Measuring the market expansion, business stealing, and cannibalisation effects of new movie entries

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Abstract

I empirically measure the impact of new movie releases using detailed entry data across cinemas from a typically large urban market in China. I identify and measure three primary effects following the release of new movies: market expansion of the entire industry, business stealing across different cinemas, and cannibalisation of movies within a cinema. I find that differentiated product entry in the movie exhibition industry has a strong market expansion effect, weak cannibalisation, and modest business stealing effects, implying that the extensive release of new movies increases industry profits and expands consumer choice.

Keywords: market expansion, business stealing, cannibalisation, new product entries, nesting structure

JEL classification: L13, L82

1. Introduction

There is an interesting phenomenon in the movie industry in many countries in the entry every year of numerous new products in the movie exhibition industry.[1] This trend raises several questions. First, is it profitable to release so many movies per year, and does this cause changes in revenue for the entire industry? Second, do so many new releases cause excessive competition in the industry by stealing revenue from other cinemas, and do new movies affect the business of other cinemas? Third, does the release of new movies affect the revenue of other films that are currently being shown in the same cinema?

The above questions are critical because the release of a new movie may fail if a cinema ignores the potential business stealing and cannibalisation effects of the new film. First, excessive fixed costs may be incurred if other cinemas recognize

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This article is a revised version of Chapters 2 and 3 of my PhD thesis from the University of Sydney in 2019.
[1] The number of movies released in the US reached 728 in 2017: http://www.boxofficemojo.com/yearly/chart/?yr=2017.
Australia released 407 movies in 2017: http://www.boxofficemojo.com/intl/australia/yearly/?yr=2017&p=.htm.
Japan released 1,187 movies in 2017: http://news.mtime.com/2018/01/26/1577701-all.html.
China released 566 movies in 2016: https://www.sohu.com/a/159387620_115178.

that a new movie may steal clients from their current screening movies. They may, as a result, modify their behavior to thwart the entry of a new movie by reducing prices or increasing their own product variety. Second, a cinema could damage its own profit if the cannibalisation effect is too strong. The new movie could merely capture the profits of others being screened in the same cinema. However, cinemas will accept these entries rather than erect costly barriers if releasing a new movie attracts more consumers away from outside goods (other leisure activities) and generates more profit for the entire industry.

Some researchers focus on and estimate the impact of the entry of new firms into the market. Berry and Waldfogel (1999) raise a fundamental question regarding whether the entry of new radio stations would steal business from incumbent stations or attract new audiences from other leisure activities. The authors compare revenues from paired markets of identical sizes selling different products and build an entry model to understand the nature of competition. Davis (2006a) observes quarter-on-quarter revenue and entry/exit data over time for cinemas across markets in the US, measuring the within-market and within-product effects following the entry of a new theater. However, neither Berry and Waldfogel (1999) nor Davis (2006a) observe data following the entry of a new product (movie). Einav (2007) estimates market expansion of release timing using weekly product data with a one-level nested logit model to separate the market expansion effects of "hit" entries from seasonal demand. They observe that the release of hits amplifies the underlying seasonality of demand. Chiou (2008) analyzes cannibalisation within genres by extending Einav's (2007) one-level nested logit model to three levels, finding no evidence of cannibalisation among titles within genres and newly released movies. However, both Chiou (2008) and Einav (2007) ignore the impact of business stealing between cinemas.

This study measures the market expansion (attracting new customers from other leisure activities), business stealing (poaching customers from rival cinemas), and cannibalisation (diverting customers from other movies in the same cinema) effects of introducing a new movie. It identifies an asymmetric pattern of these effects among different cinemas.

For this purpose, I collected extensive and detailed entry data from the Chinese mainland movie industry, including box office revenues, rate of occupation, prices[2] across movies, release time, and auditoriums.

Following the logic of Einav (2007) and Chiou (2008), I explain the variation in box office earnings as containing two parts: real underlying demand and market reaction. The first reflects customers' desire to watch a movie, and the second is the change in their intent to watch a movie caused by the marketing reactions of cinemas. I consider four marketing reactions in (1) price, (2)

[2] Unlike other markets in which there is price rigidity across different types of movies (for example, the US, Europe, Australia), the Chinese mainland cinema industry is a rare exception in which substantial price variations can be noted across different movies, release times, and auditoriums.

allocation of screens,[3] (3) run length, and (4) decisions on new movie releases. I explain the real demand part of total revenue following the strategy of demand estimation in Davis (2006b) and de Roos and McKenzie (2014) and include differences in the characteristics of the movie, time, and cinema. I capture the marketing reactions by estimating the parameters of the variation in prices, allocation of screens, and length of the run.

I design a three-level nesting structure to empirically estimate the effects of releasing a new movie. This structure includes two levels of competition, assuming the market size of a city and considering the competition between cinemas within the city. The first level of competition captures substitution between outside and inside goods to evaluate the effects of market expansion. The second and third levels capture substitution across cinemas and within each cinema, which allows me to separate the business stealing effects across cinemas from the cannibalisation effects of movies within one cinema. Finally, asymmetric patterns of both business stealing between cinemas and cannibalisation within each cinema are observed by calculating and analyzing cross-price elasticities of demand among cinemas and within each cinema.

The nesting structure demonstrates strong market expansion effects because the entry of a new movie can bring around 65.1% of consumers from outside goods (other leisure activities). The business stealing effect is stronger than the cannibalisation effect but weaker than the market expansion effect. A new movie draws around 8% of consumers away from other movies within the same cinema, whereas only 27.6% of consumers are drawn away from other cinemas.

Cross-price elasticities expose highly imbalanced cannibalisation and business stealing effects. The wide range of variation of elasticities both within cinema and across different cinemas is caused by the Sensitivity to the change two-level inside shares. Differences in the pricing strategy of cinema chains significantly affect the asymmetric pattern of both cannibalisation and business stealing of movie entries. Dadi, exerting a low pricing tactic, had the lowest cannibalisation and highest business stealing. By contrast, Wanda's pricing features the highest mean price level and degree of variation, exhibiting relatively lower business stealing and higher cannibalisation effects. Zhong Ying, the fixed-price cinema chain, shows the lowest level of business stealing.

The location of cinemas has a significant influence on business stealing and cannibalisation effects. Jianghanlu Wanda, located in the city center, faces more competitors than other cinemas when it introduces a new movie. According to the standard economic intuition for a geographically differentiated product market, cinemas located in the business center area are more likely to draw sales from other products within their own cinema than steal consumers from other cinemas.

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[3]Allocation of screens: total number of screens arranged to show a movie. I did not use allocation of seats because allocation of screens and seats share a variation pattern. (Detailed information is included Figure 1(a) of my working paper: *Entry, exit, expectations, and performance over the movie life cycle*)

The rest of the paper is structured as follows. Section 2 describes the Chinese movie industry. Section 3 explains the data sources and patterns, and Section 4 defines and identifies the market-level nesting structure model. Section 5 discusses the results. Section 6 presents the limitations, and, finally, Section 7 concludes.

