The Vertical Spillover Effect of Import Liberalization: A Study of the Chinese Movie Theater Industry

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Abstract

I study how liberalization of upstream imports leads to downstream retail expansion—a "forward spillover" effect—which subsequently increases consumer access to upstream domestic products—a "backward spillover" effect in China's movie market. I estimate consumer demand for domestic and foreign movies and theater profit with a Hotelling-style spatial competition model. I estimate theaters' fixed operating costs from inequality optimality conditions for entry and exit. Imported movies have little substitutability with domestic movies and are economically important for theaters to compensate for fixed costs. Simulations of a return to the protectionist quota suggest that the liberalization benefited consumers and domestic upstream movie producers and that the benefit is magnified by import-induced theater entry into the market.

Keywords: Vertical Spillover Effects, Import Liberalization, Spatial Competition

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1. Introduction

A longstanding debate about globalization concerns whether import liberalization has benefited or harmed producers in importing countries. Conventional wisdom highlights the trade-off between the "business-stealing" effect, wherein imports and domestic products are substitutes in the same segment, and the "forward vertical spillover" effect, wherein the upstream imports facilitate domestic downstream production. In this paper, I study a third effect that arises from the networked structure of production: trade-induced downstream retail and distribution sector growth makes upstream domestic products more accessible to consumers—an indirect "backward vertical spillover" effect.[1]

The debate over the relative importance of business stealing and vertical spillovers is central to trade policy-making. Over the past decades, globalization has given rise to free-trade policies that provide consumers with higher-quality products and exploit productivity and knowledge spillovers. Nonetheless, a wide range of protectionist policies through tariffs, subsidies, and import quotas have been implemented to constrain the adverse effect of business stealing. These protectionist policies benefit consumers to the extent that business stealing outweighs vertical spillovers, but empirical studies that jointly evaluate the two effects remain in short supply. In particular, little is known about mechanisms governing the magnitudes of spillovers.

I study the vertical spillover effects between the upstream production and the downstream exhibition sectors in the Chinese movie industry. In this context, a spillover exists because of the inter-dependence of theaters and movie demand: industry reports suggest that movie producers' revenue mostly comes from theater screening and theater revenue depends on the quality of available movies. To study this, I exploit the quasi-experimental variation arising from the liberalization of the annual quota on imported movies in 2012 from 20 to 34 movies, which allowed fourteen extra US blockbusters to enter the Chinese market each year. This policy change provides a clean setting to study forward and backward spillover effects. The forward spillover effect is the growth of the theater sector due to the import of additional foreign movies. With more theaters, domestic movie producers have more outlets to reach consumers. Measuring this backward spillover is the focus of this study.

Three features of the Chinese movie industry make it an ideal setting to study vertical spillovers. First, there is no exclusive movie distribution due to the regulatory mandate that

[1] Henceforward, the "forward vertical spillover" and "backward vertical spillover" effects are respectively referred to as the "forward spillover" and "backward spillover" effects for short, and the "vertical spillover" effects refer to both.

movies be released in all theaters. Second, digital movie copies admit a common technological standard and are compatible with every theater. Therefore, the causal effects of vertical spillover can be identified without complications from confounding factors such as exclusivity and compatibility. Lastly, movie theaters, which are the key to propagating vertical spillovers, are geographically differentiated. The backward spillover effect, defined as the increase in consumer access to movies driven by trade-induced theater entry, is well-measured by the change in the proximity of theaters to consumers.

The analysis proceeds in four steps. First, I collect and compile data on the Chinese movie industry from numerous sources. The primary data is collected from a website that published weekly theater-level domestic and foreign movie sales. I complement the data with movie information (including countries of origin, release dates, initial runs, and total sales in each city) and theaters (including exhibition technology, locations, and entry dates). With a geocoding API, the data is matched to three web-scraped census block-level panel datasets, which include new shopping mall information, land value imputed from primary land market transactions, and the spatial distribution of population reported in Brinkhoff (2022).

Second, I exploit the quasi-experimental policy change to provide reduced-form evidence for business-stealing and vertical spillovers. Using the average pre-liberalization city-year level sales share of imported movies as a measure of "pro-foreign" preference, I find little evidence of business stealing: the average growth rate of domestic box-office sales was similar in the pre- and post-liberalization periods. The gap in this growth rate between "pro-foreign" and "pro-domestic" cities slightly decreased after the quota increase. Moreover, I find evidence of forward spillover: the gap in per capita theater entry between "pro-foreign" and "pro-domestic" cities became significantly larger after liberalization. Both results control for time-varying city characteristics and cross-city differences in movie market development.

Next, I jointly estimate consumer movie demand and theater visits with a Hotelling-style model of spatial competition. The correlation in consumer preferences across movies of the same origin (i.e., domestic or foreign) is embedded in the model by a nested-logit specification. I estimate travel cost, substitutability between domestic and foreign movies, and price sensitivity with theater-origin-quarter-level sales data. Finally, using model-predicted variable profit, I estimate theaters' fixed costs with an inequality estimator derived from the following optimality conditions: (i) non-negative net profits of incumbent theaters and (ii) negative net profits of exiting theaters. The exercise uses data from the last sample year, 2017, when the market structure is the most mature and variable profit is most informative about fixed costs.

There are three key findings from the demand estimation. First, consistent with the findings by Ho et al. (2021), substitution between domestic and foreign movies is very small. This substitution pattern implies that imported movies mostly divert consumer demand away from the outside option (i.e., not going to a theater) instead of away from domestic movie sales. Second, spatial competition between theaters is mostly local, and the elasticity of substitution between two theaters goes to zero quickly as their distance increases. Combined with the fact that theaters are clustered in space and show the same government-selected movies, this finding suggests that many theaters are minimally differentiated from their local rivals. Third, consumers are sensitive to prices, and theaters' markups are low, with a median of 10%. Foreign movie imports are economically important for theaters to compensate for fixed costs and stay profitable.

Lastly, to shed light on the importance of vertical spillovers from import liberalization, I conduct two counterfactual simulations where there is a return to the old quota in 2017 (i.e., only 20 out of the 34 released foreign movies are shown). The first simulation holds the observed theaters fixed and investigates how the import restriction affects consumer surplus, theater profit, and government tax revenue. The second simulation compares theaters' counterfactual variable profits with their fixed costs. Then it predicts the counterfactual theater market structure and changes in consumer access to movie theaters.

The results obtained in the first counterfactual indicate that consumer surplus, theater profit, and government tax revenue all drop by 3%–5% with import restrictions. Although theaters' profits from domestic movies would slightly increase by 0.49%–0.54%, their profits from foreign movies would drop by 6.14%–11.14%. The results are consistent with the low estimated domestic-foreign movie substitutability and suggest that the business-stealing effect is small and the forward spillover effect is significant. A cross-city comparison suggests that pro-foreign cities have greater welfare loss.

In the second counterfactual, 23.74%–24.74% of the theaters would be unprofitable, from which domestic movies receive 7.32%–8.62% of their sales. Welfare cost is larger when imports are of higher quality. Compared with the results in the first counterfactual, backward spillover is of a similar magnitude to that of the direct forward spillover. Both effects are at least as important as consumer gain from foreign varieties. In conclusion, import restrictions lead to protectionism without winners, and changes in market structure amplify the welfare cost.

1.1. Related Literature

This paper investigates how import competition affects domestic consumers and producers, with a focus on the vertical linkage between upstream movie production and downstream movie exhibition. I build on three strands of literature: demand for differentiated goods, network effects, and trade liberalization.

First, it is important to note that imported and domestic movies are imperfect substitutes, so imports cannot entirely replace domestic products or cause product fragmentation—a phenomenon often observed in homogeneous or vertically differentiated goods industries. To measure the substitutability between domestic and imported movies, I follow the literature in industrial organization on demand for differentiated products developed by Berry (1994) and Berry et al. (1995). Applications of this method in the movie industry include Einav (2007), Ferreira et al. (2016), Chen and Hodgson (2018), Ho et al. (2021), and Chen et al. (2022). I incorporate this literature into a Hotelling-style model of spatial competition following Davis (2006) and Houde (2012) to capture the inter-dependence of theaters and movie demand: higher quality movies increase theater sales, and theater expansion increases the accessibility of movies to consumers.

Moreover, my paper contributes to the longstanding industrial organization literature on indirect spillover/network effects between complementary markets (e.g., software-hardware and platform-content). Related studies examine industries such as CD players and CD titles (Gandal et al., 2000), personal digital assistant hardware and software (Nair et al., 2004), video game consoles (Dubé et al., 2010), electric vehicles and charging stations (Li et al., 2019; Springel, 2021), and 4G handsets and 4G wireless service networks (Chatterjee et al., 2022). My empirical context differs from those in the existing literature. Due to the regulatory mandate that movies be released in all theaters with digital copies produced following a common technological standard, there is no product exclusivity in movie distribution or product incompatibility in movie exhibition. I can provide reduced-form evidence on vertical spillover without complications from confounding exclusivity or incompatibility mechanisms.

Lastly, this paper is related to the vast literature on the effects of trade liberalization. Substantive empirical work has studied the direct effects of import trade and foreign direct investment (FDI) in a sector on the productivity, R&D activities, and product variety of domestic producers in complementary sectors.[2] In contrast to previous studies, I exam-

[2] Javorcik and Spatareanu (2011), Arnold et al. (2011), and Amiti and Konings (2007) find productivity spillovers in their respective contexts of the Association Agreement between Romania and the European Union (EU), Czech service liberalization, and decreasing import tariffs in Indonesia. Gorodnichenko et al. (2020) find

ine the *indirect* spillover effect of import liberalization. I find that trade-induced growth in domestic downstream sectors can benefit domestic firms in the upstream liberalized sector. The key mechanism—spillover through vertical linkages between upstream and downstream sectors—is similar to Chatterjee et al. (2022) and Fieler et al. (2018): high-quality input imports facilitate production in final goods sectors and further create a derived demand for domestic inputs that are imperfect substitutes.

The rest of the paper is structured as follows. Section 2 provides the industry background, data, and stylized facts that motivate the reduced-form tests and structural models. Section 3 presents reduced-form evidence of the effects of import liberalization on domestic and foreign movie sales and theater entry using a difference-in-differences strategy. Section 4 presents the model of consumer movie demand and theater sales. Section 5 discusses details on the estimation and identification of the model. Section 6 presents the estimation results. Section 7 presents results for counterfactual simulations. Section 8 concludes.

2. Industry Background and Data

2.1. Vertical Structure and Regulations

The current movie supply chain has three segments: producers (studios), distributors, and exhibitors (theater chains and theaters). While distributors, theater chains, and the vast majority of theaters are domestic firms, movies can be produced by Chinese and foreign studios.[3]

Figure 1 visualizes the industry's structure. The regulatory authority, the State Administration of Radio, Film, and Television (SARFT), grants movie distribution permits after censorship. Domestic movie producers select their distributors, whereas the distribution of foreign movies is monopolized by two state-owned companies, *China Film* and *Huaxia Distribution*.

Upon issuance a distribution permit, SARFT centrally coordinates a vertical contract between a movie's distributors and all theater chains. Two regulatory mandates make China's movie market different from other markets. First, movies are released in all theater chains on nationwide release dates. Second, the industry admits the same revenue-sharing scheme: the government, upstream firms (producers and distributors combined), and downstream firms

positive spillovers from FDI and trade on product and technology innovation. Goldberg et al. (2010) finds that a decrease in import tariffs causes a wider variety of final products in India.

[3]The vast majority of theaters are owned by theater management companies where foreign ownership is limited to 50%. Theater management companies under multinational joint ventures have a very small market share. For example, in 2017, the national market share of the largest multinational joint venture theater management company was 3%, whereas that of the largest domestic company was greater than 25%.

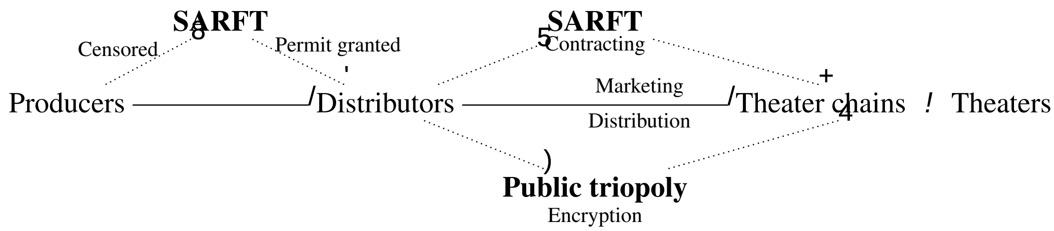


Figure 1: Industry Structure

Notes: SARFT is an acronym for State Administration of Radio, Film, and Television. SARFT, the public triopoly, and the industry association supervised by it are in bold. Solid arrows denote the flow of movies, and dotted arrows denote administrative procedures.

(theater chains and theaters combined) receive 8.3%, 39.5%, and 52.2% of the gross sales revenue, respectively. The detailed revenue-sharing scheme is summarized in Table A1.

Finally, digital copies of movies are created by producers following a common technological standard. Then the copies are encrypted by three state-owned firms.[4] These firms create screen-movie-specific decryption keys, which expire after the release window set by the SARFT. Consequently, theaters only have access to the set of films selected by the government.

2.2. Pricing and Movie Provision

Unlike the US movie market, there is significant variation in price and movie provision (i.e., the number of showings of each movie in a theater in a week). However, their variances are attributed to different factors. The two most important components of ticket prices are a movie-specific reference price and a theater-specific markup. A movie's reference price is specified in the centrally-coordinated exhibition contract, which is common across all theaters in the same market. Using sales data of a greater granularity during 2012–2017, I decompose the variance of theater-movie-week level price into a movie component, a theater component, and residual variance, similar to Card et al. (2018). The results are reported in Table A2 of Appendix A.2. The results in Column (4) of Panel A suggest that 65.85% of price variance is explained by theater-origin-quarter level variation while 10.07% is explained by movie-week level variation. Together the two components explain more than 75% of price variation.

I also do the same decomposition analysis for movie-theater-week level showings per screen. Results are reported in Panel B Table A2. The results in Column (4) suggest that 70.74% of the variance is explained by movie-week level variation, and 8.58% of the vari-

[4] The state-owned firms that encrypt the copies are *China Film*, *Huaxia Distribution*, and the *Film Digital Certificate Management Platform* of SARFT.

ance is explained by the theater-origin-week level variation, which is drastically different from the decomposition results for prices. The main reason is described in Section 2.1: movies are released in all theaters at their respective national release dates and their initial runs are centrally controlled by the government. Given this regulatory background, theaters allocate screening capacity to movies, but this decision accounts for only a small portion of the variation in showings.

2.3. The Movie Import Liberalization in 2012

Following its accession to the World Trade Organization, China imposed an import quota for foreign movies. Each year at most 20 foreign movies could be imported for domestic release, six of which were reserved for non-US movies. In 2007,the US filed a WTO dispute against China's quota restriction on imported movies. As a settlement of the dispute, in February 2012, China agreed to increase the quota movie imports from 20 to 34. The incremental 14 movies were required to be enhanced format (3D or IMAX) US movies. Foreign producers' share of final box-office sales increased from 13% to 25%.

