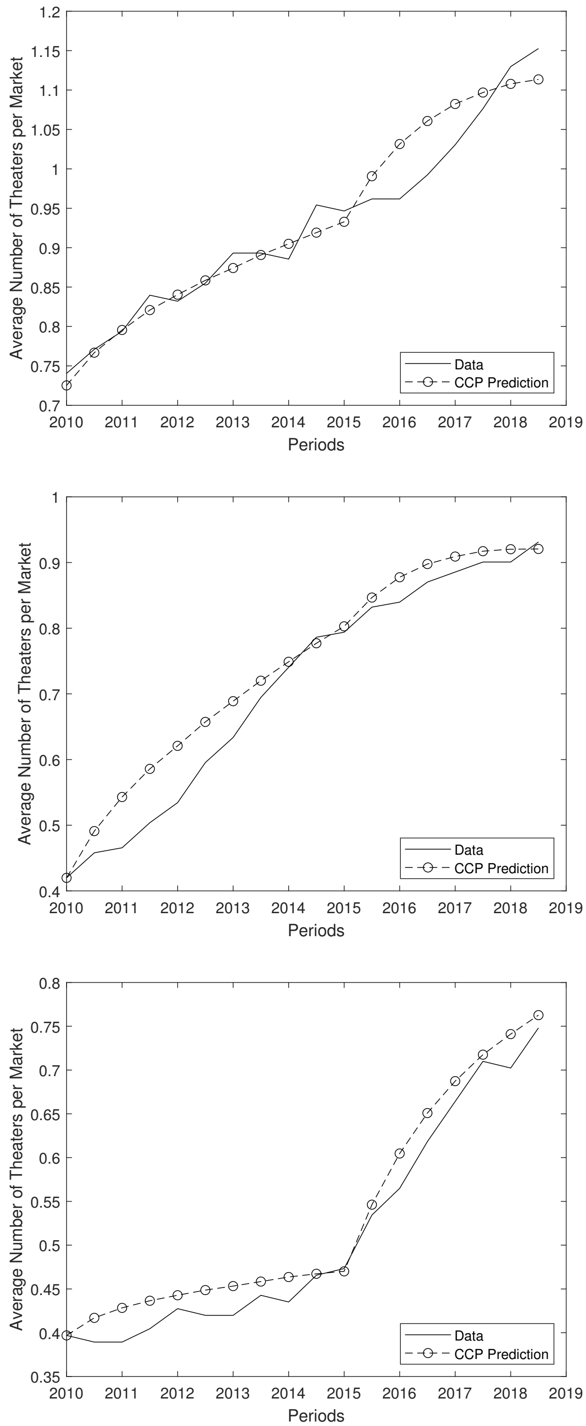

Figure 8: The Average Number of Theaters per Market

Note. Data are simulated using the estimated CCPs and market type-specific demand process D^{μ}. The predicted moments are obtained by averaging 500 simulations.

C Estimates of model with only theater entry decision

This appendix estimates a typical dynamic entry model in which the corresponding action space is $\{-1, 0, 1\}$, where -1 indicates an exit of a theater, whereas 1 indicates an entrant. Similar to the equilibrium policy function of the benchmark model, I can characterize the equilibrium policy function of this model as an ordered probit regression. Using the estimated policy function, I perform a forward simulation method to estimate the underlying structural parameters. Upon the estimation of the model, I perform the same counterfactual exercise to quantify the effect of lowering entry barriers on the producer surplus.

Tables C.1, C.2, and C.3 report the estimated CCP coefficients, variable profit parameters, and fixed- and sunk-cost parameters, respectively.

Table C.1: Ordered Probit on Extensive Marginal Theater Entry-Exit Decision

Covariates	(1)
# own chain theaters	-0.7449^{***}
	(0.0858)
# rival chain theaters	-0.5137^{***}
	(0.0535)
population (thousand people)	0.0098^{***}
	(0.0014)
GDP per capita (thousand KRW)	0.0057
	(0.0050)
Property value per m^2 (million KRW)	-0.4707^{**}
	(0.2183)
Market Dummies	✓
Log likelihood	-1204.93
Observations	6,681

Note. Estimated using a strongly balanced panel of the chain-market-time level. Standard errors are in parenthesis. Asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All units are expressed in one standard deviation of the standard Normal distribution.

Table C.2: Restricted Model: Estimates of Variable Profits per Theater

	Estimates	SEs
Competitive Effects: γ		
Cannibalization	-119.2102	11.9863
Rival competition	-135.2731	19.1731
Demand Shifters: λ		
Population (thousands)	2.5474	0.2632
GDP per capita (thousand 2011 KRW)	1.2615	0.2408

Note. Early-regime sunk entry cost parameter is calibrated to 1,800 million KRWs, which is quoted from a business report. All units of the other estimates are expressed in millions of 2011 constant KRW. Standard errors are calculated via subsampling.

Table C.3: Restricted Model: Estimates of Fixed Operating and Sunk Entry Costs

	2010H1-2014H2		2015H1-2018H2	
	Estimates	SEs	Estimates	SEs
Fixed Cost Parameters:$\phi_i^{FC}(\mu_m)$				
CGV in market category 1	-625.6663	59.1033	-567.4308	52.8206
CGV in market category 2	-214.9851	29.8943	-155.7225	18.4651
CGV in market category 3	133.5679	19.6595	163.9915	23.6065
Lottecinema in market category 1	-595.2884	67.2614	-597.5310	55.3321
Lottecinema in market category 2	-211.8450	30.1368	-180.4478	15.6520
Lottecinema in market category 3	164.1895	18.5007	135.8644	26.5437
Megabox in market category 1	-667.5595	66.8960	-580.2130	57.9888
Megabox in market category 2	-263.7131	27.6147	-170.6763	16.5021
Megabox in market category 3	67.3320	18.5322	153.5719	25.5545
Fixed Cost Parameters:ϕ_R^{FC}				
Property Values per m^2 (million 2011 KRW)	-87.2158	12.8121	-	-
Sunk entry cost parameters				
6-screen (ϕ^{EC})	*1,800.00*	N/A	1221.87	58.5511
standard deviation (ν)	405.810	–	-	-

Note. This table displays the fixed operating and sunk entry cost parameters. Early-regime sunk entry cost parameter is calibrated to 1,800 million KRWs, which is quoted from a business report. All units of the other estimates are expressed in millions of 2011 constant KRW. Standard errors are calculated via subsampling.