2. Industry description

The Chinese mainland movie market has, since its reform in 2002, emerged as the world's fastest-growing market and has been the second-largest international cinema market since 2012.[4] The top section of Table 1 shows the rapid growth trajectory of box office revenue in China, which has increased more than 60-fold from 0.11 billion USD in 2002 to 6.8 billion USD in 2015.[5] The compound annual growth rate of box office revenue approached 32.25% between 2002 and 2015. Meanwhile, audience members increased more than 28-fold over this same period. The projection resources have also increased exponentially, which is evident from the increasing number of cinemas and screens from 2002 to 2015, as shown in the bottom section of Table 1.

Alongside the rapid growth of the movie industry, however, one of the most striking details is the extremely high unreleased rate of movies in the Chinese mainland market. Table 2 shows that each year more than 500 local movies (around 70%) could not be publicly released; this rate is especially in 2012 when 666 films went unreleased. Although all cinemas and screens were running at full capacity, cinemas still shut their doors to many movies because of a lack of projection resources.[6]

2.1 Market power of exhibitors

China's movie industry has three divisions: production, distribution, and exhibition. Major studios have integrated production and distribution, but in China, the exhibitors are not vertically integrated with producers or distributors as they are in many other countries such as the US (Einav 2007) and Australia (de Roos & McKenzie 2014).

However, China's movie industry is dominated by exhibitors,[7] while producers are dominant in other countries. Exhibitors – cinemas and cinema chains – determine ticket prices, allocate seats and screens, and decide when to terminate films. They also receive a larger share of box office revenue than producers and

[4] *China box office round-up 2012: China becomes world's second biggest market*, 21/1/2013, https://www.screendaily.com/china-box-office-round-up-2012-china-becomes-worlds-second-biggest-market/5050843.article

[5] Data from *National Bureau of Statistics of China*, http://data.stats.gov.cn/

[6] There are serious problems in China's movie industry: 70% of movies cannot go public http://ent.qq.com/a/20130513/013901.htm.

[7] 'Who is the one controlling the movie industry in China?' (08/07/2013), http://ent.qq.com/a/20130708/011193.htm. , *China Business.*

distributors. There are 46 cinema chains operating in the current market. Table 3 lists the details of the top-ten cinemas. Wanda, with a market share of 14.89%, is China's most popular cinema chain. The total box office revenue of the top-five cinema chains accounts for half of the revenue of the domestic market, and the top-ten cinema chains together control more than 70% of the market.

Exhibitors have a strong influence in the release process of new films.[8] After negotiating the release date with distributors, cinema chains provide lists of new movies and imminent release dates to their cinemas. However, each individual cinema makes the final decision on the allocation of screens and seats for a specific movie on a specific day. Cinema managers usually make these decisions based on three dimensions: 1) characteristics of the movie, such as reviews, advertising investment, and the movie star's reputation; 2) characteristics of their own cinema, such as the total number and size of screens, and local demand; and 3) long-term relationships between cinema chains and both producers and distributors.

Market power differs among cinema chains. Bigger cinema chains can usually negotiate better deals with producers than smaller chains. These bigger chains, such as Wanda (the top chain in China),[9] have better locations and projection equipment to draw larger audiences and earn a larger market share. Larger cinema chains allow significant economies of scale from shared facilities (popcorn stands) and reduced per-screen staffing costs (particularly shared ushers and auditorium-cleaning teams). Moreover, larger cinema chains own a greater number of cinemas and screens, which means they have more choices in deciding prices, the number of screens dedicated to a particular film, and runtimes. Flexibility in auditorium allocation is of utmost importance for cinemas; it directly affects the decision to introduce a new movie if they can easily select the number of screens and auditorium size allocated to a new movie, the pricing of the movie at different times, and its screening in different auditoriums. With more screens, cinemas can provide more combinations of old and new movies.

2.2 Ticket pricing

Prior to release, the distributor and cinema chain usually jointly decide on a province- and city-level "minimum price" for each movie. They do so by first considering the size and gross domestic product (GDP) of the city in question. Unbalanced negotiation power between distributors and cinema chains also affects the minimum price, providing a lower bound for fierce low-price competitors and preventing damage to the producer's interests. Any type of concession ticket must be priced higher than the minimum price, including student discounts or promotional tickets. If a cinema sells a ticket for less than

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[8] Mysteries of allocation of screens and seats', *Huxiu*, 28/09/2016, http://m.huxiu.com/article/165514.html

[9] Wanda movie: profits reached 1.5 billion RMB in 2017, financial analysis about Wanda cinema chain http://finance.ce.cn/sub/ybnzt/dftd/yj/201805/02/t20180502_29003676.shtml

the minimum price, it must make up for the shortfall (Fu 2014). Minimum resale prices[10] are legal in China, although they are illegal and categorized as anti-competitive behavior (Einav 2007) in the US and Australia, where it is illegal for suppliers to pressure businesses to charge their recommended retail price.[11]

Following the establishment of a minimum price, each cinema chain sets an overall pricing strategy at the city level, based on the asymmetric market power across different cities. For instance, Dadi, established in Guangdong, has better locations, operates more cinemas, and has more experienced staff in Guangdong than in other provinces. The chain implements price discrimination more widely in Guangdong by setting a wider range of prices across movies, screening times, and cinemas. Outside Guangdong (for example, in Wuhan City), their lack of market power means that Dadi executes a low-price strategy to compete with other cinema chains. Apparently, cinemas from the same chain work as a team.

Finally, the manager of a cinema determines the final retail ticket price by considering both the overall pricing strategy of the cinema chain and local demand shocks.[12] Managers are most familiar with the demand shocks and consumer habits of the locality in which their cinema is located.

2.3 Box office revenue-sharing options

A movie can earn additional profits if its broadcast rights are sold to public television or for release on DVD after the end of its cinema-screening life. However, the box office remains the main source of income for a movie, accounting for more than 80% of the total revenue (Gai 2016).

For domestic movies, producers and distributors in mainland China receive a smaller portion (39.43%) of the net revenue, while exhibitors gain a larger share (52.27%) after the government and China Film Special Fund levy (8.3% of the total box office revenue).[13] Conversely, in the US, the distributor and producer receive the greatest fixed share—either 90% of net revenues or a 70% share of gross revenues (Einav 2007). The revenue share in China usually does not vary with the length of the movie.

Revenue sharing in China differs for foreign (imported) movies. There are three ways to import foreign movies into mainland China. First, 34 foreign movies can be imported annually using a revenue-sharing model (excluding 3D and IMAX movies, which are imported as special movies). The producer receives a 35% share; the distributor—the China Film Group Corporation (CFGC), with a

[10]Minimum price was higher than 19.9 RMB during the 2018 spring festival. http://m.sohu.com/a/217612586_114733

[11] Definition of the imposition of minimum resale price in Australia: https://www.accc.gov.au/business/anti-competitive-behaviour/imposing-minimum-resale-prices

[12] Chao Fu, Ticket price of movie has become cheaper. What happened?, *Gui Quan*, http://ent.qq.com/original/guiquan/g150.html

[13] The China Film Special Fund was set up in 1996 to protect the movie industry in mainland China. It is used to build cinemas in economically developing areas and invest in the production of small mass-market films like histories and documentaries. It is also the funding source of the Chinese Box Office Database System.

monopoly on foreign movies—obtains 17%, and the exhibitor receives 48% (Zheng 2013). The producer pays the advertising costs. Hollywood blockbusters account for approximately 90% of the revenue-sharing quota.