This new policy was one of the US-China trade dispute resolutions negotiated during Chinese economic officials' visit to the US. As reported in many news articles and empirically documented in Section 3, the liberalization came unexpectedly, which is the nature of most trade negotiations. Its immediate enactment makes the *exact* timing of policy implementation largely exogenous to domestic movie market conditions.[5]

2.4. Data and Sample Construction

I collect and compile several data sources to conduct empirical analysis: (1) weekly theater-origin (domestic or foreign) sales, (2) characteristics of theaters and movies, and (3) market characteristics (spatial distribution of consumers, commercial real estate, and land prices in the primary market). I describe the datasets in this subsection.

2.4.1. Sales Data

Sales data is collected from a website that published weekly theater-level box office data before 2019.[6] The data is sourced from SARFT's electronic system that monitors the box-office sales in the universe of Chinese movie theaters. The system was established in 2005

[5]As mentioned by Ho et al. (2021), China also imports around 30 movies under flat-fee contracts, which are unaffected by the policy change. In addition, Chinese and foreign studios co-produce movies exempted from quota restrictions. These two types of movies account for a very small share of the total box office and are dropped from the samples used in subsequent analysis.

[6]Data source: http://www.cbooo.cn/cinemaweek (retrieved in November 2018).

and upgraded in 2012. I use two sales datasets from 2009 to 2017. The first is at the theater-origin-week level, and the second is at the movie-city-week level. These are the most granular datasets that span pre- and post-liberalization years.[7] Similar datasets from SARFT have been used in a few other papers (e.g., Ho et al., 2021; Gil et al., 2022; Hodgson and Sun, 2022; Chen et al., 2022; Fan et al., 2022).

In the reduced-form analysis, I keep 108 cities that account for 79.31% of national box office sales. The reason for this restriction is that demographic data for the remaining 222 cities is not available. This gives me 2,043,270 theater-origin-quarter level observations, of which 940,828 are from theaters that entered the market before 2012. In the structural analysis, I further restrict the sample to 24 largest cities where market boundaries are clearly defined. These cities are nationally representative of taste for foreign movies. Demand is modelled at the theater-origin-quarter level and this aggregation gives me 36,751 observations.[8] More discussion on market definition is in Section 4.1.

2.4.2. *Theater and Movie Characteristics*

I complement the sales data with information on movies and theaters in the sales dataset.[9] The observed theater characteristics include the numbers of screens, seats, and enhanced format screens, location, chain affiliation, and entry date. There are 3,380 theaters in the reduced-form analysis sample. The movie characteristics used in the later sections include the countries of origin, release date, and initial run. There are 601 Chinese movies and 248 imported movie in my demand estimation sample.

2.4.3. *Market Characteristics*

The sales and theater datasets are matched to web-scraped sub-city level panel datasets using AMap API, the service provider for Apple Maps in China. The scraped market characteristics include shopping mall information, land value imputed from primary land market transactions, and population size.

The shopping mall data is collected from a website that publishes the profiles of commercial properties built since the 1920s.[10] Shopping malls' opening dates and location information are of particular use to the reduced-form analysis.

[7] Movie-theater-week level sales data is unavailable for the full sample period.

[8] The following observations are dropped from the structural analysis: (1) theater-quarter pairs with less than 50 admissions, (2) theaters that constantly show a significantly smaller portion of movies than other theaters, and (3) 38 non-profit theaters and 178 theaters that entered in the last two quarters of 2017.

[9] Data source: EntGroup China, the leading consulting firm specializing in the Chinese media industry.

[10] Data source: https://www.winshangdata.com (retrieved in January 2022).

I use the universe of land transaction records in the primary land market during my sample period to proxy for rent costs faced by theaters. The data is published online by China's Ministry of Natural Resources.[11] Because local governments often give different discounts to buyers of industrial land, industrial land prices are less informative about location-specific land value. I follow Chen and Kung (2019) and restrict my sample to commercial and residential land transactions. For the same reason, I further restrict the transactions to those made via auction instead of a bilateral agreement between the government and firms. The details on land value imputation are described in B.1.

Lastly, population size by census block in 2010 and 2020 is provided by Brinkhoff (2022). I interpolate population in non-census years with district-level population growth rates.[12] The median area of a census block in my data is 3.94 km^2. The median number of census blocks in a city is 40.

2.4.4. Summary Statistics

Table 1 reports theater-year-level summary statistics for 4 cross-sectional sub-samples (2 before the 2012 liberalization and 2 after). Price and sales are deflated by the consumer price index. Theater characteristics (the numbers of screens, enhanced format screens, and seats) were stable over the sample period. The same is true for sales, admissions, and price with a notable exception in 2012, the year when liberalization took place.

Compared to the sales and showings in 2011, the sales of domestic movies were smaller despite higher showings in 2012. Meanwhile, the showings and sales of foreign movies had a discrete jump. These changes reflect the immediate impact of import liberalization when theater market structure did not drastically change. The changes suggest that theaters did not operate under full capacity before the liberalization. The introduction of new movie imports significantly increased theaters' capacity and their sales.

2.5. Descriptive Evidence

In the post-liberalization period from 2012 to 2017, national box-office sales of domestic and imported movies had similar annual growth rates, 8.27%, and 8.8%, respectively. The number of movie theaters increased from 431 to 3,380. These statistics are consistent with the views of policymakers and practitioners that waves of import liberalization in the movie

[11]The universe of land transaction records are published online at http://www.landchina.com. The Law of Land Management requires sub-national bureaus of land and resources to report land transactions in their jurisdictions to this online system.

[12]A Chinese city is divided into districts. Districts are then divided into census blocks. For example, in the 2010 census, urban Beijing had 6 districts and 97 census blocks.

Table 1: Summary Statistics on Theater Characteristics, Price, and Sales

	2009 Mean/SD	2011 Mean/SD	2012 Mean/SD	2017 Mean/SD
Sales (*10^6), domestic	5.34	4.37	4.23	4.51
	(6.31)	(5.47)	(5.15)	(4.16)
Sales (*10^6), foreign	4.60	4.85	5.38	4.51
	(6.21)	(6.82)	(7.54)	(5.26)
Admissions (*10^6), domestic	0.17	0.12	0.12	0.13
	(0.18)	(0.14)	(0.13)	(0.11)
Admissions (*10^6), foreign	0.14	0.13	0.14	0.13
	(0.17)	(0.15)	(0.17)	(0.13)
Showings (*10^3), domestic	4.46	4.56	4.76	5.96
	(3.45)	(3.40)	(3.15)	(2.94)
Showings (*10^3), foreign	3.97	3.88	5.11	6.76
	(3.43)	(3.13)	(3.81)	(3.60)
Price	29.33	33.11	33.31	31.90
	(7.10)	(8.86)	(8.02)	(6.50)
Screens	6.42	6.38	6.43	6.87
	(2.97)	(2.99)	(2.89)	(2.68)
Enhanced screens	0.24	0.21	0.20	0.25
	(0.55)	(0.52)	(0.51)	(0.55)
Seats	981.35	923.62	915.38	928.22
	(509.03)	(500.66)	(492.71)	(482.49)
Observations	431	868	1,182	3,380

Note: An observation is a theater-year pair. Sales and prices are measured in 2009 Chinese Yuan. Standard deviations are reported in parentheses.

industry do not destroy demand for domestic movies but instead greatly contribute to entry in the downstream theater sector.[13] In this subsection, I show more descriptive evidence.

2.5.1. Aggregate Trends Pre- and Post-Liberalization

During the sample period, there were massive theater entry and sales growth (displayed in Figure 2(a)).[14] Figure 2(b) zooms in on sales growth and shows the growth trajectories separately for domestic and foreign movie sales. After the quota increase first took place in 2012, foreign movie sales exceeded domestic sales for the first and only time. This is often referred

[13]Policymakers and practitioners in the Chinese movie industry have long recognized the importance of vertical spillovers. In 1994, a proponent of the upstream liberalization policy, then president of the state monopoly *China Film Import and Export Corporation* claimed that imported films would "enable 500,000 employees of film distribution companies to survive and make a living." After the success of Avatar in 2009, IMAX CEO Rich Gelfond claimed that "Avatar changed everything for IMAX—catapulting our brand into the stratosphere and putting us on the map in China." More interviews with practitioners are available from Su (2010) and Zhou (2019).

[14]A domestic blockbuster movie contributed to the significant increase in the domestic movie sales in 2015.

to as business-stealing: in the short run when entry response is muted, demand substitutes from domestic to foreign movies. Starting from 2013, domestic movie sales have led foreign movie sales by a margin which has been increasing over time.

Figures 2(c) and 2(d) depict for each year between 2008 and 2017, the number of movies released and per-movie sales, respectively. Figure 2(c) plots the numbers of domestic and foreign movies released from 2008 to 2017. Before and after the 2012 liberalization, the quota on imported foreign movies was binding. Furthermore, since there are no restrictions on the production and distribution of domestic movies, the number of domestic movies released seems to be unaffected by the 2012 liberalization. Figure 2(d) plots per-movie sales for domestic and foreign movies separately, from 2008 to 2017. There was no significant change in the per-movie sales of domestic movies.

Comparing the two figures with Figure 2(b), one can infer that domestic movie sales growth was mainly driven by the sharp increase in the titles released. Meanwhile, since quota restriction was enforced, aggregate imported movie box-office growth can only be driven by average sales per movie. From 2008–2017, average movie sales increased by 3 and 8.5 times for domestic and foreign movies, respectively.

2.5.2. Growth Decomposition: Theater Entry and Revenue

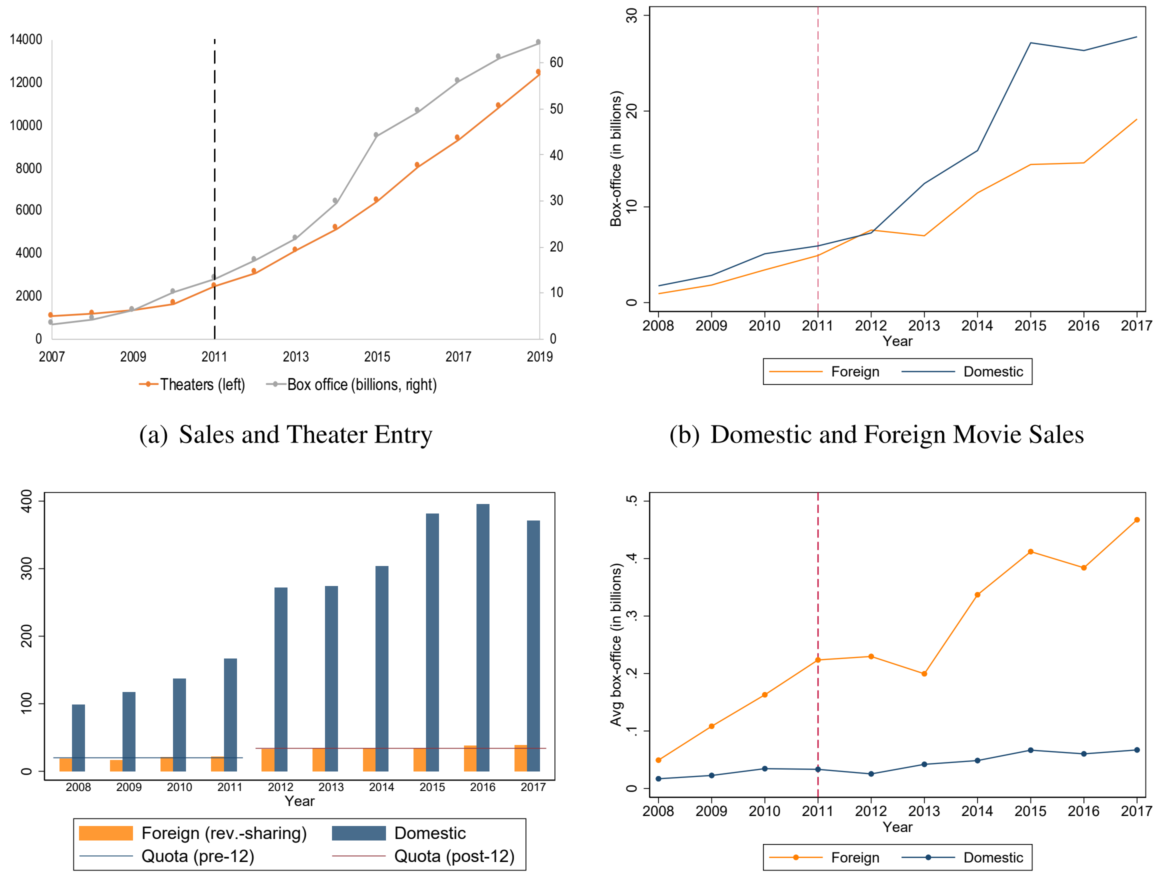
I decompose the annual sales growth shown in Figure 2(b) to contributions from incumbents, entrants, and exiting theaters. Let $\mathcal{F}_t$ and R_{jot} denote the set of operating theaters in year t and the revenue of origin o (foreign/domestic) movies in theater j in year t, respectively. I take a long difference between years t and t':

$$\begin{aligned}\sum_{j\in\mathcal{F}_{t'}} R_{jot'} - \sum_{j\in\mathcal{F}_t} R_{jot} &= \sum_{j\in C_{t'}} (R_{jot'} - R_{jot}) + \sum_{j\in E_{t'}} R_{jot'} - \sum_{j\in X_t} R_{jot} \\ &= N_C(R^C_{gt'} - R^C_{gt}) + N_E R^E_{gt'} - N_X R^X_{gt} \end{aligned} \tag{1}$$

where $C_{t'}$ denotes the set of continuing theaters in year t, $E_{t'}$ denotes the set of entrants in year t', and X_t denotes the set of incumbents exiting before year t'. The equality holds from the partition $\mathcal{F}_t = C_{t'} \cup X_t, \mathcal{F}_{t'} = C_{t'} \cup E_{t'}$. Equation (1) decomposes the aggregate sales growth into intensive margin incumbents' growth and extensive margin changes (entrants' and exiting theaters' revenue difference).

The decomposition results are reported in Table 2. There are two notable results. First, the average entry rate and average exit rate were higher in the post-liberalization period.[15]

[15] Note that I exclude entrants that enter in the endpoint years (94 in 2011, 52 in 2017) because they did



(a) Sales and Theater Entry

(b) Domestic and Foreign Movie Sales

(c) Count of Movies Released

(d) Per-Movie Box-Office Sales

Figure 2: Descriptive Evidence on Aggregate Growth

Notes: Figures 2(c) and 2(d) plot the number of movies released and per-movie sales, for domestic and foreign movies separately, in each year. Figure 2(a) plots theater entry and sales growth. Figure 2(b) plots the total domestic and foreign movie sales in each year.

Second, the business stealing effect is consistent with changes in average incumbent sales between 2011 and 2012. Average domestic movie sales decreased by 29% while for foreign movies it dropped by 16%.

Lastly, the vertical spillover effect is also consistent with two facts. First, more movies distributed are associated with higher downstream entry, which is possibly driven by higher profitability. The annual entry rate grew from 86% to 112.3% after the liberalization.[16] Second, the import-domestic per-theater sales gap significantly shrank after liberalization. This gap should have widened if there was no supply response after the quota increase.

not operate through the endpoint years and will mechanically bias the entrant sales downward. I include those observations in demand estimation.