All other foreign movies (with a single exception) are imported using a one-time buyout model. Distributors pay a one-time fixed price to producers for exclusive rights to screen the film in the mainland market. As in a wholesale transaction, the reseller (distributor) buys the product (movie) from the producer and resells it to a specific market. Therefore, distributors are responsible for all the profits and risks in the mainland Chinese market. The number of one-time-buyout movies is greater than the number of revenue-sharing imports. Most buyout movies come from Europe, Japan, and South Korea; others are Hollywood movies made by small companies. These films increase content diversity and competition in the Chinese market. The state-owned CFGC handles the import of movies and determines which will be imported through the revenue-sharing model and those that will be one-time buyouts.

In the exceptional case mentioned above, co-produced movies made in association with a Chinese company are released in the Chinese market. Producers, including Chinese and foreign companies, can receive 39.43% of net revenue, as with domestic movies. For a film to qualify for this category, more than one-third of the main cast must come from mainland China.[14]

No differentiated product barriers exist in the Chinese movie industry when a new movie enters the market. In most cases, all cinemas take similar actions when releasing a new movie, and cinemas usually release a movie on the same day across chains, especially blockbusters.

Currently, both producers and cinema chains are attempting to expand their business and integrate upstream and downstream industries in China. Hua Yi Brothers, one of the biggest movie producers, has built 19 cinemas in the past six years and invested in the Dadi cinema chain to capture distribution power.[15] Wanda, the top cinema chain in China, invested 3.5 billion USD in acquiring the US movie production company, Legendary Pictures.[16]

3. Data and summary of key variables

3.1 Movie and cinema characteristics

I collected transaction data (8,458,892 observations) across 191 cities of all sizes from March 12, 2013, to May 16, 2014, from the Chinese box office database,[17] which includes detailed film information, including seat allocation and occupancy, box office revenue, and ticket price per auditorium.

[14] How to produce a co-production movie? http://news.mtime.com/2016/02/08/1552287.html
[15] Huayi Brothers buying Dadi cinema chain http://finance.sina.com.cn/roll/2017-01-12/doc-ifxzqnva3297600.shtml
[16] Wanda spends 23 billion RMB to purchase Legendary Pictures. Is it too risky? http://ent.sina.com.cn/m/c/2016-01-12/doc-ifxnkkuy7978720.shtml
[17] Chinese box office database: http://58921.com/

From the 191 cities covered, Wuhan is selected as the data source for this paper. Wuhan's 2014 GDP was about 1.0069 trillion RMB (163.769 billion USD), the eighth highest in mainland China and with 10.22 million residents; the city has the 13th largest urban population in China. I use 194,397 observations covering 307 movies from 20 cinemas and five cinema chains. Throughout the analysis, relatively small movies are removed, and I focus on those that lasted more than one week in a cinema. My final dataset comprises 206 movies and 168,155 real-time observations. These titles account for 98% of the revenues of the 307 movies in the original sample.

Table 4 provides a summary of the data. The Baidu Index[18] indicates a movie's cast appeal and analyzes the average monthly internet searches for its actors and directors. The ratings for movie reviews are from Douban,[19] the most popular movie review site in mainland China. Douban uses a five-star system with two points for each star and 10 points in total. I observe cinema characteristics at the auditorium level, including location, VIP room, and the total number of screens and seats. The size of the screening rooms is from Mtime,[20] which allows me to combine the transaction data with the local demographic characteristics of each cinema.

I only collect approximately 50% of the data of the entire market because the Chinese Movie Database is still being developed and does not cover all cinemas in China. All famous and large cinema chains, such as Wanda, Dadi, Jin Yi, and Zhong Ying, are included in the dataset.

3.2 Variation in price

The substantial price variations across movies within a given cinema, across screening times within a given cinema, and across multiple cinemas within a chain are shown in Tables 5, 6, and 7, respectively. Each table includes the mean, minimum, and maximum values along with the standard deviation, skewness, and number of observations.

Table 5 shows a substantial price variation across genres within a cinema, although there is no clear variation pattern for either the average values or degrees of dispersion. Table 6 provides a basic account of the price variation across screening times in a cinema. The top panel shows that cinemas usually offer the highest price during the evening (including the peak hour from 7 pm to 9 pm) and the lowest price during the morning, as expected. The middle panel shows that over the weekend – Saturday and Sunday – prices are slightly higher than on weekdays; during public holidays, the price is 10 RMB higher than on non-statutory holidays. The bottom panel reveals that the average price for a holiday

[18] Baidu is the biggest search engine in mainland China. The market share of Baidu was more than 85% in 2015.
[19] Link to Douban movie: https://movie.douban.com/
[20] Link to Mtime: http://www.mtime.com/

show is slightly higher on weekends, and the weekend price is slightly higher than that on a weekday.

Table 7 presents price variations across cinema chains and cinemas. I find that a cinema chain plays an important role in price variation. Wanda, the largest cinema chain, has the highest average price and standard deviation. As a state-owned cinema chain, Zhong Ying fixes ticket prices, and these exhibit the lowest standard deviation. Dadi, acting as a price leader, always charges the lowest median or mean price in the Wuhan market. Cinemas adjust the final retail price based on the cinema chain's overall pricing strategy.

3.3 Variation in film revenue and audience numbers

Tables 8 and 9 reflect three fundamental facts about the entire screening life of a movie, from entry to exit. Table 8 shows the pattern of audience numbers by the week of a movie's run. As expected, a clear declining trend is apparent from entry to exit. Consumers tend to watch movies soon after their release. However, there was a significant increase in the seventh week because only two movies in the sample (*The Croods* and *Frozen*) lasted more than seven weeks. During the fifth week of *Frozen*'s run in China, it won the Academy Award for Best Animated Feature Film, drawing extensive attention in China. Consequently, cinemas extended the movie's screening life, and many consumers wanted to watch it before the end of its run.

Table 9 shows that revenue follows a trend similar to that of audience numbers: it declines from entry to exit, implying that a new movie's entry increases industry demand as old movies fade away. Therefore, I predict that the effect of market expansion is strong. A similar increase occurs in week seven, again reflecting the two special cases of *Frozen* and *The Croods*.

4 Methodology

4.1 Definition of market

I designed a nesting structure identifying the entire city of Wuhan as the market and the population of the city as the market size M. This structure implies that within Wuhan, cinemas compete and steal consumers from each other. Introducing a new movie may attract customers from outside goods (i.e., other leisure activities), other cinemas, or even other movies within the same cinema.