[16] Annualized entry rate is calculated as $(\text{Entrants}_{t^0}/(\text{Incumbents}_{t^0} + \text{Exitors}_t))^{1/(t^0 \;\; t)}$.

Table 2: Decomposition of Aggregate Box Office Revenue Growth

	Pre-liberalization (2009–2011)		Post-liberalization (2012–2017)	
	Domestic	Imported	Domestic	Imported
Incumbents (N_C)	418		1017	
R^C_{gt}	5.46	4.72	4.69	5.99
$R^C_{gt^\theta}$	6.61	7.14	5.82	6.11
$R^C_{gt^\theta}$ R^C_{gt}	1.15	2.42	1.12	.12
Entrants (N_E)	319		2107	
$R^E_{gt^\theta}$	2.85	3.46	4.13	4.12
Exitors (N_X)	13		165	
R^X_{gt}	1.31	.77	1.39	1.64

Notes: This table shows the decomposition result of Equation (1) for the pre-liberalization (2009–2011) and post-liberalization (2012–2017) periods. The count N and average sales R of incumbent theaters, entrants, and theaters are reported. Average sales are in millions of 2009 Chinese Yuan.

3. Reduced-Form Evidence

The before-after liberalization comparison of the import-domestic gap in Table 2 is similar to a difference-in-differences (DID) design. However, one obstacle to causally interpreting these results is that import liberalization occurred while theater construction became more frequent and willingness to watch movies increased. For example, before liberalization, per-theater box-office of foreign movies had a 16.2% annual growth rate and the annual theater entry rate was 30%.

In this section, I exploit cross-sectional variation in local consumers' foreign taste for movies and use a more rigorous DID design to identify the impact of liberalization. Specifically, I relate the difference in supply responses (theater entry and resulting changes in domestic and foreign movie sales) to differential exposure to liberalization measured by the pre-liberalization local sales share of foreign movies.

3.1. Evidence of the Forward Spillover Effect

I first provide reduced-form evidence of the forward spillover effect. In the context of the liberalization of movie imports, forward spillover refers to the fact that imported movies increase the expected downstream theater profit and therefore theater entry. The testable hypothesis is that the gap in theater entry between "pro-foreign" and "pro-domestic" cities was widened after the liberalization. Using the average pre-liberalization city-year-level total sales share of imported movies as a measure of regional "pro-foreign" preference, the DID model is specified as follows:

$$y_{ct} = \beta Post_t \quad s_c + \gamma_1 g_{ct}^{pop} + \mu_c + \tau_t + \gamma_2 x_{c,2011} \quad t + \varepsilon_{ct} \tag{2}$$

where y_{ct} is new theaters per million population built in city c year t , $Post_t$ is a dummy for liberalization, s_c is city c's annual sales share of foreign movies averaged across years before liberalization, μ_c, and τ_t are the city- and the year-fixed effects, respectively, g_{ct}^{pop} is the population growth rate in city c year t, and $x_{c,2011} \quad t$ is a time trend that depends on city c's pre-liberalization per-capita income $x_{c,2011}$ (a specification similar to Nunn and Qian, 2011; Lu et al., 2019).

3.1.1. *Identification*

The key parameter of interest, β, measures how the gap in new theater entry between cities with different regional preferences for foreign movies changes after liberalization. The empirical strategy hinges on the following assumption: conditional on covariates g_{ct}^{pop}, μ_c, τ_t, $x_{c,2011} \quad t$, the key variable of interest $Post_t \quad s_c$ is mean independent of the ***temporary*** shocks to theater entry ε_{ct}.

The main threat to this identification assumption is that the policy change $Post_t$, as a settlement to the 2007 trade dispute is not perfectly exogenous and that pre-liberalization market shares of foreign movies s_c are not randomly assigned. I address this issue in two ways. First, as described in Section 2.3, the nature of trade negotiations makes the exact timing of this policy change largely unexpected. The time fixed effects τ_t control for the growth of overall movie demand and city characteristic dependent time trends $x_{c,2011} \quad t$ control for cross-city difference in movie market development. Hence, the indicator of policy change $Post_t$ is plausibly exogenous to ***temporary shocks*** to theater entry—ε_{ct}. I also conduct a set of placebo tests in Section 3.1.2. Results in Table 3 suggest that the gap in other characteristics such as per capita shopping mall and per capita income between pro-foreign and pro-domestic cities does not change after liberalization. Second, recall that theaters show the same government-selected movies. Therefore, the long-run average foreign movie market shares mostly capture taste differences. As a robustness check, I also instrument market shares with pre-liberalization city demographics in Appendix C.1 (similar to Berry and Waldfogel, 2001).

3.1.2. Estimation Results

Table 3 reports the estimation results of Equation (2). Results in Column (1) suggest that the liberalization significantly changes the gap in theater entry between cities with different regional preferences for foreign movies. Compared with other cities, those with a one standard deviation higher pre-liberalization foreign movie sales share (6%) have 0.24 (= 6% $\hat{\beta}$) more theater entrants per million population each year after the liberalization.

To interpret the estimates, as reported in Table 2, the 106 cities in the reduced-form exercises had 2107 theater entrants after liberalization (3.97 per million population for a city with 5 million population). The coefficient estimate translates to 6% more theater entrants in cities with one standard deviation higher measured "pro-foreign" preference.

Lastly, Columns (3) and (4) present the results for the placebo tests. Specifically, I run Equation 2 with per million population shopping mall and log per capita income as the dependent variables, respectively. Results suggest that the gap in other characteristics such as shopping mall and income between pro-foreign and pro-domestic cities does not change after liberalization

Table 3: Reduced-Form Evidence for Forward Spillover

VARIABLES	(1) Theater entry/pop	(2) I(entry>0)	(3) Mall entry/pop	(4) Log per capita income
$Post_t$ Avg foreign share	3.990***	0.213	0.137	0.127
	(1.202)	(0.426)	(1.682)	(1.832)
Pop Growth	-0.018	-0.003	-0.005	-0.002
	(0.022)	(0.008)	(0.023)	(0.013)
Observations	944	944	944	944
R-squared	0.332	0.265	0.460	0.302
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Cities	106	106	106	106

Note: Standard errors clustered at the city level are reported in parentheses. Columns (1)–(3) also control for the interaction between the time trend and log income in 2011.

3.2. Evidence of business-stealing

I use the following theater-origin(domestic/foreign)-quarter level regression to document the business-stealing effect. Here, time subscript t indexes weeks rather than quarters.

$$\log(R_{jot}) = \beta^o Post_t \times s_{c(j)} + \mu_j + \tau_{o,t} + \varepsilon_{jot}. \tag{3}$$

where R_{jot} is total box-office revenue of origin $o \in \{\text{domestic, foreign}\}$ movies in theater j quarter t, $Post_t$ is the liberalization dummy, $s_{c(j)}$ is average city-level foreign movie sales share before liberalization, μ_j is the theater fixed effect, $\tau_{o,t}$ is the origin-week fixed effect that control for origin-specific time trend and seasonality in movie demand respectively.[17]

The key parameter of interest, β^o, measures how the origin-specific gap in average theater-level sales growth changes (after controlling for theater- and origin-week factors) between cities with different regional preferences for foreign movies changes after liberalization. The identifying assumption is the same as the one in Section 3.1 in that the exact timing of the liberalization policy is exogenous to shocks to theater revenue ε_{jot}.

The presence of massive theater entry makes the data a heavily unbalanced panel and the DID estimates should be interpreted with caution. The estimate of β^o may capture entrant-incumbent difference if entrants are systematically different from incumbents. I estimate the regression twice using the full sample and the incumbent subsample and results are reported in Columns (1) and (2) of Table 4. Results are quantitatively similar.

To interpret the estimated effect on theater-level sales growth is 10% (= 1.712×0.06) higher for foreign movies and 6.69% (= 1.115×0.06) lower for domestic movies.

3.3. Summary of Reduced-Form Results and the Need for a Model

In Sections 3.1 and 3.2, I show that after 2012, cities where there is a high regional preference for foreign movies had 29% more theater entry. The effect is robust after controlling for cross-city differences in time trends. Moreover, comparing weekly theater sales across cities with consumers with different degrees of "pro-foreign" tastes, I find that, after liberalization, theaters in "pro-foreign" cities have 10% higher growth in foreign movie sales and 6.69% lower growth for domestic movies. I include a rich set of fixed effects to control for import policies and origin-specific seasonality. The indirect backward spillover effect—the increase in domestic movie sales arising from trade-induced theater sector expansion—cannot be directly tested. Nonetheless, a back-of-envelope comparison between the two sets of results

[17] Here I exploit the institutional background that Chinese theaters have access to the same set of movies. So the set of released movies is a function of time (i.e., year and quarter).

Table 4: Reduced-Form Evidence for business-stealing

VARIABLES	(1) log(box office)	(2) log(box office)
Effects on foreign movies		
$Post_t$*Avg foreign sales share	1.633***	1.623***
	(0.504)	(0.061)
Effects on domestic movies		
$Post_t$*Avg foreign sales share	-1.476***	-1.467***
	(0.490)	(0.048)
Observations	2,043,230	940,828
R-squared	0.856	0.383
Sample	All	Pre-12 Incumbents
Theater FE	Yes	Yes
Week*Origin FE	Yes	Yes

Notes: Standard errors clustered at the city level are reported in parentheses. Column (1) uses the full sample and Column (2) uses the subsample of incumbent theaters.

suggests that the entry response to import liberalization is more significant than the within-theater substitution between domestic and foreign movies.

To evaluate the overall impact on consumer and producer surplus of the import liberalization policy, I need to structurally model consumer demand and theater supply for two reasons. First, as in previous trade literature, gains from trade are computed as the difference between the factual welfare and the welfare under the no-trade counterfactual. Both welfare measures require a structural model. Second and more importantly, movie theaters, which are the key to propagating vertical spillovers, are spatially differentiated. The spatial nature of theater differentiation and consumer distribution means that import liberalization may have important effects on the spatial configuration of theaters and therefore equilibrium movie pricing and consumer access to theatrical movie exhibition may be differently impacted by import policy depending on their locations. The reduced-form exercise of analyzing the responses on theater sales to policy change is informative about the average effect but abstracts away from differential changes in theater market structure.

4. Model

The structural model of this paper consists of two parts. The first part is a static consumer quarterly demand for domestic and foreign movies. The second part is the structure of theaters' marginal cost which, together with consumer demand, determines theaters' quarterly variable profit.

4.1. Market Definition, Market Size, and Time Aggregation

A market is defined as a city c quarter t pair. The geography of city c is defined by census blocks $i = 1, ..., L_c$. I drop consumers and theaters in rural census blocks because the market definition for theaters in rural areas cannot be clearly defined.[18]

The demand model is estimated at a quarterly frequency because the goal is to evaluate gain from new movies and theater entry. As criticized by Ho et al. (2021), consumer choice set dynamics are important for welfare calculation when analyzing demand at a high frequency. Hence, instead of modeling the week-by-week change in the set of available movies, I model demand at the quarter level, exploiting the quarterly variation in released movies and theater entry/exit.[19]

A mass M_{it} of representative consumers are in location i. I assume consumers can watch at most one movie per week. Therefore, the potential market size for movies M_{ct} is specified as population size (M_{ct}) times the number of weeks in quarter t.

4.2. Demand

4.2.1. Consumer Demand for Theaters and Movies

I start with a nested logit model of consumers' choice of theater-movie pairs (j, k). Movies are classified by their origin o with $o = 0$ and 1 respectively indexing domestic and foreign movies. Consumers can also choose not to watch any movie, which is captured by the outside option $(j, k) = 0$. Figure 3 illustrates the nesting structure of consumer theater-movie choices.

The indirect utility of watching an origin o movie k in theater j is specified as

$$u_{ijkt} = \begin{cases} \delta_{jkt} + \mu_{ijt} + \zeta_{ot}(\rho) + (1 - \rho)\varepsilon_{ijkt} & (j,k) \neq 0 \\ \varepsilon_{i0t} & (j,k) = 0 \end{cases}$$

where δ_{jkt} is the mean utility of product (j, k) common across individuals, μ_{ijt} is individual-specific, ζ_{ot} is common to all theaters showing origin o movies with the unique distribution

[18] First, many rural theaters are non-profit or government-sponsored, hence it is not obvious how their prices are set and whether their objectives are profit maximization. Second, rural areas have a very low density of movie theaters and on average these theaters are more than 30 km away from the city centroid point. So it is not plausible to assume that those theaters compete with theaters in urban areas.

[19] More than 75% of the movies in my sample were only shown within a quarter. For the remaining movies with initial runs spanning across quarters, I assign them to the quarter when they had the highest sales share.

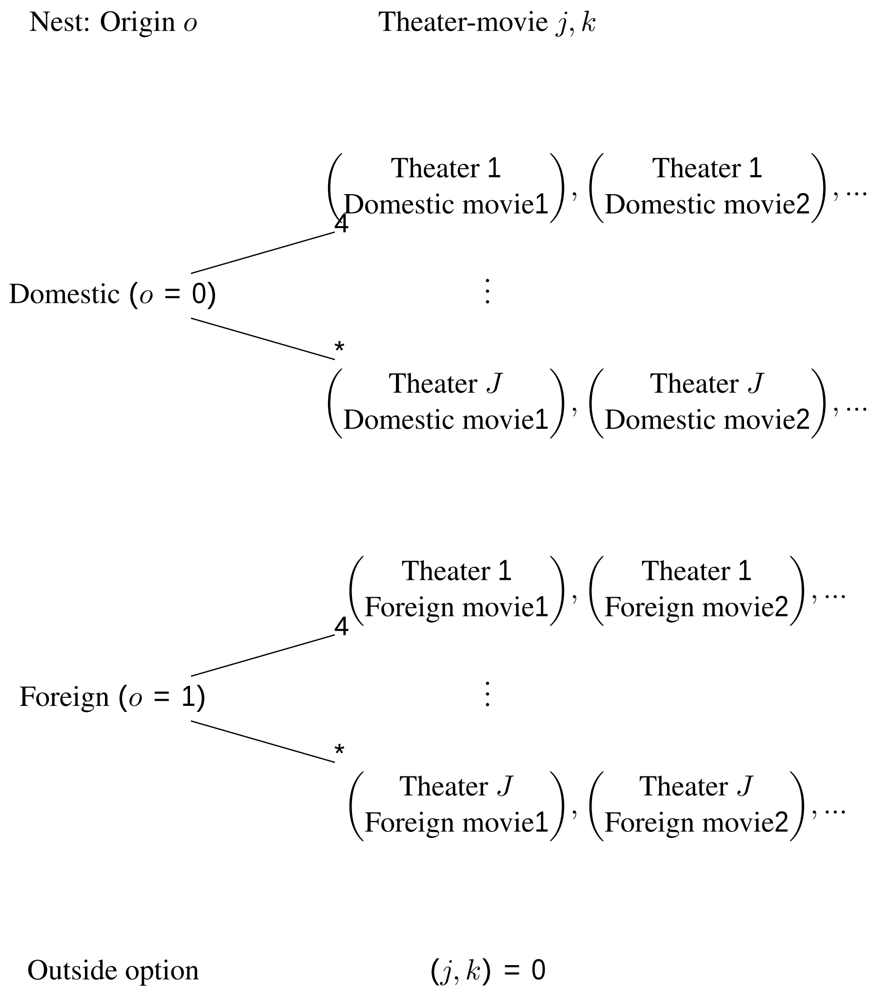


Figure 3: The Nested-Logit Structure of Consumer Choice

such that both ε_{ijot} and $\zeta_{ot}(\rho) + (1 - \rho)\varepsilon_{ijot}$ follow type-1 extreme value distribution. The utility from the outside option (e.g., online streaming) is a type-1 extreme value shock ε_{i0t}. I parameterize the mean and individual utility as follows:

$$\delta_{jkt} = \delta_{ck} + \delta_j + \alpha p_{jot} + \beta x_{jt} + \xi_{jot} \tag{4}$$

$$\mu_{ijt} = \begin{cases} \lambda d_{ij} & \text{if } d_{ij} < 15km \\ 1 & \text{otherwise} \end{cases}$$

where δ_{ck} is the city c-specific taste for movie k, δ_j is a theater fixed effect, p_{jot} is the average admission fee of origin o movie in theater j, x_{jt} is a vector of time-varying product attributes, and ξ_{jot} is a scalar that captures unobserved attributes at the theater-origin level. μ_{ijt} is the consumer-specific dis-utility from travel cost. I assume consumers only choose theaters that locate within 15 km so travel cost is infinity for theaters outside that distance ring.[20]

There are two reasons why I assume unobserved attributed ξ_{jot} is origin-specific and not product-specific. First, they are consistent with the special feature of the industry that all theaters show the same movies in a given week and screening allocation is very similar within a market. Hence, any remaining unobserved product quality is likely to be at the theater-quarter or theater-origin-quarter level. The second reason is data limitations. I do not observe product (theater-movie) specific market shares for most years in my sample. Similar to Crawford et al. (2019) and Chatterjee et al. (2022), I set unobserved attributes at a slightly aggregated level.

4.2.2. Theater-Origin Shares

Omitting time subscript t for notional simplicity, the expected maximum utility from origin o movies in theater j is

$$\begin{aligned} \delta_{jo} &= \underset{k \in K_o}{\text{Emax}} \{\delta_{jk}(\delta_{ck}, \delta_j, p_{jo}, x_j, \xi_{jo}) + \zeta_{ot}(\rho) + (1-\rho)\varepsilon_{ijkt}\} \\ &= \delta_{co} + \delta_j + \alpha p_{jo} + \beta x_j + \xi_{jo} \end{aligned} \tag{5}$$

where $\delta_{co} \equiv \text{Emax}_{k \in K_o} \{\delta_{ck} + \zeta_{ot}(\rho) + (1-\rho)\varepsilon_{ijkt}\}$ is given by the nested-logit formula $(1-\rho)\log\left(\sum_{k \in K_o} \exp\left(\frac{\delta_{ck}}{1-\rho}\right)\right)$. The probability that consumer i chooses to watch an origin o movie in theater j admits the following analytical form

$$s_{ijo} = \frac{\exp\left(\frac{\delta_{jo}+\lambda d_{ij}}{1-\rho}\right)}{\sum_j \exp\left(\frac{\delta_{jo}+\lambda d_{ij}}{1-\rho}\right)} \frac{\left(\sum_j \exp\left(\frac{\delta_{jo}+\lambda d_{ij}}{1-\rho}\right)\right)^{1-\rho}}{1 + \sum_o \left(\sum_j \exp\left(\frac{\delta_{jo}+\lambda d_{ij}}{1-\rho}\right)\right)^{1-\rho}}, \tag{6}$$

where the first term in the above expression is theater j's sales within origin o and the second term is the sales share of origin o movies.

The market share of origin o movies in theater j is obtained by integrating consumer choice probability s_{ijo} over the spatial distribution of consumers

$$s_{jo}(\boldsymbol{p}_{jo}, \boldsymbol{p}_{-j,o}) = \sum_{i=1}^{L_c} \frac{M_i}{M_c} s_{ijo}. \tag{7}$$

[20]The 15 km distance ring is chosen according to a report on Baidu Map users' mobility. In 2018, more than 80% of users chose a cinema that was located within 10 km of their residence. Nearly 90% users chose a cinema that was located within 20 km of their residence. The report is available here https://huiyan.baidu.com/cms/report/2018annualtrafficreport/index.html (retrieved in Oct 2022). Changing the distance ring of consumer choice sets does not significantly change my demand estimates.

where M_i/M_c is the share of population in location i out of total population. The summation is taken across city c census blocks $i = 1, ..., L_c$.

4.2.3. Conditional Movie-Specific Shares

For most years in my sample, I do not observe product (theater-movie) specific market shares but observe movies' total admissions at the city level. Hence, to incorporate data on city-specific movie sales, I exploit the specification that a movie's quality, δ_{ck} varies at the city level, so the probability of choosing movie k, conditional on watching a movie from k's origin is same across individuals and theaters. Let $s_{c,kjo}$ denotes movie k's conditional movie-specific share with $\sum_k s_{c,kjo} = 1$ by construction. The demand model has the following prediction for this share:

$$
\begin{aligned}
s_{c,kjo} &= \frac{\sum_{i=1}^{L_c} \sum_{j \in J_c} \Pr(k = \arg\max_{k' \in K_o} \{\delta_{ck} + \zeta_{ot}(\rho) + (1-\rho)\varepsilon_{ijkt}\}) s_{ijo}}{\sum_{i=1}^{L_c} \sum_{j \in J_c} s_{ijo}} \\
&= \Pr\left(k = \arg\max_{k' \in K_o} \{\delta_{ck} + \zeta_{ot}(\rho) + (1-\rho)\varepsilon_{ijkt}\}\right) && (8) \\
&= \exp\left(\frac{\delta_{ck}}{1-\rho}\right) \Big/ \exp\left(\frac{\delta_{co}}{1-\rho}\right) && (9)
\end{aligned}
$$

Equation (8) holds from the assumption that share is invariant across individuals and theaters in the same city. The inversion algorithm in Berry (1994) can be applied to Equation (9) to compute δ_{ck} from s_{ck}, given the estimates of the nesting parameter ρ and the expected maximum utility from origin o movies at the city level δ_{co}.

4.3. Supply

Under the uniform revenue-sharing rule, theaters retain 52% of after-tax box-office proceeds. Under an 8.3% tax rate, $\kappa = 47.85\%$ of the total box-office sales is retained by theaters. A theater maximizes its net profit by setting prices $\boldsymbol{p}_{jo} = (p_{j0}, p_{j1})$ taking other theaters' pricing $\boldsymbol{p}_{-j,o}$ as given

$$\max_{\boldsymbol{p}_{jo}} \sum_{o=0,1} (\kappa p_{jo} - mc_{jo}) s_{jo}(\boldsymbol{p}_{jo}, \boldsymbol{p}_{-j,o}) M_c.$$

The marginal cost is assumed to be log-linear in theater fixed effect ζ_j, quarter-of-year seasonality fixed effects $\zeta_{q(t)}$, linear year trend $year_t$, and the unobservable theater-origin-quarter level cost shock ζ_{jot}.

$$\log(mc_{jot}) = \gamma_1 year_t + \zeta_j + \zeta_{q(t)} + \zeta_{jot}. \tag{10}$$

The market equilibrium is characterized by the first-order conditions with respect to price p_{jo}:

$$s_{jo}(\boldsymbol{p}_{jo}, \boldsymbol{p}_{-j,o}) + \sum_{o'=0,1} \left(p_{jo'} - \frac{mc_{jo'}}{\kappa}\right) \frac{\partial s_{jo}(\boldsymbol{p}_{jo}, \boldsymbol{p}_{-j,o})}{\partial p_{jo'}} = 0. \tag{11}$$

4.4. Discussions on the Demand and Supply Specifications

4.4.1. Business-Stealing and Vertical Spillover in the Model

The business-stealing effect refers to the fact that, in the absence of any downstream theater entry, foreign movies steer consumer demand from domestic movies. This is embedded in the assumption of the potential market size for the discrete-choice demand model. In any week, consumers are assumed to watch at most one movie. The liberalization of movie import makes more foreign movies released in the market, which increases the expected maximum attainable utility from one of the available foreign movies without affecting the utility of domestic movies. Hence, demand for domestic movies will drop and the extent of substitution is determined by the nesting parameter ρ.

The spillover effects between the upstream movie distribution and the downstream movie theater sectors arise from the interdependence between movie demand and theater attendance. This is captured by the additively separable theater component $\delta_j - \lambda d_{ij}$ and movie-component δ_{co} in the utility specification. In particular, import liberalization increases the inclusive value of foreign movies. This diverts consumers from the outside option and increases theaters' variable profits, and leads to forward spillover from movies to theaters. Similarly, the increase in the number of theaters in a market increases the value of watching any movie—a backward spillover from theater expansion to movie demand.[21]

Note that the scope of spillover is within the movie industry. That is, there are no spillover effects between inside goods and the outside option. There are mainly two arguments for this specification. First, modeling spillover between the inside and the outside good is challenging because it requires an explicit specification of the component of the outside option based on which substitution patterns between the inside and the outside good are specified. This

[21] I assume theaters maximize their own profits because less than 12% theaters are owned by theater chains. From conversations with industry practitioners, theater chains only transmit movie copies from distributors to franchise theaters and provide suggestions on movie screenings. Theater managers make their own pricing and screening decisions.

requires ad hoc assumptions on what consumers do if they do not watch a movie and auxiliary data on consumer expenditure or time-spending which is not available in China. Second, the reduced-form results in Table 3 suggest that the effect of the liberalization has no impact on the most closely related industry—commercial real estate development measured by per capita new shopping centers constructed.

4.4.2. *The Nested Logit Specification*

There are three reasons for a nested-logit preference specification. First, auxiliary data confirms that origin is the most important dimension along which products differentiate from consumers' perception. Hodgson and Sun (2022) analyzes movie ratings from a large online movie rating platform and finds that a consumer tends to assign similar ratings to domestic movies and similar ratings to foreign movies. If movies are by other characteristics (e.g., genre or exhibition format), the correlation between the ratings of the same group of movies is much weaker.

Second, cultural goods are differentiated in many dimensions. Economists often select a categorical attribute that is central to their research questions and adopt a nested-logit specification (e.g., Einav, 2007; Ho et al., 2018; Chen et al., 2022, for studying movie demand). I follow Ferreira et al. (2016) and group movies by origin. The nested-logit structure of demand shocks and the individual-specific distance to theaters generate realistic substitution patterns between new theaters and the outside option and between new theaters and the incumbent theaters. Both specifications avoid the welfare implication from the logit that new goods always improve welfare.

Lastly, this specification is consistent with the findings from Ho et al. (2021), which uses the same data and estimate movie-level demand in China with a model that features dynamics in consumer choice set and horizontal movie differentiation by genre. They find that substitution mainly occurs among domestic movies and among imported movies.[22]

4.4.3. *Other Supply Decisions*

The supply side differs from Gil et al. (2022) and Chen et al. (2022) in that it features price competition and abstracts away from screening decisions. These papers argue that after eliminating the variation common to movies and theaters, vertical integration between upstream firms and downstream theater chains is correlated with *residual* variation in showings but not

[22] Ho et al. (2021) find that a 30% price increase of a domestic movie leads to a 23% increase in other domestic movie sales and a 1.36% increase in imported movie sales.

prices. My paper directly looks at the theater-specific component in decision-making and finds that pricing, instead of showings, mainly varies at the theater level.

As a robustness check, I follow Gil et al. (2022) and Chen et al. (2022) and incorporate screening decisions into theaters' marginal cost. I include *total* quarterly admissions q_{jt} as an endogenous cost shifter to allow marginal cost to change with capacity utilization:

$$\log(mc_{jot}) = \gamma_1 year_t + \gamma_2 \log(q_{jt}) + \zeta_j + \zeta_{q(t)} + \zeta_{jot}.$$

Suppose foreign movies' total admission is high so that theaters are closer to their capacity constraints. Then, both the marginal costs of admissions of domestic and foreign movies are affected. High marginal cost leads to higher pricing and lower admissions for both domestic and foreign movies.[23] That is, instead of explicitly modelling how theaters allocate their screening capacity to different movies, I allow the quality of foreign movies to affect the pricing of domestic movies through capacity-driven marginal cost change. The results are quantitatively similar to the baseline results.[24]

5. Estimation Strategy and Identification

The estimation unfolds in two parts. In Part 1, I estimate theater-origin-quarter level demand using the nonlinear GMM algorithm in Berry et al. (1995). I get estimates for demand-side and supply-side parameters, and the inclusive value of movies under each origin nest. In Part 2, I compute city-specific movie quality using movie-city sales data and the estimated inclusive value from the first step.

5.1. Step 1: Estimating Theater-Origin-Quarter Level Demand

The demand-side parameters $(\alpha, \beta, \lambda, \rho)$ and supply-side parameters γ_1 are jointly estimated. Parameters $\theta = (\alpha, \lambda, \rho)$ enter non-linearly into the GMM objective function and are referred to as non-linear parameters hereafter. This procedure has four substeps.

[23] This can be seen from the first-order conditions with respect to price $p_{jo} \quad s_{jo}(\boldsymbol{p}_{jo}, \boldsymbol{p}_{\quad j,o}) + \sum_{o^0=0,1} \left(p_{jo^0} \quad \frac{1+\gamma_2}{\kappa} mc_{jo^0}\right) \frac{\partial s_{jo}(\boldsymbol{p}_{jo}, \boldsymbol{p}_{\quad j,o})}{\partial p_{jo^0}} = 0$.

[24] The identification of the parameter on the endogenous cost shifter $\log(q_{jt})$ follows the common strategy of using the excluded demand shifter and the dummy for entry or exit as instruments. The identification assumption is that entering/exiting theaters operate through a fraction of a quarter and are less likely to be constrained by capacity.

5.1.1. Demand Inversion

Given a guess of non-linear parameters $\theta = (\alpha, \lambda, \rho)$, with the nested fixed point algorithm outlined in Appendix D.1, I get a unique vector $\hat{\boldsymbol{\delta}}$ of mean utilities $\hat{\delta}_{jo}$ that matches model-predicted theater-origin-quarter market shares in Equation (7) with their data counterparts. This step also allows me to compute the partial derivatives of the market share of a theater-origin with respect to the prices of all theater-origin pairs in the same market, $\partial s_{jk}/\partial p_{j',k'}$, using the formula in Appendix D.2.