All other leisure activities are considered outside goods, and the market share of movie j in day t and cinema m can be obtained as follows.

$$S_{j,t,m} = \frac{q_{j,t,m}}{M}, \tag{1}$$

$$S_0 = \frac{M-\sum_j q_{j,t,m}}{M} = 1 - \frac{\sum_j q_{j,t,m}}{M}, \tag{2}$$

Thus, $lnS_j - lnS_0 = \ln\left(\frac{q_{j,t,m}}{M}\right) - \ln\left(1 - \frac{\sum_j q_{j,t,m}}{M}\right),$ (3)

where $q_{j,t,m}$ is the number of seats sold for movie *j* at day *t* and cinema *m*, and M is Wuhan's population, $\sum_j q_{j,t,m}$ represents the sum of sales across all movies sold at day *t* and cinema *m*.

I calculate the market share based on the daily definition and aggregate for each movie in each cinema of prices, seats sold, and allocation of screens by day to match the market share. The total number of observations for the daily periods is 23,271. The weighted average price is calculated in two steps as follows.

$$WT_t = \frac{Seats\ sold_{j,st,m}}{\sum(Seats\ sold_{j,st,m})}$$

$$P_{j,t,m} = \sum(WT_t * P_{j,st,m}).$$

I calculate the weight of the daily price, WT_t, by first using the seats sold for each screening time divided by the seats sold during day *t*. Subsequently, I obtain the weighted daily price by summing the product, $WT_t * P_{j,st,m}$.

4.2 Demand model

I build a three-level nested logit model with unobserved consumer heterogeneity, following Berry, Levinsohn, and Pakes (1995), Davis (2006), Einav (2007), Chious (2008), and de Roos and McKenzie (2014). The indirect utility function of consumer *i* for choosing movie *j* on day *t* in cinema *m* is expressed as follows:

$$U_{i,j,t,m} = \delta_{j,t,m} + V_{i,j,t,m} \tag{4}$$

where $\delta_{j,t,m}$ is the mean utility, and $V_{i,j,t,m}$ is an idiosyncratic individual error term that represents the consumer's inclination to view a movie at a cinema on day *t*.

Following Berry (1994), the mean utility is specified for movie *j*, day *t*, and cinema *m* as follows:

$$\delta_{j,t,m} = \tau_j + \theta_t + \eta_m + X_{j,t,m}\beta - \alpha P_{j,t,m} - \lambda D_{i,m} + \xi_{j.t.m} \tag{5}$$

$X_{j,t,m}$ contains observed product characteristics, including characteristics of the movie, day, and cinema, such as movie content, reviews, the reputation of its stars, and the week of its run. The ticket price $P_{j,t,m}$ varies according to the movie, screening time, and cinema, $D_{i,m}$ are demographic variables accounting for the distance between consumer *i* and cinema *m*, and the number of rival cinemas close to the location of cinema *m*, according to the spirit of Davis (2006). The unobserved product characteristics, such as advertising fees, are represented by $\xi_{j.t.m}$. I did not obtain these data but cinemas used the information to set the final retail price. The movie fixed effect, τ_j, does not change over time and across cinemas, θ_t and η_m represent the time-varying[21] and cinema fixed effect, respectively.

If $V_{i,j,t,m}$ are identically and independently distributed, only the mean utility levels $\delta_{j,t,m}$ would differentiate the products. However, in the movie industry, consumers might favor one specific cinema or movie over others. This correlation can be generated by $V_{i,j,t,m}$. Following the variance-component formulation of Cardell (1997), Einav (2007), and Chiou (2008), I use a three-level nesting structure to specify $V_{i,j,t,m}$:

$$V_{i,j,t,m} = V_{i,IN} + \pi_m V_{i,m} + \pi_j \pi_m \varepsilon_{i,j,t,m}. \tag{6}$$

This nesting structure describes three choices: (1) the choice between all inside goods *IN* (movies) and outside goods (other leisure activities); (2) the choice of a specific cinema *m*, contingent on the choice to watch a movie; and (3) the choice of a specific movie *j*, contingent on the choice of cinema. Following Cardell (1997), $V_{i,j,t,m} = V_{i,IN} + \pi_m V_{i,m} + \pi_j \pi_m \varepsilon_{i,j,t,m}$ has an extreme value distribution with π_j , π_m ∈ [0, 1] parameterizing the correlation of the idiosyncratic preferences within the cinema and inside-good groups if $\varepsilon_{i,j,t,m}$ is a type I extreme value distribution. The parameters π_j and π_m are nesting coefficients to measure the degree of substitution among alternatives in the cinema and inside groups, $0 \leq \pi_j, \pi_m \leq 1$.

The substitution between all inside goods (movies) and outside goods, π_m, is analyzed to estimate the potential market expansion of the entire industry. If π_m approaches zero, all inside goods (movies) are considered perfect substitutes. In this case, consumers have a strong appetite for watching a movie, which means that the new movie can easily attract consumers from other movies but not from other leisure activities. If π_m approaches one, the substitution between outside and inside products is strong, which implies that new movies attract consumers from other leisure activities rather than from other movies.

I use π_j to analyze the extent of business stealing among cinemas and cannibalisation within one cinema. If π_j approaches zero, then movies within a cinema are perfectly correlated, indicating a strong cannibalisation effect within each cinema. When a movie is launched in the market, it attracts consumers from the same cinema rather than from other cinemas. Conversely, if π_j approaches 1, no substitution occurs within a cinema, and the business stealing among cinemas is strong.

The indirect utility from the outside option is

$$U_{i,0,t} = \delta_{0,t} + V_{i,0} + \pi_m V_{i,0} + \pi_j \pi_m \varepsilon_{i,0,t}. \tag{7}$$

The utility of the outside option or of no purchase is normalized to zero. The market share $S_{j,t,m}$ of movie *j* at time *t* in cinema *m* is

[21] I have listed detailed information about time-varying dummy variables, including the base case, in Appendix 3.

$$S_{j,t,m} = \left(S_{j,t,m|IN,t,m}\right)\left(S_{IN,t,m|IN,t,A}\right)(S_A) = \frac{e^{\frac{\delta_{j,t,m}}{\pi_m \pi_j}} \cdot E_J^{\pi_j - 1} \cdot D_G^{\pi_m - 1}}{\left[1 + \sum_A D_G^{\pi_m}\right]}, \tag{8}$$

in which the inclusive value terms are

$$\mathrm{E}_J = \sum_{j \in m} \exp\left(\frac{\delta_{j,t,m}}{\pi_m \pi_j}\right) \tag{9}$$

$$\mathrm{D}_G = \sum_{m \in A} E_J^{\pi_j}. \tag{10}$$

Taking the logs of both sides of Eq. (8) yields a share equation for movie *j* in cinema *m* at time *t*:

$$lnS_{j,t,m} - lnS_0 = \tau_j + \theta_t + \eta_m + \beta X_{j,t,m} - \alpha P_{j,t,m} + \left(1 - \pi_m \pi_j\right) \ln S_{j,t,m|IN,t,m} + (1 - \pi_m) \ln S_{IN,t,m|IN,t,A} + \xi_{j.t.m} \tag{11}$$

where $\ln S_{j,t,m|IN,t,m}$ is the share of movie *j* out of all movies shown in cinema *m* on day *t*, while $\ln S_{IN,t,m|IN,t,A}$ is cinema *m*'s share of the whole market, Wuhan City, on day *t*.