5.1.2. Marginal Cost Inversion

I first stack first-order conditions (11) into a matrix

$$\mathrm{s}(\boldsymbol{p}) + (\boldsymbol{\Omega} \quad \boldsymbol{\Delta}(\boldsymbol{p}))\,(\boldsymbol{p} \quad \boldsymbol{mc}/\kappa) = 0, \tag{12}$$

where $\mathrm{s}(\ ) = (s_{10}(\boldsymbol{p}), s_{11}(\boldsymbol{p}), ..., s_{J0}(\boldsymbol{p}), s_{J1}(\boldsymbol{p}))'$ is the market share vector defined in Equation (7), $\boldsymbol{\Omega}$ is the ownership matrix (i.e., $\ _{i,j} = 1$ iff the i-th and the j-th arguments in the market share vector are from the same theater), denotes the element-by-element product operator, and $\boldsymbol{\Delta}(\boldsymbol{p})$ is the matrix of price derivatives of the demand system (i.e., $\boldsymbol{\Delta}_{i,j} = \partial s_i/\partial p_k$). Then given the non-linear parameter guess γ_1, price, ownership, and market share data, and the derivatives computed from the demand inversion step, the marginal cost vector can be inverted from Equation (12)

$$\widehat{\boldsymbol{mc}} = \kappa \left(\boldsymbol{p} + (\boldsymbol{\Omega} \quad \boldsymbol{\Delta}(\boldsymbol{p}))^{\ 1}\,\mathrm{s}(\boldsymbol{p})\right).$$

5.1.3. Fixed Effects and Moment Conditions

The last step to construct the GMM objective function is to interact instrumental variables with structural errors in the inverted mean utility vector $\hat{\boldsymbol{\delta}}$ and the marginal cost vector $\widehat{\boldsymbol{mc}}$ with their respective instrumental variables z^D_{jo} and z^S_{jo}. Following Conlon and Gortmaker (2020), I apply the Frish-Waugh-Lovell theorem (Frisch and Waugh, 1933; Lovell, 1963) to remove the fixed effects in Equations (4) and (10) and get the structural errors $\hat{\xi}_{jo}$ and $\hat{\zeta}_{jo}$.[25]

The moment conditions are constructed from the orthogonality between structural errors

[25] With high dimensional fixed effects $(\xi_j, \xi_{c(j)ot}, \zeta_j, \zeta_{q(t)})$, I get the residualized instrumental variable matrices $Z^D = (z^D_{10}\ z^D_{11} ... z^D_{J0}\ z^D_{J1})'$ and $Z^S = (z^S_{10}\ z^S_{11} ... z^S_{J0}\ z^S_{J1})'$, the matrices of demand and supply covariates X^D and X^S, and the mean utility vector $\hat{\boldsymbol{\delta}}$ and the marginal cost vector $\widehat{\boldsymbol{mc}}$. Following Appendix A.1 in Conlon and Gortmaker (2020), the residual vectors $\hat{\boldsymbol{\xi}}$ and $\hat{\boldsymbol{\zeta}}$ can be calculated with a GMM regression using the above matrices.

in Equations (4) and (10) with their respective instrumental variables z_{jo}^D and z_{jo}^S:

$$g(\theta) = \begin{bmatrix} g_1(\theta) \\ g_2(\theta) \end{bmatrix} = \begin{bmatrix} E(\xi_{jo} z_{jo}^D) \\ E(\zeta_{jo} z_{jo}^S) \end{bmatrix} \tag{13}$$

5.1.4. The Objective Function

The estimator for θ is the minimizer of the GMM objective function

$$\hat{\theta} = \arg\min_{\theta} n g_n(\theta)' W_n g_n(\theta),$$

where $g_n(\theta) = [\frac{1}{n}\sum_{jo} \xi_{jo} z_{jo}^D \quad \frac{1}{n}\sum_{jo} \zeta_{jo} z_{jo}^S]'$ is the sample analogue of the population moment conditions (13), and the weighting matrix $W_n(\theta)$ is a consistent estimate of $\left(E(g_n(\hat{\theta}) g_n(\hat{\theta})')\right)^{-1}$. Following Nevo (2001), I use a two-step GMM to get parameter estimates. I first use the weighting matrix in linear IV regressions under the homoscedasticity assumption and get consistent estimates.[26] Then I use the estimates to construct the inverse variance matrix of moment conditions $W_n(\hat{\theta})$ as the weighting matrix for the second step estimation.

5.2. Step 2: Estimating City-Level Movie Quality

Given the parameter estimates, the city-origin inclusive value is given by Equation (5):

$$\hat{\delta}_{co} = \hat{\delta}_{jo} - \hat{\delta}_j - \hat{\alpha} p_{jo} - \hat{\beta} x_j - \hat{\xi}_{jo}$$

. According to Equation (9), there is a unique mapping between the city-specific taste for movie k (δ_{ck}), city-origin inclusive value δ_{co} and the observed movie's market share within movies of the same origin in that city-quarter $s_{c,kjo}$. I then estimate city-level movie quality using the following formula:

$$\hat{\delta}_{ck} = \hat{\delta}_{co} + (1 - \hat{\rho}) \log\left(\frac{s_{ck}}{\sum_{k \in K_{co}} s_{ck}}\right).$$

5.3. Identification

The identification of the model parameters relies on the assumption that the evolution of local market structure (i.e., the entry and exit of theaters in a location) is unrelated to temporary

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[26] The weighting matrix in the first step of the two-step GMM estimation is $\begin{bmatrix} (Z^{D'} Z^D)^{-1} & 0 \\ 0 & (Z^{S'} Z^S)^{-1} \end{bmatrix}$.

shocks to consumer movie demand or those to marginal cost. In this section, I discuss how I use fixed effects and instrumental variables to construct valid moments.

5.3.1. Fixed Effects

Theater and city-origin-quarter fixed effects are added to the utility function to address the concern that entry is correlated with variables that are unobservable to the econometrician. The timing of theater entry responds to the quantity and quality of movies in the release. Potential entrants' location choices also depend on unobserved location characteristics. Hence, instrumental variables constructed from rival characteristics are not orthogonal to a focal theater's unobservable attributes ξ_{jo}. Theater fixed effects absorb time-invariant theater unobservables and city-origin-quarter fixed effects control for movies' attractiveness to consumers in a city. Therefore, the moment conditions in the GMM objective function (13) are defined with temporary shocks to demand (e.g., weather and traffic conditions).

This assumption is valid if theaters' entry and exit decisions are based on the time-invariant unobserved location characteristics (captured by the theater fixed effects) or secular trend of the quality of movies in release (captured by the city-origin-quarter fixed effects), but not their temporary fluctuations (similar to Houde, 2012).[27]

5.3.2. Instrumental Variables

Linear parameters on exogenous demand and cost covariates are identified from their orthogonality to the respective structural errors. To identify the non-linear parameters $(\alpha, \lambda, \rho, \gamma_1)$, I construct instrumental variables to formulate relevant moment conditions.

To identify the non-linear parameter on price (α), I construct instruments that measure changes in local market structure (Houde, 2012; Gandhi and Houde, 2019): rival theater count within 2 distance rings (0–2 km and 2–5 km) as well as the average size difference between theater j and its rivals in the aforementioned two distance rings:

$$IV1 = \left\{ \sum_{j' \in J_{ct}} 1_{d_{j,j'} \in (0,2)}, \sum_{j' \in J_{ct}} \frac{1_{d_{j,j'} \in (0,2)} (Screen_{j'} - Screen_j)}{\sum_{j' \in J_{ct}} 1_{d_{j,j'} \in (0,2)}}, \right.$$
$$\left. \sum_{j' \in J_{ct}} 1_{d_{j,j'} \in (2,5)}, \sum_{j' \in J_{ct}} \frac{1_{d_{j,j'} \in (2,5)} (Screen_{j'} - Screen_j)}{\sum_{j' \in J_{ct}} 1_{d_{j,j'} \in (2,5)}} \right\}.$$

[27] At least two arguments are supportive to this assumption. First, theater entry was primarily driven by urbanization and the initial scarcity of movie theaters (see Section 2.1). Second, entering a local market involves large sunk costs and a non-negligible construction period so theater chains are likely to make entry and exit decisions based on average profitability but not the short-run fluctuation in profitability, especially when the industry exhibits considerable seasonality.

The identification assumption is that the longitudinal change in the number and the characteristics of the competing theaters near theater j is predictive of the over-time change in theater j's pricing.

To identify the non-linear parameter on distance (λ), I use instruments constructed from the spatiotemporal distribution of population and its interaction with local market structure: time-varying population size within 5 km $\left(pop^{5km}_{jt}\right)$ and its interaction with rival counts within 5 km. The identification relies on consumer diversion from incumbent to entrant theaters. Both cross-sectional and longitudinal variations in market structure and time-varying population distribution determine this substitution and are informative about travel cost (λ).

$$IV2 = pop^{5km}_{jt} \times \left\{1, \sum_{j' \in J_{ct}} 1_{d_{j,j'} \in (0,5)}\right\}.$$

The identification of ρ follows previous literature that has estimated a random-coefficient nested logit model. Miller and Weinberg (2017) and Miravete et al. (2018) use the number of products under each nest as an instrument since it shifts the product group market shares. In my model, the number of products under each origin nest is the number of operating theaters in each quarter, which is invariant across theaters and absorbed into city-origin-quarter fixed effects (see Figure 3). I circumvent this issue in two steps. First, the IVs outlined above can shift group market shares. To see this, in Appendix D.2, I derive the analytical expression of price derivatives in a nested-logit model. The nesting parameters are related to the difference in substitution within the nest (i.e., same movies in other theaters) versus that across nests (e.g., different movies in the same theater).

If a theater is a local monopoly, within-nest substitution is likely to dominate. On the other hand, if a theater faces many local rivals, cross-nest substitution is more likely to dominate. Table D6, Column (3) reports the estimates from regressing within-nest share on local rival counts.

Moreover, imported movies' share of screenings in enhanced formats is twice higher than domestic movies. Hence the entry of advanced technology theaters has asymmetric impacts on domestic and foreign movie sales in its rival theaters. The last IV is the difference in enhanced exhibition technology between a focal theater and its rivals within 5 km interacted with movie origin indicators. The results in Table D6, Columns (5)–(6) confirm that imported movies are more responsive to the entry of theaters with enhanced exhibition technology.

$$IV3 = \left(\sum_{j' \in J_{ct}} \frac{1_{d_{j,j'} \in (0,5)}(Enhanced_{j'} - Enhanced_j)}{\sum_{j' \in J_{ct}} 1_{d_{j,j'} \in (0,5)}}\right) \times \{1_{j,o=0}, 1_{j,o=1}\}.$$

6. Results

6.1. Parameter Estimates

The demand estimates are reported in Table 5. The specification in Column (1) uses the first two sets of instrumental variables. The specifications in Columns (2) and (3) use all instrumental variables. In addition, Column (3) allows marginal cost to depend on total admissions of theater j in quarter t. The upper part of the table reports the parameter estimates. The bottom part of the table reports reduced-form elasticities to understand the results.

The price coefficient estimate ranges between -0.069 to -0.063 and the distance parameter estimate ranges between -0.4309 to -0.387. Both are robust across specifications. The implied willingness to travel for a \$1 lower price is small, ranging between 1.12 km and 1.17 km. This suggests that the scope of the spatial competition is local. The median price elasticity is on the same scale as the previous literature (e.g., Ho et al., 2018; Chen et al., 2022; Gil et al., 2022) although with a slightly larger magnitude.

I also calculate markups predicted by the demand model. The formula is found as $(\kappa p$ $mc)/p$ where κ is theaters' revenue share, p is the admission fee, and mc is the marginal cost. Across specifications, the median markup ranges from 8.12% to 12.35%. The low markup is partly due to the low revenue share κ = 47.85% that goes to theaters.

Table 5: Demand Estimates

	(1)	(2)	(3)
Specification	IVs 1–2	IVs 1–3	IVs 1–3
Non-linear parameters			
Price (α)	-0.069	-0.065	-0.063
	(0.0018)	(0.0526)	(0.040)
Distance (λ)	-0.4309	-0.388	-0.387
	(0.0507)	(0.0362)	(0.032)
Nesting parameter (ρ)	0.8434	0.7572	0.7506
	(0.060)	(0.1864)	(0.158)
Product attributes (x_j)			
Entry/exit dummy	-2.0415	-2.056	-2.037
	(0.247)	(0.301)	(0.2493)
Cost parameters			
Year trend	0.0133	0.011	-0.005
	(0.0034)	(0.0020)	(0.0021)
Quantity dependent mc	No	No	Yes
Median own elas.	-8.56	-5.35	-6.12
Median markup	8.12 %	12.35 %	8.73%
Median domestic-foreign elas.	0.002	0.003	0.002
Willingness to travel for 1$ lower price	1.12 km	1.17 km	1.14 km

Notes: Consumer choice set is theaters within 15 km. Standard errors and weighting matrix are clustered at the location level. $IV1$ refers to the instruments that measure the local market structure. $IV2$ refers to the interaction between the local population and market structure measures. $IV3$ refers to the interaction between 3D rival counts and movie origins.

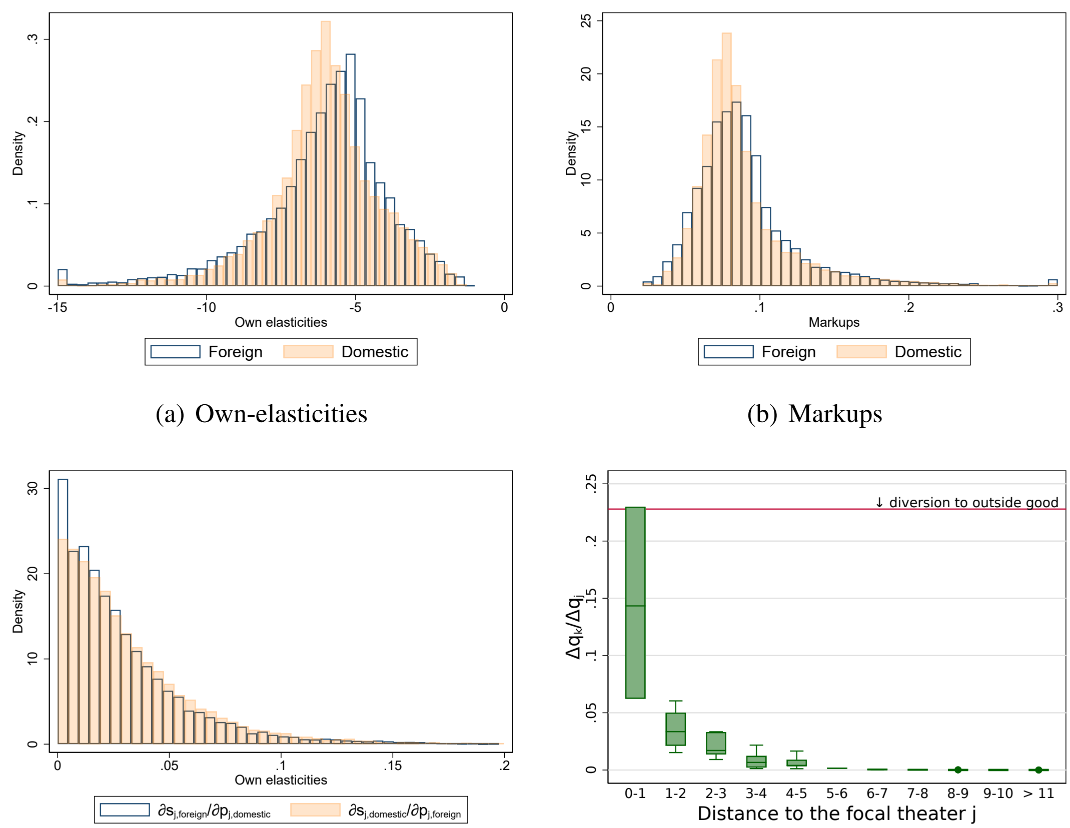
6.2. Substitution Patterns

Figure 4 reports the estimated distributions of own price elasticities, within-theater cross-origin elasticities, markups, and diversion ratios across theater-origin pairs implied by the first part parameter estimates reported in Table 5. In what follows, I will describe the definition of these elasticities and discuss their empirical distribution.

Figures 4(a) and 4(b) show own-price elasticities $\partial s_{jo}/\partial p_{jo}$ and markups $(p_{jo} \quad mc_{jo})/p_{jo}$, respectively. Demand for foreign movies is slightly more inelastic than that for domestic movies. Consistent with this, the markups of foreign movies are on average higher than those of domestic movies.

Figure 4(c) shows the distribution of origin o movie demand elasticity with respect to the price of movies of the other origin within each theater $\partial s_{j0}/\partial p_{j1}$ and $\partial s_{j1}/\partial p_{j0}$. The results suggest that the business-stealing effect is small, even within the same theater, and domestic movie demand is more responsive to foreign movie prices than foreign movie demand to domestic movie prices.

Lastly, Figure 4(d) plots the diversion ratios between a theater j and its rivals k's in different distance rings. It is calculated as the fraction of consumers who leave theater j after a price increase and switch to theater k. Here, I plot a $\frac{1}{2}$ standard deviations increase in the medium theater in the 2017 sample of my dataset. Results are consistent with consumers' low willingness to travel in that demand diversion decays quickly with distance from the focal theater. That means spatial competition is local.



(a) Own-elasticities

(b) Markups

(c) Within-theater cross elasticities

(d) Diversion ratios

Figure 4: Distribution of Elasticities, Markups, and Diversions

Note: Reported are the estimated distributions of own price elasticities, within-theater cross-origin elasticities, markups, and diversion ratios across theater-origin pairs implied by the first part parameter estimates reported in Table 5.

7. Counterfactual

In this section, I conduct two counterfactual simulations to shed light on the importance of vertical spillovers from import liberalization. Both simulations compute the market outcomes where there is a return to the old quota in 2017 (i.e., from 34 to 20, similar to Ho et al., 2021).

The simulations proceed in three steps. First, in Section 7.1, using the variable profit predicted by the estimated demand system, I estimate theater fixed costs with an inequality estimator derived from the following optimality conditions. The variable profits net of fixed costs (i.e., net profits) of incumbent theaters are assumed to be positive and those of exiting theaters are assumed to be negative. The exercise uses data from the last sample year, 2017, when the market structure is mature and variable profits are most informative about fixed costs.

Next, in Section 7.2, based on city-specific taste for each movie found in the second step of demand estimation, I compute the national population-weighted average movie quality index. I assume policymakers select movies according to this quality index and simulate the set of movies for two extreme cases. For the two counterfactual sets of foreign movies, I separately compute the inclusive value of domestic and foreign movies under the old quota.

Lastly, using the inclusive value and the estimated consumer preference and marginal cost function in Table 5, I predict the theater-origin-quarter level market shares, prices, and variable profits. The predicted variable profits are used for two simulations.

I report results from the first simulation in Section 7.4. I hold the observed theaters fixed and investigate how import restrictions affect consumer surplus, producer profit, and government tax revenue. This exercise quantifies the business-stealing and forward spillover effects.

I report results from the second simulation in Section 7.5. I compare the counterfactual variable profit with the per-period fixed cost estimated in Section 7.1 and identify trade-induced theater entrants (i.e., theaters that would be unprofitable in the absence of the 14 extra US blockbusters imported after liberalization) and compute domestic movie sales in those theaters. This exercise is suggestive of the magnitude of backward spillover.

7.1. Estimation of Per-Period Fixed Cost

Motivated by the fact that there is an active secondary market for exhibition equipment, I assume that theaters lease projectors instead of making purchases upon entry and receiving scrape payoffs upon exit. Therefore, theater j's net annual profit is equal to

$$
\begin{aligned}
\Pi_j(in) &= \underbrace{\pi(\delta_j|\boldsymbol{\delta}_c, \boldsymbol{\mu}_c)}_{\text{variable profit}} - \exp(\gamma_0 + \gamma_1 z_{1j} + \gamma_2 z_{2j} + \gamma_3 z_{1j} z_{2j}) + \nu_j^{\text{in}} \\
\Pi_j(out) &= \nu_j^{\text{out}}
\end{aligned}
$$

where z_{1j} is the number of screens, z_{2j} is log average contemporaneous census block land price, and ν_j^{out} are respectively unobservable measurement error for theaters in and out of the market. Under this specification, the cross-market cost difference is captured by location-year-specific land price.

7.1.1. Nash Conditions

Nash optimality conditions for incumbents' stay/exit and entrants' entry decisions imply that, holding fixed rivals' observed decisions, theater j's net profit is greater than the profit under alternative entry/stay/exit choices.

- $J^{(1)} = \{j : j$ entered before 2015 and operate in 2017$\}$ stay in the market (683 inequalities)

$$
\begin{aligned}
E_\nu(\Delta\Pi^{(1)}) &\equiv E_\nu(\Pi_{j,2017}(in) - \Pi_{j,2017}(out)|\gamma_1, \gamma_2, \gamma_3) \\
&= E_\nu(\Pi_{j,2017}(in)|\gamma_1, \gamma_2, \gamma_3) \geq 0
\end{aligned}
$$

- $J^{(2)} = \{$exitors in year 2017$\}$ exit (12 inequalities):

$$
\begin{aligned}
E_\nu(\Delta\Pi^{(2)}) &\equiv E_\nu(\Pi_{j,t}(out) - \Pi_{j,t}(in)|\gamma_1, \gamma_2, \gamma_3) \\
&= E_\nu(-\Pi_{j,t}(in)|\gamma_1, \gamma_2, \gamma_3) \geq 0
\end{aligned}
$$

For the last set of inequalities, I compute simulated profit when entering with average characteristics for $\Pi_{j,t}(in)$. The upper and lower bounds of fixed cost are respectively bounded by inequalities for $J^{(1)}$ theaters and $J^{(2)}$ theaters. Assuming that fixed cost components (z_{1j}, z_{2j}, z_{3j}) are orthogonal to measurement errors $\left(\nu_j^{\text{in}}, \nu_j^{\text{out}}\right)$, the following moment inequality conditions hold:

$$
E_v\left(z_j^{(k)}(\Delta\Pi_j^{(k)} + \nu_j)\right) = E_v\left(z_j^{(k)}(\Delta\Pi_j^{(k)})\right) \geq 0, \forall j \in J^{(k)}
$$

where $z_j^{(k)} = \{1, z_{1j}, z_{2j}, z_{1j} z_{2j}\}, \forall j \in J^{(k)}$.

7.1.2. *The Estimator and the Objective Function*

The fixed cost parameters are estimated by minimizing the violation of these inequality conditions in the sample. When implementing the moment inequality estimator, I construct the objective function as the weighted average return to observable choices $\ _j^{(k)}$. The weight is larger for negative returns (i.e., the violation to optimality).[28]

$$r_j^{(k)} = \frac{1}{1 + \exp\left(\quad _j^{(k)}\right)} \quad _j^{(k)} z_j^{(k)}, \forall j \in J^{(k)}$$

where $\frac{1}{1+\exp\left(\quad _j^{(k)}\right)}$ is the weight on the inequality constructed from theater j (see Figure 5 for visualization). Fixed cost parameter estimates are estimated by minimizing the average smoothed violation to entry/stay/exit optimality conditions

$$(\hat{\gamma}_0, \hat{\gamma}_1, \hat{\gamma}_2, \hat{\gamma}_3) = \arg\min_{\gamma_0,\gamma_1,\gamma_2,\gamma_3} \sum_k \left(\sum_{j \in J^{(k)}} r_j^{(k)} / sd(r_j^{(k)}) \right)^2 \tag{14}$$

where $sd(r_j^{(k)})$ is the standard deviation of the sample inequality condition $r_j^{(k)}$.

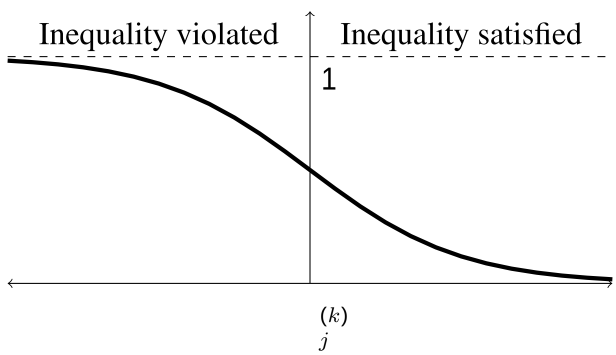


Figure 5: Weight on Inequalities

Note: This graph shows inequality conditions and their weight respectively on the horizontal and the vertical axes.

7.1.3. *Results*

The per-period fixed cost estimates are reported in Table 6. Fixed cost is increasing in theater size measured by the number of screens and log land price index. The estimate for the

[28] Another more straightforward way to implement this estimator is to set the objective function as the average "violation" to optimality conditions (e.g., Crawford and Yurukoglu, 2012): $\sum_k \sum_{j \in J^{(k)}} \min\left(0, z_j^{(k)} \quad _j^{(k)}\right)$.

interaction between theater size and land price is negative ($\hat{\gamma}_3 = -0.04$), which might be a result of cost efficiency or rent discount.

Table 6: Estimates for Fixed Cost Structure $\exp(\gamma_0 + \gamma_1 z_{1j} + \gamma_2 z_{2j} + \gamma_3 z_{1j} z_{2j})$

Parameter	Fixed cost variable z	Estimate $\hat{\gamma}$
γ_0	Constant	9.1778
γ_1	Screens	0.56547
γ_2	log land price	0.35697
γ_3	Screens $\times$ log land price	-0.0400

Note: The estimates for the structure of fixed cost $\exp(\gamma_0 + \gamma_1 z_{1j} + \gamma_2 z_{2j} + \gamma_3 z_{1j} z_{2j})$ are reported. z_{1j} and z_{2j} are the number of screens and log land price index, respectively.

7.2. Selecting Movies under the Old Quota Rule

First, based on the city-specific taste for each movie k estimated in Section 5.2, I calculate a "national mean utility" as their population-weighted average $\hat{\delta}_k \equiv \sum_c \frac{M_c}{\sum_c Mc} \hat{\delta}_{ck}$. Second, for each quarter, I keep the two movies with the highest national mean utilities since those are likely blockbusters released globally and less likely to be constrained by quota restrictions. Then, the old quota of 20 movies allows for 12 additional foreign movies. By ranking movies according to their national mean utilities $\hat{\delta}^{(1)}, \hat{\delta}^{(2)}, ..., \hat{\delta}^{(K)}$, I construct two extreme movie selection rules: 12 movies with highest qualities $\left(\hat{\delta}^{(1)}, \hat{\delta}^{(2)}, ..., \hat{\delta}^{(12)}\right)$ and 12 with lowest qualities $\left(\hat{\delta}^{(K-11)}, \hat{\delta}^{(K-10)}, ..., \hat{\delta}^{(K)}\right)$.

$$K^{(1)} = \{\forall \text{ Quarterly blockbusters}, (1), (2), ..., (12)\}$$
$$K^{(2)} = \{\forall \text{ Quarterly blockbusters}, (K-11), (K-10), ..., (K)\}$$

7.3. Predicting Counterfactual Variable Profit

Based on selected 20 foreign movies imported in China and their quality in each city δ_{ck}, I first compute the city-specific inclusive value of available origin o movies in the two scenarios:

$$\hat{\delta}_{co}^{(1)} = \text{Emax}_{k \in K^{(1)}} \hat{\delta}_{ck} = (1-\rho) \log \left(\sum_{k \in K^{(1)}} \exp\left(\frac{\delta_{ck}}{1-\rho}\right)\right)$$
$$\hat{\delta}_{co}^{(2)} = \text{Emax}_{k \in K^{(2)}} \hat{\delta}_{ck} = (1-\rho) \log \left(\sum_{k \in K^{(2)}} \exp\left(\frac{\delta_{ck}}{1-\rho}\right)\right)$$

Given a vector of prices $(\boldsymbol{p}_{jo}, \boldsymbol{p}_{\ j,o})$, Equation (7) gives the predicted theater-origin level market shares. However, prices in the counterfactual experiments are the fixed point to the first order conditions (11) under new inclusive values $\hat{\delta}_{co}^{(1)}$ and $\hat{\delta}_{co}^{(2)}$. I follow Petrin (2002) and rewrite Equation (11) as the follow updating rule for prices[29]

$$\boldsymbol{p} \quad \boldsymbol{mc}/\kappa \quad (\boldsymbol{\Omega} \quad \boldsymbol{\Delta}(\boldsymbol{p}))^{\ 1}\,\mathrm{s}(\boldsymbol{p}). \tag{15}$$

By the iteration in Equation (15), the new equilibrium prices and variable profits can be computed.[30]

7.4. Business-Stealing, Forward Spillover and Their Welfare Implications

In the first counterfactual exercise, I compute the following measures: prices for domestic and foreign movies, admissions, theaters' variable profits, the total revenue that goes to domestic producers, distributors, and theaters, and consumer surplus. I hold the theater market structure fixed in this part so the change in theater variable profit mainly comes from the substitution between domestic and foreign movies and is indicative of the scale of business-stealing.

Results are reported in Table 7. The two columns correspond to the two counterfactual experiments where two different sets of 20 foreign movies were imported. There are several notable conclusions. First, price response to the policy change is small. This is because I use an average price index in the demand model and a large portion of price variation in theater-specific rather than movie-specific. Second, Consistent with the demand estimates in Section 6, the admissions, variable profits in theaters, and total revenue that goes to domestic firms significantly drop for foreign movies and slightly rise for domestic movies. Lastly, consumers and theaters are worse off in both simulations. Their welfare is lower when the quality of movies in release is lower.

7.4.1. Heterogeneity in Business-Stealing and Forward Spillover

Next, I investigate the heterogeneous business-stealing and forward spillover effects across cities with different regional "pro-foreign" preferences. Preference is measured by the aver-

[29] Given an initial price vector in the n^{th} iteration, $\boldsymbol{p}^n$, predict market shares $\mathbf{s}(\boldsymbol{p}^n)$ and the matrix of price derivatives $\boldsymbol{\Delta}(\boldsymbol{p}^n)$ to get the right hand side of Equation (eq:new-foc). Then I use the left-hand side price vector as the initial price vector for the $(n+1)^{th}$ iteration.

[30] Morrow and Skerlos (2011) proves that Equation (15) is not a contraction mapping and formulate the problem in an alternative way. In practice, I find the price vector always converge to a fixed point when the step size used for updating the price vector between iterations is smaller than 1.

Table 7: The Business-Stealing and Forward Spillover Effects

	Top 12 + 8 Blockbusters	Bottom 12 + 8 Blockbusters
Price (domestic)	0.0 (0.0)	0.03 (0.09)
Price (foreign)	-0.0 (-0.01)	-0.02 (-0.05)
Quantity (domestic)	0.77(0.5)	0.86(0.56)
Quantity (foreign)	-10.51(-6.18)	-18.8(-11.05)
Theater variable profit (domestic)	7.46(0.49)	8.25(0.54)
Theater variable profit (foreign)	-102.06(-6.14)	-185.16(-11.14)
Total revenue (domestic)	25.81(0.5)	28.47(0.55)
Total revenue (foreign)	-267.29(-6.13)	-485.51(-11.14)
Consumer surplus	-184.42(-3.18)	-338.37(-5.84)

Notes: This table summarizes the changes in aggregate welfare compared to the factual welfare measures. Absolute changes are measured in millions of 2009 Chinese Yuan except for prices. Price changes are measured in 2009 Chinese Yuan. Percentage changes are reported in parentheses.

age pre-liberalization city-year-level total sales share of imported movies.