My data set contains substantial and complicated context to movies' entry into the market: 1) A movie *j* is released by one cinema *m* on a day *t* upon which other cinemas do not launch the movie. 2) One movie is released by more than two cinemas on the same day, while the remaining cinemas do not release it; the extreme version of this situation is that a movie is released by all cinemas on the same day. 3) More than two movies are released by one cinema (or more than two cinemas) on the same day while the remaining cinemas launch one movie or none at all. The nesting structure can deal with the substantial and complicated movie entry data.

4.3 Identification

Price and allocation of screens in the demand model are likely to be endogenous when cinemas have more information about $\xi_{j.t.m}$ than I do while choosing price $P_{j,t,m}$ and product characteristics. One such source of endogeneity arises because I could not collect data on advertising spending. Cinemas may set higher prices and arrange more screens for movies with big advertising budgets. I adopted an approach to deal with endogeneity, consistent with Nevo (2001) and Davis (2006), by introducing a full set of movie and cinema dummy variables to control for the impact of movies and cinemas. I also control for time-varying effects by including school and public holidays, seasonality, and weekend and weekday dummies, as shown in Table 10. Thus, I consider endogenous problems through unobservables that are not absorbed by these effects, which affect the variation in prices and allocation of screens.

I instrument for price using the total number of screens across rival cinemas.[22] I tested several instruments for prices, including measures of average price for the same movie across rival cinemas, but these did not affect the estimate of the price coefficient. I considered Berry, Levinsohn, and Pakes' (1995) own- and rival-product characteristics, such as the allocation of screens for the same movie across rival cinemas. However, movie allocation is made on a high-frequency basis, which may not provide a valid instrument. Therefore, I follow Davis' (2006) method and use non-price cinema characteristics and the number of screens as an instrument. This is correlated with price, as managers of cinemas will consider the fixed cost when they set the ticket price. It is not correlated with demand shock, as the number of screens is fixed once the cinema is built and cannot vary with demand.

I instrument for allocation of screens using two variables: average allocation of the same movie across cinemas of the same size within Wuhan and the number of rival movies at the same cinema. I consider two reasons for using these variables. First, similar-sized cinemas make similar allocation choices, meaning that the impact of costs or constraints of making decisions on the allocation of screens for a particular movie is correlated across cinemas of a particular size. The second instrument correlates with the number of competitors in the movie. An assumption is required to make this a valid instrument. I assume that demand shocks, except those that are captured by fixed effects τ_j, η_m, and θ_t are not correlated across markets. An example of shocks captured by fixed effects is movie-specific national advertising. Demand shocks that remain in $\xi_{j.t.m}$ and that are not correlated across markets could include the local cinema's advertising posters and promotional activities.

The share of a movie within a cinema $S_{j,t,m|IN,t,m}$ and that of the cinema within the movie industry $S_{IN,t,m|IN,t,A}$ are also expected to be endogenous in demand estimation, leading to the assumption that unobserved shocks will simultaneously affect market share $S_{j,t,m}$ and inside shares ($S_{j,t,m|IN,t,m}$ and $S_{IN,t,m|IN,t,A}$). For example, movies that face rivals with higher advertising spending tend to have lower within-group market shares. Similar to the approach for allocation of screens, I control movies, cinemas, and time-varying fixed effects first. I then instrument for $lnS_{j,t,m|IN,t,m}$, introducing the average of $lnS_{j,t,m|IN,t,m}$ for the same movie–day pair across rival cinemas, as suggested by Berry (1994) and Berry, Levinsohn, and Pakes (1995) for using rival-product characteristics in the nests as instrument variables. I take the average over other cinemas to account for any demand shocks that may affect both the cinema's portfolio choice and demand for movie j. Similarly, $lnS_{IN,t,m|IN,t,A}$ is instrumented using the average of $lnS_{IN,t,m|IN,t,A}$ for the same day across rival cinemas.

[22] Number of screens: how many screens a cinema owns determines its capacity to allocate screens to a specific movie.

The first-stage results in Table 11 show that all the instruments are significantly correlated with price, allocation of screens, and the inside shares of the nesting structure with the expected signs. The parameter estimation in Table 12 shows that the parameters of price, allocation of screens, and inside shares in columns (4) and (8) (the OLS results) are significantly different from columns (1) and (5), in which the instruments are applied. I consider this a sign that the instruments are working as expected.

4.4 Elasticities

In this section, I estimate the elasticities. The own-price elasticities for movie *j* at day *t* in cinema *m* defined by Eq. (12) are as follows:

$$\frac{ES_{j,t,m}}{EP_{j,t,m}} = \left(\frac{dS_{j,t,m}}{dP_{j,t,m}}\right)\left(\frac{P_{j,t,m}}{S_{j,t,m}}\right)$$

$$= \quad -\alpha_j P_{j,t,m}\left[\frac{1}{\pi_j\pi_m} - \frac{1-\pi_j}{\pi_j\pi_m}S_{j,t,m|IN,t,m} - \frac{1-\pi_m}{\pi_m}S_{j,t,m|IN,t,m}S_{IN,t,m|IN,t,A} - S_{j,t,m}\right] \quad (12)$$

Both π_j and π_m appear in this equation, which affects the scale of own-price elasticities. $S_{j,t,m|IN,t,m}$, $S_{IN,t,m|IN,t,A}$, and $S_{j,t,m}$ vary by movie, day, and cinema, affecting the level of variation in the elasticities.

The corresponding cross-price elasticities for movie *j* at day *t* in cinema *m* regarding other movies, *j'*, across cinemas (*j'*∈*m'*) and within the same cinema (*j'*∈*m*) are calculated as follows:

$$\frac{ES_j}{EP_{j'}} = \begin{cases} \alpha P_{j',t,m'}\left(\frac{(1-\pi_m)}{\pi_m}S_{j',t,m'|\mathrm{IN},t,m'}S_{IN,t,m'|IN,t,A} + S_{j',t,m'}\right) & j' \in m' \\ \alpha P_{j',t,m}\left(\frac{1-\pi_j}{\pi_j\pi_m}S_{j',t,m|IN,t,m} + \frac{(1-\pi_m)}{\pi_m}S_{j',t,m|IN,t,m}S_{IN,t,m|IN,t,A} + S_{j',t,m}\right) & j' \in m \end{cases}$$
(13)

These cross-price elasticities reveal details of the asymmetric pattern of business stealing across cinemas and the cannibalisation effect within each cinema.

5. Results

In this section, I focus mainly on two sets of results. First, I discuss the nesting-structure results in relation to market expansion, business stealing, and cannibalisation of new movie releases. Second, I turn to the elasticities and expose the asymmetric pattern of business stealing and cannibalisation.