Specifically, I classify cities into quartiles according to their foreign movie market shares with 1 indexing the least pro-foreign cities and 4 indexing the most pro-foreign cities. A box plot is created for the following four variables: theater sector profit from domestic and from foreign movies, admissions of domestic movies and of foreign movies.

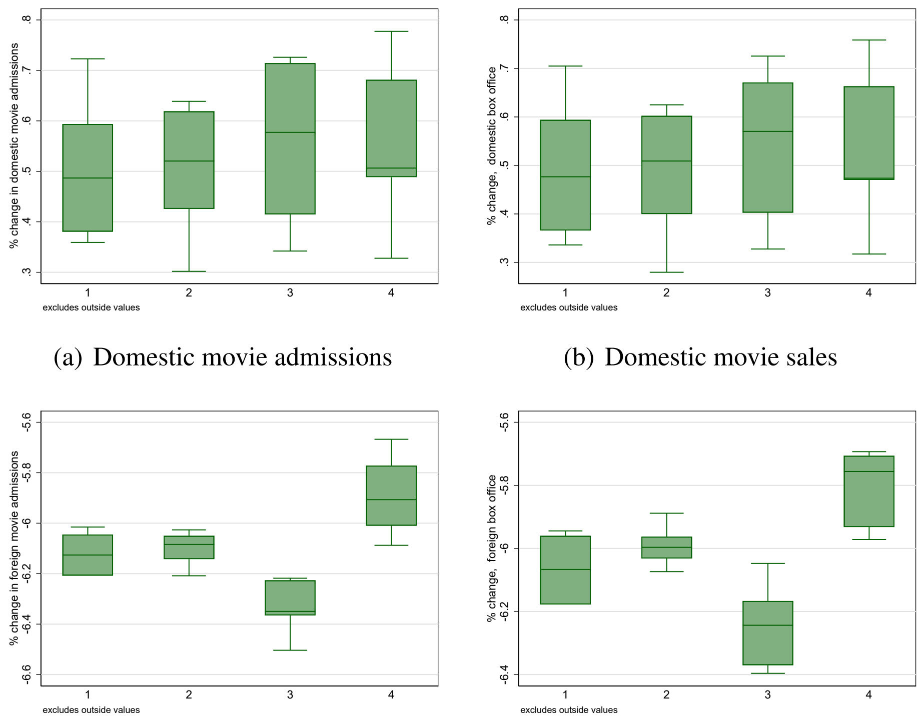
Figure 6 plots the results for the outcome where the top 12 quality movie and quarterly blockbusters are kept. The heterogeneity in the four welfare measure is limited across cities with different preferences for foreign movies.

Figure 7 plots the results for the outcome where the bottom 12 quality movie and quarterly blockbusters are kept. The heterogeneity in the four welfare measures is more significant than that in Figure 6. This suggests that quality of the marginal movies introduced due to the liberalization policy matters for the distributional welfare impact.

7.5. The Backward Spillover Effect

In this section, I compare the variable profit computed in Section 7.4 with the fixed cost estimates computed in 7.1 and calculate two measures: the number of unprofitable theaters (i.e., counterfactual variable profit smaller than the actual fixed cost) and the share of actual domestic movies sales in those theaters.

Results are reported in Table 8. Admittedly, the inequality estimator is not as accurate as a parametric model of theater entry/exit. There are 200 violations to the optimality conditions in Section 7.1.1. Nonetheless, 2% of the theaters would be unprofitable due to the quota



(a) Domestic movie admissions (b) Domestic movie sales

(c) Foreign movie admissions (d) Foreign movie sales

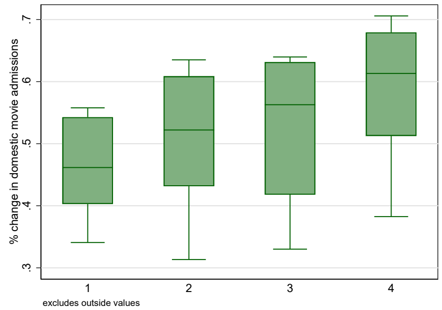
Figure 6: Heterogeneity in Business-Stealing and Forward Spillover (Top 12 + 8 Blockbusters)
Notes: The four graphs plots the cross-city distribution of changes in admissions and sales by different regional "pro-foreign" preferences.

restriction, which account for 2.33% of the total domestic movie sales. Both fixed operation cost and variable profit from imported movies matter for the magnitude of backward spillover.

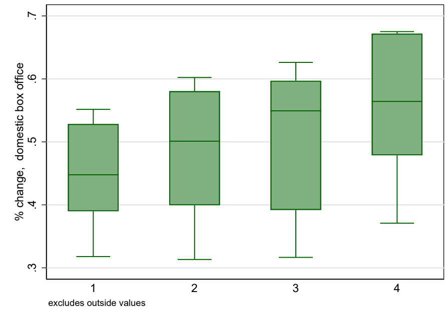
8. Conclusion

This paper studies how liberalization of upstream imports leads to downstream retail expansion—a "forward spillover" effect—which subsequently increases consumer access to upstream domestic products—a "backward spillover" effect. Using China's liberalization of the import quota on foreign movies in 2012 as the empirical context, I document that cities with a high regional foreign movie preference had more post-liberalization theater entries.

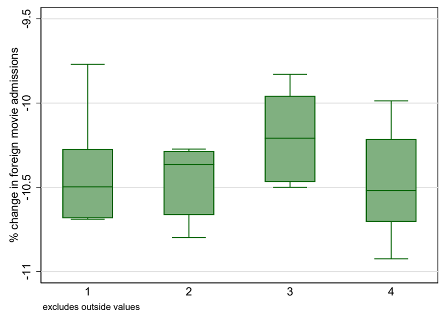
Based on the reduced-form results, I jointly estimate consumer movie demand and theater sales with a Hotelling-style model of spatial competition where consumers have heterogeneous tastes for foreign and domestic movies. With model predicted variable profit, I estimate theaters' fixed cost with an inequality estimator derived from the following optimal-



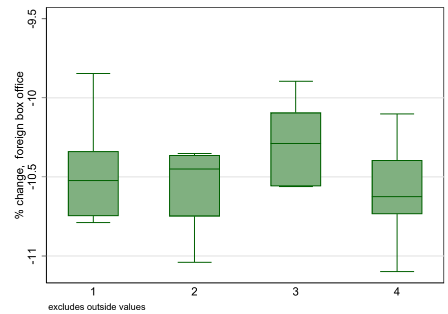
(a) Domestic movie admissions



(b) Domestic movie sales



(c) Foreign movie admissions



(d) Foreign movie sales

Figure 7: Heterogeneity in Business-Stealing and Forward Spillover (Top 12 + 8 Blockbusters)
Notes: The four graphs plots the cross-city distribution of changes in admissions and sales by different regional "pro-foreign" preferences.

ity conditions: (i) non-negative net profits of incumbent theaters and (ii) negative net profits of exiting theaters. The exercise uses data from the last sample year, 2017, when the market structure is the most mature and variable profit is most informative about fixed costs.

I conduct two counterfactual simulations to investigate the welfare implications of the "business-stealing" and the "vertical spillover" effects of the quota increase. In the first counterfactual, I hold the observed theaters fixed and investigate how import restrictions affect consumer surplus, producer profit, and government tax revenue. I find that all three welfare measures drop by 3%–5%. The welfare cost is larger when the set of imported foreign movies have poorer qualities and is larger in pro-foreign cities. The second simulation compares theaters' counterfactual variable profits with their fixed costs and finds that 2.4% theaters would be unprofitable from which domestic movies receive 2.33% of their sales. Putting the results together, I find that import restrictions lead to protectionism without winners and the welfare effect is amplified by changes in market structure.

The paper suggests that the vertical spillover effect is economically important in deter-

Table 8: Forward and Backward Spillovers

		Unprofitable theaters
Top 12 + 8	# theaters	212
	% domestic movie sales	7.32
Bottom 12 + 8	# theaters	221
	% domestic movie sales	8.64
Factual	# theaters	200
	% domestic movie sales	6.31

Note: The number of theaters is 893. “# theaters” is the count of theaters with negative net profit under the counterfactual quota policy. “% domestic movie sales” is the share of domestic box-office sales in these unprofitable theaters.

mining the welfare effects of an import liberalization policy. One limitation of the research design is that it cannot be directly used for simulating a new policy. It is because instead of directly modeling how theaters enter the market, I took an indirect approach to simulate the number of theater exits when there is a return to protectionist quota policy. A fully specified theater entry game in the spirit of this paper's exit model is a potential direction for future research.

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Appendix A. Institutional Background

A.1. Details on Revenue Sharing

First, 3.3% of the total box office will be paid for value-added taxes and 5% for administrative fees. The after-tax box office will be transferred from theaters to theater chains and then to upstream producers and distributors. Theaters and theater chains keep 57% of the after-tax revenue. Franchise theaters pay a membership fee to theater chains (around 5% of the after-tax revenue). The remaining 43% of the after-tax revenue is split between producers and distributors. If a movie is produced by domestic firms, then about 8.5% of the after-tax revenue goes to distributors. Otherwise, the domestic distribution of imported movies is monopolized by *China Film* and *Huaxia Distribution*. Their revenue share from distributing a movie is 30% before 2012 and 18% after 2012. For flat-fee foreign movies, distributors need to pay a fraction (around 12%) box-office sales to *China Film*.

Table A1: After-Tax Revenue-Sharing Schemes in China

	Domestic	Foreign (revenue-sharing)		Foreign (flat fee)
		Pre-2012	Post-2012	
Producers	34.5%	13%	25%	
Distributors	8.5%	30%	18%	43%

Data Source: https://piaofang.maoyan.com/rankings/year, Hou and Wu (2014) and *Memorandum of Understanding between the People's Republic of China and the United States of America Regarding Films for Theatrical Release*.

A.2. Variance Decomposition

I use the decomposition method in Card et al. (2018) to verify with data that showings are directed by chains and prices are set by theaters, as described in Section 2. I decompose a movie's average weekly price and per-screen showings in a theater to movie-week level variation exhibitor level variation (ξ_{jt}). Specifically, I regress movie k's average price in theater j in week t, y_{jkt} on movie-week fixed effects ξ_{kt} and theater-week ξ_{jt} or chain-week fixed ξ_{Jt}. Take variance:

$$Var(y_{jkt}) = Cov(y_{jkt}, \xi_{jt}) + Cov(y_{jkt}, \xi_{kt}) + Cov(y_{jkt}, \xi_{jkt}).$$

Table A2 reports the decomposition results. For price variation decomposition, movie-week fixed effects control for the declining popularity over time. Theater-week fixed effects account for 64% of the price variation while chain-week fixed effects only account for 11%. This suggests that there is significant price variation across theaters under the same chain, possibly driven by differences in retail competition.

The decomposition results for showings share are also consistent with the institutional background. The set of movies available to exhibitors is controlled by the government so around 30% variation in per-screen showings is at the movie-week level. Moreover, 30% of the per-screen showings the total variation is explained by the chain-movie fixed effects. Theater-movie fixed effects capture chain-level variation and downstream market conditions (e.g., capacity utilization and consumer tastes); the latter accounts for more than 20% of the total variation. In summary, theater chains significantly affect screening decisions.

Appendix B. Data

B.1. Approximating Land Value

The raw data is the price of land i in year t, denoted as p_{it}. By restricting the sample to commercial and residential land transactions via auction, I have a sample of 11,983 transactions for urban areas in 24 cities from 2009 to 2017. The goal of this subsection is to construct an index of location-specific land value from the p_{it} data.

I first eliminate the price difference driven by the differences in floor rate restrictions and land areas. I regress log land price on land parcel characteristics (maximum allowed floor rate and land area), location population density (measured by population within 2km),

Table A2: Variance Decomposition for Theater-Movie-Week Level Price and Showings

Panel A: Price

	Mean = 32.69, standard deviation = 8.88					
	(1)	(2)	(3)	(4)	(5)	(6)
Movie	7.21 (9.14)	7.15 (9.07)	7.52 (9.54)			
Movie-week				7.94 (10.07)		
Movie-week-city					23.49 (29.84)	23.65 (30.18)
Theater	43 (54.53)					
Theater-origin		44.62 (56.58)				
Theater-origin-quarter			52 (65.94)	51.93 (65.85)	38.02 (48.3)	
Theater-origin-week						42.05 (53.66)

Panel B: Showings

	Mean = 4.26, standard deviation = 4.1					
	(1)	(2)	(3)	(4)	(5)	(6)
Movie	4.66 (27.77)	4.67 (27.83)	4.92 (29.32)			
Movie-week				11.87 (70.74)		
Movie-week-city					12.42 (73.97)	12.48 (74.2)
Theater	1.07 (6.38)					
Theater-origin		1.14 (6.79)				
Theater-origin-quarter			1.57 (9.36)	1.44 (8.58)	1.32 (7.86)	
Theater-origin-week						1.87 (11.12)

Notes: The sample is movie-theater-week level prices and showings from 2012–2017. Prices are in 2009 Chinese Yuan. The percentages of the variance of the dependent variable explained by fixed effects are reported in parentheses.

a district-specific time trend $\alpha_{d(i)}t$, and a district fixed effect $p_{d(i)}$

$$\log(p_{it}) = \alpha_{d(i)}t + p_{d(i)} + \beta_1 \text{Floor rate}_{it} + \beta_2 \text{Land area}_{it} + \beta_3 Popden_{it} + \varepsilon_{it}.$$

With the regression coefficient estimates, I get the land price predicted with variables other than land parcel characteristics $\hat{\alpha}_{d(i)}t + \hat{p}_{d(i)} + \hat{\beta}_3 Popden_{it}$ for all 11,983 locations and extrapolate the prediction to the 9 years in the sample period. I calculate the average predicted land price within 2 km from a theater as the proxy for rent it pays in year t.

Appendix C. More Reduced-Form Results

C.1. Instrumenting Pre-Liberalization Foreign Movie Sales Share

I follow Sequeira et al. (2019) and relate, in Equation (17), differences in local tastes for foreign movies, measured by sales share of foreign movies, to demographic characteristics (share of employment, college students, pre-college students and log average wage). The model is estimated with the pre-liberalization 2009–2011 sub-sample. Year fixed effects are included to control for demand fluctuations (e.g, changes in movie quality). City fixed effects are not included since the panel is short and the goal is to explain across-city rather than within-city taste differences.

$$s_c = \phi \hat{s}_c + \nu_c = \phi \left(z_c \hat{\gamma} \right) + \nu_c \tag{16}$$

$$\hat{s}_{ct} = z_c \hat{\gamma} + \hat{\kappa}_t \tag{17}$$

I present the estimation results for Equation (2) using the instrumental variable strategy described above in Table C3.

Table C3: Reduced-Form Evidence for Forward Spillover

VARIABLES	(1) Foreign sales share
Employment share	0.158***
	(0.057)
log(income)	0.017*
	(0.010)
log(population)	0.023***
	(0.007)
Per capita theaters (pre 2009)	0.007
	(0.004)
Per capita box office	0.000***
	(0.000)
Observations	311
R-squared	0.424
City FE	No
Year FE	Yes
F	21.59
Cities	108

Note: Standard errors clustered at the city level are reported in parentheses.