The parameter estimates in Eq. (11) are presented in Table 12. Column (4) reports the estimates of the OLS model without instrument variables. Column (1) presents estimates of the nested logit model in which all demographic variables are included and considered as "distance rings" around each cinema, according to Davis' (2006) definition. For example, Pop [0, community] and Pop (community, suburb] are the populations within the same locale as cinema *m* and outside the community but within the suburb in which the cinema is located, respectively. The number of rival cinemas [0, community] and number of rival cinemas (community, suburb] are the cinema counts running within the community where cinema *m* is located and outside the community but within the suburb of the cinema location, respectively. Column (2) presents the population counts that are not included in the model, while column (3) shows that the number of competing cinemas is not considered.

The coefficients on price suggest that demand is relatively elastic. In the nested logit model, the price sensitivity parameter is −0.082. This translates to own-price elasticities of around 6.319; this magnitude is nearly twice higher than the result in de Roos and McKenize (2014) and similar to that in Ho, Liang, Weinberg, and Yan (2018). All other important variables for demand estimation, such as allocation of screens and week of the run, are significant with an expected sign.

5.1 Market expansion, business stealing, and cannibalisation

According to the model, specifically Eq. (11), column (1) of Table 12 presents the parameters of $\left(1-\pi_m\pi_j\right)$ and $(1-\pi_m)$, equaling 0.485 and 0.349, respectively, in my daily model. Therefore, π_m equals 0.651 while π_j equals 0.791. These results reveal the following important findings.

First, a high value of π_m implies a strong market expansion effect; $\pi_m = 0.651$ in the daily model, indicating that when a new movie enters a cinema, 65.1% of consumers come from outside goods, and the remaining 34.9% come from inside the industry. Second, of the 34.9%, $\pi_j = 0.791$; therefore, 79.1% of the consumers are drawn from other cinemas (business stealing), and the other 20.9% are attracted from other movies within the same cinema (cannibalisation). In other words, when a new movie is launched in a cinema, 65.1% of consumers come from outside goods, 27.6% (34.9%*79.1%) come from other cinemas, and 7.3% (34.9%*20.9%) come from other movies in the same cinema.

5.2 Own-price elasticities

Table 13 presents own-price elasticities disaggregated by cinema. My demand estimates generate high mean own-price elasticities of 6.319[23] with a standard deviation of 1.489. These results reflect the elastic demand of the movie industry and the overall price level in the Chinese movie market is too high to serve the purpose of maximizing profit. Why do cinemas not drop prices to increase profits?

[23] The own-price elasticities for the daily model are nearly two times higher than de Roos and McKenize's (2014) results, and close to those of Ho, Liang, Weinberg, and Yan (2018).

I conjecture that this may be the result of the relatively high cannibalisation effects. Although cross-price elasticities among movies within a cinema range from 0.2 to 0.5 in Table 14, which is relatively inelastic, this value only reflects sales that could be drawn from each incumbent movie when a new movie enters. On average, every cinema screens six movies per day. Therefore, the overall cannibalisation is equal to the cross-price elasticities multiplied by five, which is not negligible. Once a cinema drops the price for a specific movie, it may attract numerous consumers from other movies shown in the same cinema, thereby affecting their own profit. Cinemas have an incentive to avoid dropping the price. The high own-price elasticities overall reveal an irrational and inefficient pricing behavior in the Chinese mainland market, which could hurt the profit of the entire industry. The high market expansion effect evidenced by the demand estimation means the reduction in the overall industry price may stimulate the growth of the entire industry.

Own-price elasticities of cinemas in the same chain are close to each other, which reflects the cooperation among cinemas owned by the same chain. I review the differentiated pricing strategy among cinemas in Table 5 and note that of all cinemas, Dadi, the price leader, shows the smallest elasticities. Jin Yi cinemas, with a moderate price variation, have the second-largest elasticities. Wanda cinemas, with the greatest variation in price, have the highest magnitude of elasticities, almost twice the magnitude of Dadi's elasticities. Although cinemas can make the final decision on the ticket price, they must follow the pricing strategy of cinema chains, such as average price level, and the range and frequency of price variation.

5.3 Asymmetric pattern of business stealing and cannibalisation

In this section, I use the cross-price elasticities of movies in the same cinema and across different cinemas to discuss the asymmetric patterns of cannibalisation and business stealing through Tables 14 and 15.

Table 14 presents detailed information on cross-price elasticities of rival movies within the same cinema, which represents the asymmetric pattern of cannibalisation effects across cinemas and chains.

The cross-price elasticities of movies within the same cinema are lower than one as I expected. A highly unbalanced pattern of cannibalisation across cinemas is shown in Table 14. For example, the median of Jiangxia Yijia Gouwu Guangchang (Dadi chain), highlighted in green, is only 0.186, whereas the mean of Jianghanlu Wanda, highlighted in red, reaches 0.569. The wide range of variation of elasticities across different cinemas is caused by the sensitivity to a change in $S_{j\prime,t,m|IN,t,m}$ and $S_{IN,t,m|IN,t,A}$, shown in Eq. (13). Without nesting structure, I will only use $S_{j\prime,t,m}$ to estimate the elasticities. Owing to the introduction of the nesting structure, I must consider insider shares $S_{j\prime,t,m|IN,t,m}$ and $S_{IN,t,m|IN,t,A}$ in the estimation of cross-price elasticities.

Table 14 also reveals that differences in the pricing strategy significantly affect the asymmetric pattern of cannibalisation of movie entries as follows. First, Dadi charges the lowest price in the market and exhibits the smallest degree of price variation. It has the lowest median elasticities and the smallest difference in the median and mean elasticities. Second, Jin Yi has the most moderate average price level and degree of price variation of the cinema chains. Hence, it has moderate elasticities and a moderate distance between the median and mean. Third, Wanda's pricing strategy features the highest average price level and degree of price variation. Consequently, it exhibits the most substantial gap between the median and mean price elasticities.

Table 15 details the estimates on cross-price elasticities of rival movies across cinemas, which can be treated as business stealing effects. Most of the elasticities are in the vicinity of 0.03. This is far less than the elasticities within cinemas, indicating that business stealing effects among cinemas are considerably smaller than the cannibalisation effects. This result is not consistent with the coefficients of the nesting variables (π_j and π_m). According to the regression results, business stealing effects are approximately triple the cannibalisation effects, whereas cross-price elasticities within each cinema (cannibalisation) are five times larger than elasticities across cinemas (business stealing effects) on average.

In the regression results, business stealing effects indicate how many consumers a cinema can draw from others when it releases a new movie. Cross-price elasticities show how many consumers a new movie can steal from other movies in other cinemas. In other words, the regression results indicate business stealing among cinemas, whereas cross-price elasticities indicate business stealing among individual movies. In respect of 15 cinemas in my dataset, the model estimation is consistent with the elasticities results.