C.2. Import Liberalization and Sales Growth: Theater-Level Evidence

Table C4: Two-Stage-Least-Square Estimates

Panel A: Evidence for Forward Spillover

VARIABLES	(1) Theater entry/pop	(2) I(entry>0)	(3) Mall entry/pop
$Post_t$ *Avg Foreign share	6.607**	1.523*	-1.551
	(2.912)	(0.811)	(3.391)
Pop Growth	-0.020	-0.004	-0.004
	(0.023)	(0.008)	(0.023)
Observations	944	944	944
R-squared	0.026	0.003	-0.002
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Cities	106	106	106

Panel B: Evidence for business-stealing

VARIABLES	(1) log(box office)	(2) log(box office)
Effects on foreign movies:		
$Post_t$*Avg foreign share	2.715***	2.715***
	(0.956)	(0.007)
Effects on domestic movies:		
$Post_t$*Avg foreign share	-1.386*	-1.382***
	(0.760)	(0.006)
Observations	1,520,302	773,466
R-squared	0.004	0.405
Sample	All	Incumbents
Theater FE	Yes	Yes
Year*Origin FE	Yes	Yes
WOY*Origin FE	Yes	Yes

Note: Standard errors clustered at the city level are reported in parentheses.

C.3. Rival Entry and Theater Pricing, Showings, and Sales

In Columns (1) and (3), Table C5, I examine how the number of rivals affect a theater's weekly sales and admissions. I use two specifications: rival counts in different distance rings ($<$ 1 km, 1–2 km, 2–5 km, $>$5 km) and rival counts in the same or different sub-districts. Theater fixed effects and week fixed effects are included to control for theater-level characteristics and fluctuations in weekly demand. The results suggests that, all else equal, 1 more rival within the 2 km ring leads to 11.5% reduction in sales and 9.6% reduction in admissions. The reduction in sales and admissions arising from rival entry outside 2 km rings respectively shrink to 3% and 2.5%. I also show that sub-district boundary well measures the scope of spatial competition: rival presence within the same district leads to a 8.7% reduction in sales and a 6.8% reduction in admission. Rivals in a different sub-district do not affect a theater's sales and admissions.

I also do the same analysis for pricing and screening decisions. Here I use log average ticket price and log total screenings for domestic and foreign movies as the dependent variables and include theater fixed effects and week-origin fixed effects. The results hold in pricing regressions, but not in screening regressions. This is because while pricing response to rival entry is clear given most theaters are independent franchises, screening can response in either way. Theaters can compete in screenings to attract consumers or decrease screenings when demand is significantly diverted to entrant rivals.

Table C5: Rival Entry and Theater Pricing, Showings, and Sales

VARIABLES	(1) log(Sales)	(2) log(Admissions)	(3) log(price)
Theaters (<1km)	-0.107***	-0.086***	-0.021***
	(0.014)	(0.013)	(0.003)
Theaters (1–2km)	-0.109***	-0.093***	-0.017***
	(0.010)	(0.010)	(0.001)
Theaters (2–5km)	-0.029***	-0.024***	-0.005***
	(0.006)	(0.005)	(0.001)
Theaters (>5km)	0.001**	0.001	0.001***
	(0.001)	(0.001)	(0.000)
Observations	1,921,186	1,921,186	1,921,186
R-squared	0.859	0.848	0.677
Theater FE	Yes	Yes	Yes
Week-Origin FE	Yes	Yes	Yes

Notes: This table reports regression of log sales, log admissions, and log price on the numbers of rivals in different distance rings. An observation is a theater-origin pair. Standard errors clustered at the city level are reported in parentheses.

Appendix D. Technical Details for Demand Estimation

I embody linear high-dimensional fixed effect estimation (Loualiche and Gomez, 2022) to the nested fixed point algorithm to BLP Schrimpf (2020).

D.1. Demand Inversion

Index with $\tilde{j} = (j, o)$ the theater-origin tuple, then for each market (i.e, city-quarter $c(j), t$), a system of Equations (7) defines a mapping between mean utility vector $\boldsymbol{\delta} = (\delta_1, ..., \delta_{\mathcal{J}})$ to the market share vector $\boldsymbol{s} = (s_1, ..., s_{\mathcal{J}})$, conditional on the individual specific utility $\boldsymbol{\mu}$ = $f \mu_{i\tilde{j}} g_{i2(c(j),t),\tilde{j}=1,...,\mathcal{J}}$

$$s_{\tilde{j}} = s_{\tilde{j}}(\boldsymbol{\delta}; \boldsymbol{\mu}), \tilde{j} = 1, ..., \mathcal{J}.$$

D.1.1. BLP Inversion

Berry et al. (1995) use the following inversion to solve for the fixed point of this system of equations:

$$\delta_{\tilde{j}}^{h+1} = \delta_{\tilde{j}}^{h} + \log\left(s_{\tilde{j}}^{data}\right) \quad \log\left(s_{\tilde{j}}(\boldsymbol{\delta}; \boldsymbol{\mu})\right)$$

D.1.2. SQUAREM Inversion

Reynaerts et al. (2012) formulate the problem as the solution to $\log\left(s_{\vec{j}}^{data}\right) - \log\left(s_{\vec{j}}(\boldsymbol{\delta};\boldsymbol{\mu})\right) = 0$. Then near the true parameter vector $\boldsymbol{\delta}$,

$$\begin{aligned}\log\left(s_{\vec{j}}^{data}\right) = \log\left(s_{\vec{j}}(\boldsymbol{\delta};\boldsymbol{\mu})\right) &= \log\left(s_{\vec{j}}(\boldsymbol{\delta}^h;\boldsymbol{\mu})\right) + J(\boldsymbol{\delta}^h)(\boldsymbol{\delta}^h - \boldsymbol{\delta})\\ \boldsymbol{\delta}^h - \boldsymbol{\delta} &= J(\boldsymbol{\delta}^h)^{-1}\left(\log\left(s_{\vec{j}}(\boldsymbol{\delta};\boldsymbol{\mu})\right) - \log\left(s_{\vec{j}}(\boldsymbol{\delta}^h;\boldsymbol{\mu})\right)\right)\end{aligned}$$

A Newton update step can be added to the Berry et al. (1995) algorithm

$$\boldsymbol{\delta}^{h+1} \leftarrow \boldsymbol{\delta}^h + J(\boldsymbol{\delta}^h)^{-1}\left(\log\left(s_{\vec{j}}^{data}\right) - \log\left(s_{\vec{j}}(\boldsymbol{\delta}^h;\boldsymbol{\mu})\right)\right)$$

where J is the Jacobian matrix that can be calculated from logit algebras:

$$J \equiv \frac{\partial \log\left(s_{\vec{j}}(\boldsymbol{\delta}^h;\boldsymbol{\mu})\right)}{\partial\left(\boldsymbol{\delta}^h\right)'} = (diagm(\boldsymbol{s}) - \boldsymbol{s}\boldsymbol{s}')./\boldsymbol{s}.$$

D.1.3. Grigolon-Verbonven Inversion

For a nested-logit demand model, Grigolon and Verboven (2014) proves that the Berry et al. (1995) inversion becomes[31]

$$\delta_{\vec{j}}^{h+1} = \delta_{\vec{j}}^h + (1 - \rho_{h(\vec{j})})\left(\log\left(s_{\vec{j}}^{data}\right) - \log\left(s_{\vec{j}}(\boldsymbol{\delta}^h;\boldsymbol{\mu})\right)\right).$$

[31]For RCNL, inversion with a Newton update step is slower than BLP inversion due to the complexity of derivative matrix in nested-logit.

D.2. The Derivative Matrix in Nested-Logit Demand

I express demand derivatives based on the results from Miller and Weinberg (2017).

- If $j = k$,

$$\begin{aligned}
\frac{\partial s_j}{\partial \delta_k} &= \frac{1}{1 \quad \rho_o} s_j \left(1 \quad s_j \quad \rho_o(s_{jjg} \quad s_j)\right) \\
&= \frac{1}{1 \quad \rho_o} s_j \quad \frac{1}{1 \quad \rho_o} s_j^2 \quad \frac{1}{1 \quad \rho_o} \rho_o s_j (s_{jjg} \quad s_j) \\
&= \frac{1}{1 \quad \rho_o} s_j \quad \frac{1}{1 \quad \rho_o} s_j^2 \quad \frac{1}{1 \quad \rho_o} \rho_o s_j^2 (1/s_g \quad 1) \\
&= \frac{1}{1 \quad \rho_o} s_j \quad \frac{1}{1 \quad \rho_o} s_j^2 (1 \quad \rho_o(1 \quad 1/s_g))
\end{aligned}$$

- If $o(j) = o(k)$,

$$\begin{aligned}
\frac{\partial s_j}{\partial \delta_k} &= \quad s_k \left(s_j + \frac{\rho_o}{1 \quad \rho_o} s_{jjg}\right) \\
&= \quad \frac{1}{1 \quad \rho_o} s_k s_j \left(1 \quad \rho_o + \rho_o(1/s_g)\right) \\
&= \quad \frac{1}{1 \quad \rho_o} s_k s_j \left(1 \quad \rho_o(1 \quad 1/s_g)\right)
\end{aligned}$$

- If $o(j) \neq o(k)$,

$$\frac{\partial s_j}{\partial \delta_k} = \quad s_j s_k$$

The above three terms can be expressed in matrix form. Partition the market share vector as $\boldsymbol{s} = (\boldsymbol{s}_0, \boldsymbol{s}_1)'$. Recall that

$$J \quad \frac{\partial \log \left(s_{\mathcal{J}}(\boldsymbol{\delta}^h; \boldsymbol{\mu})\right)}{\partial \left(\boldsymbol{\delta}^h\right)'} = \frac{\partial \left(s_{\mathcal{J}}(\boldsymbol{\delta}^h; \boldsymbol{\mu})\right)}{\partial \left(\boldsymbol{\delta}^h\right)'} ./\boldsymbol{s}$$

$$\begin{aligned}
\frac{\partial \left(s_{\mathcal{J}}(\boldsymbol{\delta}^h; \boldsymbol{\mu})\right)}{\partial \left(\boldsymbol{\delta}^h\right)'} &= \begin{bmatrix} \frac{\partial \boldsymbol{s}_0}{\partial \boldsymbol{\delta}_0} & \frac{\partial \boldsymbol{s}_0}{\partial \boldsymbol{\delta}_1} \\ \frac{\partial \boldsymbol{s}_1}{\partial \boldsymbol{\delta}_0} & \frac{\partial \boldsymbol{s}_1}{\partial \boldsymbol{\delta}_1} \end{bmatrix} \\
&= \begin{bmatrix} \frac{diagm(\boldsymbol{s}_0) \quad \boldsymbol{s}_0 \boldsymbol{s}_0'(1 \quad \rho_0(1 \quad 1/\boldsymbol{s}_0))}{1 \quad \rho_0} & \boldsymbol{s}_0 \boldsymbol{s}_1' \\ \boldsymbol{s}_1 \boldsymbol{s}_0' & \frac{diagm(\boldsymbol{s}_1) \quad \boldsymbol{s}_1 \boldsymbol{s}_1'(1 \quad \rho_1(1 \quad 1/\boldsymbol{s}_1))}{1 \quad \rho_1} \end{bmatrix}
\end{aligned}$$

D.3. First-Stage Regression for Demand Estimation

Table D6: Demand Estimation: First Stage Results

VARIABLES	(1) Price	(2) Price	(3) Price	(4) $\log\left(\frac{s_{jo}}{s_o}\right)$	(5) $\log\left(\frac{s_{jo}}{s_o}\right)$	(6) $\log\left(\frac{s_{jo}}{s_o}\right)$
Entry/exit dummy	-1.599***	-1.598***	-1.581***	-1.826***	-1.826***	-1.829***
	(0.167)	(0.167)	(0.167)	(0.046)	(0.045)	(0.045)
# theater rivals (<2km)	-0.499***	-0.499***	-0.296**	-0.082***	-0.080***	-0.113***
	(0.079)	(0.080)	(0.122)	(0.014)	(0.014)	(0.019)
# theater rivals (2–5km)	-0.066	-0.066	0.139	-0.030***	-0.031***	-0.064***
	(0.055)	(0.055)	(0.104)	(0.008)	(0.008)	(0.016)
Avg rival size (0–2km)	-0.083**	-0.083**	-0.105***	0.001	-0.000	0.003
	(0.035)	(0.035)	(0.037)	(0.005)	(0.005)	(0.006)
Avg rival size (2–5km)	-0.124*	-0.124*	-0.144**	-0.000	0.004	0.006
	(0.066)	(0.069)	(0.069)	(0.009)	(0.008)	(0.008)
Avg tech difference (0–5km) Foreign		-1.444*	-1.354*		-0.261**	-0.252**
		(0.783)	(0.802)		(0.105)	(0.105)
Avg tech difference (0–5km) Domestic		1.468*	1.557**		-0.148	-0.139
		(0.761)	(0.777)		(0.105)	(0.105)
Population (0–5km)			6.542*			0.365
			(3.825)			(0.598)
Population (0–5km) # theater rivals (0–5km)			-0.144**			0.022**
			(0.071)			(0.011)
Observations	36,744	36,744	36,744	36,744	36,744	36,744
R-squared	0.838	0.844	0.845	0.852	0.852	0.853
Theater FE	Yes	Yes	Yes	Yes	Yes	Yes
City-origin-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
F stat	27.95	41.90	33.14	329.8	246.2	193.2

Notes: Standard errors clustered at the location level.

Appendix E. Bounding Fixed Cost with 5th and 95th Percentiles

I construct two bounds for theaters' per-screen fixed operation cost. The upper bound is the 5th percentile of per-screen variable profit of $J^{(1)}$ theaters described in Section 7.1.1. The lower bound is the 95th percentile of per-screen variable profit of $J^{(2)}$ theaters described in Section 7.1.1.

Results are reported in Table E7. The two columns "Lower bound" and "Upper bound" correspond to the counterfactual results under the two bounds of fixed cost. The three sections of rows "Top 12 + 8", "Bottom 12 + 8", and "Factual" correspond to the three scenarios of imported movie in release: top 12 quality movies and 8 quarterly blockbusters, bottom 12 quality movies and 8 quarterly blockbusters, and the actual released imported movies. This classification gives me six counterfactual experiments. For each experiment, I report the number of theaters that would have negative net profit and the share of domestic movie sales in those theaters.

Table E7: Forward and Backward Spillovers

		Lower bound	Upper bound
Top 12 + 8	# theaters	81	105
	% domestic movie sales	2.643	3.704
Bottom 12 + 8	# theaters	83	109
	% domestic movie sales	2.722	3.767
Factual	# theaters	70	93
	% domestic movie sales	2.176	3.077

Note: The number of theaters is 893. The two columns "Lower bound" and "Upper bound" correspond to the counterfactual results under the two bounds of fixed cost. The three sections of rows "Top 12 + 8", "Bottom 12 + 8", and "Factual" correspond to the three scenarios of imported movie in release: top 12 quality movies and 8 quarterly blockbusters, bottom 12 quality movies and 8 quarterly blockbusters, and the actual released imported movies.