The impact of business stealing shows a significant asymmetric pattern. The mean of the Jin Yi Zhong Nan cinema, highlighted in green, is only 0.018, whereas the mean of Jiangxia Yijia Gouwu Guangchang cinema, highlighted in red, reaches 0.261, which is more than 14 times the former figure. I conjecture that the nesting structure enhances the variability of elasticities. Without the nesting structure, the variability of elasticities would only be affected by $S_{j',t,m'}$. However, according to Eq. (13), the variability of elasticities is also affected by both inside shares, $S_{j',t,m'|IN,t,m'}$ and $S_{IN,t,m'|IN,t,A}$.

I also find asymmetric patterns in the cinema chains. Dadi, employing a low pricing tactic, exhibits the highest business stealing effects. Wanda, with the highest degree of price variation, shows the second-highest business stealing effects. Jin Yi practices moderate price variation, which results in a middle position in respect of stealing business from other cinema chains. Zhong Ying, the fixed-price cinema chain, has the lowest elasticities.

Dadi cinemas have high elasticities across rival cinemas but low within-cinema elasticities, indicating relatively high business stealing and low cannibalistaion.

The above implies that the low-price strategy of the Dadi cinema chain might work well in stealing consumers from rival cinemas and building market share. In particular, the Jiangxia Yijia Gouwu Guangchang, one of the Dadi cinemas, highlighted in green in Table 14 and in red in Table 15, shows that cross-price elasticities across rival cinemas are even higher than within-cinema elasticities. Given that Dadi was trying to enter the Wuhan market and build the market share during the 2013–2014 period, their low-price tactic seems a reasonable one. Wanda, employing the highest degree of price variation, has relatively high cannibalisation and moderate business stealing, but the own-price elasticities reach the highest level of all the cinema chains. I conjecture that the market expansion effect of introducing a new movie is quite strong for Wanda.

In addition to pricing strategy, cinema location has a significant influence on business stealing and cannibalisation. The most obvious example is Jianghanlu Wanda, highlighted in red in Table 14. It exhibits the highest within-cinema elasticities (cannibalisation), but an average cross-cinema elasticity (business stealing), as set out in Table 15. Compared to other Wanda cinemas, the prices of Jianghanlu Wanda are relatively low. This finding shows that Jianghanlu Wanda, located in the city center, face more competitors than other cinemas when it introduces a new movie. According to the standard economic intuition of a geographically differentiated product market, cinemas located in the business center area are easy to draw sales from other products within their own cinema more than steal consumers from other cinemas.

6. Limitations

I use daily data to estimate the model, which may overstate the market expansion effect because daily models do not allow substitution across days. The only products in the consumer's choice set are movies offered on a given day. Thus, when a cinema releases a movie on a given day, the change in consumption is at the expense of other movies shown on that day and outside goods. In fact, some consumers may choose different days within a week. In my next series paper, I will study the structural changes in the time series of movie prices and focus on the consumer's time choice.

The data sample used in this study covers only 50% of the Wuhan market, which may lead to an overestimation of the impact of market expansion but an underestimation of business stealing and canibalisation. This is attributable to business stealing and cannibalisation effects that exist among both observed and unobserved cinemas, which may be incorrectly absorbed by the market expansion. Thus, the market expansion effect may be less than 65.1%.

However, this problem may not be severe. The regression results and cross-price elasticities verify that the business stealing effects of new movie releases on the revenue of incumbent cinemas are indeed localized. Wuhan is a large city with an urban area of 1528 km^2. When a cinema releases a new movie, it may attract consumers from nearby cinemas (within a district or suburb) instead of cinemas from another side of the city. Missing cinemas are mainly concentrated in two suburbs (Optics Valley of China and Wuhan Plaza) rather than scattered evenly across every district. Therefore, the underestimation of business stealing may not be critical.

7. Conclusion

In the Chinese movie exhibition industry, new movies are launched in the market, on average, every day. In this study, I collected and analyzed high-frequency box office revenue across movies, screening times, and cinemas. Using these raw data, I built a three-level nested logit model to measure the effects of market expansion, business stealing, and cannibalisation following the introduction of a new movie. Furthermore, I calculate the price elasticities to show an asymmetric pattern of these effects by cinema.

In the market-level nesting structure, I discover (1) a strong market expansion effect in the vicinity of 65.1%, (2) weak cannibalisation effects of about 7.3%, and (3) a relatively strong business stealing effect of around 27.6%. Thus, when a cinema releases a new movie, 65.1% of consumers come from outside goods, 27.6% come from other cinemas, and 7.3% come from other movies in the same cinema.

Cross-price elasticities expose highly imbalanced cannibalisation and business stealing effects. The wide variation of within- and cross-cinema elasticities is caused by the sensitivity of change of two-level inside shares. Without the nesting structure, I only use market share S_j, to estimate the elasticities. Two-level inside shares enhance the sensitivity of cross-price elasticities.

Differences in the pricing strategy of cinema chains significantly affect the asymmetric pattern of both cannibalisation and business stealing of movie entries. Dadi, exerting a low-price tactic, had the lowest cannibalisation and highest business stealing. By contrast, Wanda's pricing featured the highest mean price level and degree of variation, with relatively lower business stealing and higher cannibalisation. Zhong Ying, the fixed-price cinema chain, exhibited the lowest business stealing. Dadi's low-price tactic seemed to work well in its efforts to enter the Wuhan market and build its market share during the 2013–2014 period. Wanda, employing the highest degree of price variation, has relatively high cannibalisation and moderate business stealing, but the own-price elasticities reach the highest level of the cinema chains. I conjecture that the market expansion effect of introducing a new movie is quite strong for Wanda.

The location of cinemas has a significant influence on the business stealing and cannibalisation effects. Jianghanlu Wanda, located in the city center, face more competitors than other cinemas when it introduces a new movie. By the standard economic intuition of a geographically differentiated product market, cinemas located in the business center area more easily draw sales from other products within their own cinema than steal consumers from other cinemas.

High mean own-price elasticities of 6.319 for the estimation reveal that the current price level for all movies is too high, which may hurt the entire industry's profit. With a high market expansion effect, I suggest that the decrease in overall industry prices could stimulate further development of the movie industry in the Chinese mainland market.

This analysis has a few limitations. The data sample used in this study covers only 50% of the Wuhan market, which could lead to an overestimation of the market expansion effect; part of market expansion may come from missing cinemas, which should be considered in considering the business stealing effects. However, overestimation is not a severe problem. First, the results of both the regression and cross-price elasticities verify that the impact of new movie releases on incumbent revenues is indeed localized. Additionally, the missing cinemas are mainly concentrated in two areas rather than dispersed across all districts.

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Table 1 Growth of China's movie industry during 2002–2015

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
RMB (billion)	0.92	1.01	1.54	2.05	2.62	3.33	4.34	6.21	10.17	13.12	17.07	21.77	29.64	44.10
Inflation adjusted	0.92	1.00	1.48	2.01	2.58	3.17	4.08	6.25	9.83	12.41	16.63	21.07	29.2	43.45
USD (billion)	0.11	0.12	0.18	0.24	0.32	0.41	0.56	0.92	1.44	1.874	2.64	3.35	4.75	6.80
No. of audiences (hundred million)		0.44	0.56	0.73	0.98	1.3	1.7	1.82	2.37	3.45	4.62	6.12	8.3	12.56
No. of cinemas	1019	1140	1188	1243	1326	1427	1545	1680	1993	2796	3293	4583	5598	6439
No. of screens	1834	2285	2396	2668	3035	3527	4097	4723	6256	9286	11835	18195	23592	31627

Table 2 Total number of produced and unreleased movies during 2002–2015

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
No. of local movies (produced)	169	201	256	302	392	455	479	558	621	689	893	824	758	888
No. of local movies (released)										158	227	247	256	296
No. of local movies (unreleased)										531	666	577	502	592
Unreleased rate										77%	75%	70%	66%	67%
No. of imported movies (released)										70	76	58	67	62
No. of total movies (released)										228	303	305	323	358

Table 3 China's top ten cinema chains[24]

Rank	Cinema chain	Number of showings (million)	Number of viewers (million)	Box office revenue (USD million)	Market share[25]
1	Wanda	1.71	58.34	390.23	14.89%
2	Shanghai United Circuit	1.65	43.1	248.62	9.48%
3	Zhongying Xingmei	1.7	42.62	256.53	9.79%
4	Guangdong Dadi	1.89	38.53	176	6.71%
5	Zhongying Nanfang Xinganxian	1.47	34.27	208.75	7.96%
6	Guangzhou jinyi	1.26	29.83	182.56	6.96%
7	Beijing Xinyinglian	0.86	21.63	129.15	4.93%
8	Zhejiang Shidai	0.94	19.63	114.16	4.35%
9	Zhejiang Hengdian	0.86	16.87	89.12	3.40%
10	Sichuan Taipingyang	0.61	16.65	97.23	3.71%

Table 4 Summary statistics[26]

	Median	Mean	Std. Dev.	Min	Max	Skewness
Movie characteristics						
Rate of seat occupation	0.0909	0.1885	0.2472	0	1	1.9954
Price (RMB)	40	44.4248	18.2275	15	200	2.16
Baidu Index (cast appeal)	5861	17334.07	31392.1	10[27]	148280	2.9952
Review	6.4	6.3679	1.3838	2.2	8.9	-0.6776
Cinema characteristics						
No. of screens per cinema	9	8.4774	2.5056	4	15	0.685
No. of seats per cinema	1371	169.5942	73.4395	22	648	0.1636

[24] Data source: *China Film News 2013*, Vol. 1222, p. 25.
[25] Market share is defined by the share of the revenue.
[26] Number of observations is 194,391 for all variables.
[27] Some low budget movies invited several little-known artists to perform.

Table 5 Price variations across movies in a cinema[28]

Genre	Median	Mean	Min	Max	Std. Dev.	Observations	Skewness
Action	50	57.38	30	150	21.13	1187	1.46
Adventure	40	51.58	30	120	22.42	392	1.85
Biography	80	76.52	30	120	30.00	66	-0.28
Cartoon	50	49.90	30	120	11.70	1874	2.08
Crime	40	52.66	30	200	27.08	2552	2.04
Drama	40	48.46	30	120	20.29	1548	2.53
Family	40	53.33	40	120	30.68	18	1.79
Fantasy	50	65.47	30	150	29.75	1778	1.43
Romance	40	54.61	30	200	32.48	1407	2.23
Science fiction	60	63.85	30	120	22.56	2173	1.36
Supernatural	40	49.68	30	120	21.65	62	2.19
Tragedy	60	69.84	30	120	29.61	306	0.45
War	60	68.03	30	120	30.13	132	0.97

Table 6 Price variations across screening time in a cinema

Time definition	Obs.	Mean	Std. Dev.	Min	Max
Morning	3237	49.35	18.73	30	150
Afternoon	10016	53.68	22.39	30	150
Evening	8549	54.19	23.12	30	150
Night	28	53.21	22.94	30	120
Weekday	14485	52.10	21.98	30	150
Weekend	5601	53.73	20.68	30	150
Public holiday	1744	61.09	27.06	30	150
Non-school holiday	16969	54.30	22.83	30	150
School holiday	4861	49.54	19.59	30	150

Table 7 Price variation by cinemas and cinema chains

Cinema chain	Cinema	Obs.	Median	Mean	Std. Dev.	Number of screens
Dadi	Huan Feng Shang Ye	8126	30	29.22	4.19	4
	Hankou Yan Jiang Yi Hao	212	25	26.56	3.7	6
	Jiangxia Yijia Gouwu Guangchang	8714	25	27.72	3.85	6
	Xiang Long Shi Dai	8849	25	26.72	3.12	5
	Wuhan Xinshijie	5795	25	27.09	3.34	5
UA	Huanyi Xinmingzhong	3401	30	37.86	10.73	6
Jin Yi	Jin Yi Nanhu	2716	53	50.23	5.54	6
	Jin Yi Wang Jia Wan	3074	38	45.2	7.64	10
	Jin Yi Wu Jia Shan	2499	46	42.47	4.09	6
	Jin Yi Wu Sheng Lu	3207	43	47.83	5.02	8
	Jin Yi Xiao Pin Mao	4204	43	48.93	10.76	10
	Jin Yi Yang Cha Hu	3211	43	45.56	2.69	11
	Jin Yi Zhong Nan	3714	38	41.67	4.07	8
Wanda	Jianghanlu Wanda	23378	40	46.73	14.87	9
	Hanjie Wanda	13500	50	56.51	25.44	15
	Jing Kai Wanda	21104	40	51.93	20.99	9
	Leng Jiao Hu Wanda	21830	40	53.24	22.24	9
	Wanda Chun Shu Li	20140	40	42.12	15.19	8
	Wanda Hanyang Hanshang	23191	40	49.31	18.72	10
Zhong Ying	Zhong Ying Wuhan Donggou	13526	35	35.63	1.71	6

[28] I selected Leng Jiao Hu Wanda to present price variations across movies, as it is the largest cinema in my dataset and has more observations than other cinemas.

Table 8 Audience numbers by week of run

Week of run	Audience numbers						
	Mean	Median	Min	Max	Std. Dev.	Observations	Skewness
Preview	42.18	13	0	340	67.81	248	2.41
Week one	34.73	15	0	648	51.50	115912	2.74
Week two	29.62	13	0	648	44.53	51848	3.09
Week three	25.22	11	0	648	38.69	19069	3.37
Week four	21.63	10	0	648	34.74	5342	4.26
Week five	24.05	11	0	331	39.61	1498	3.83
Week six	27.21	15	0	196	31.65	304	2.35
Week seven	40.97	19	0	240	51.44	173	1.74

Table 9 Variation in revenue by week of run

Week of run	Variation in revenue						
	Mean	Median	Min	Max	Std. Dev.	Observations	Skewness
Preview	1778.02	510	0	37680	3466.93	248	5.50
Week one	1602.13	600	0	49650	2693.69	115912	3.82
Week two	1377.72	540	0	36936	2328.74	51848	4.01
Week three	1218.38	480	0	49650	2140.86	49650	4.93
Week four	1085.64	420	0	38850	1975.47	5342	5.70
Week five	1319.16	480	0	49650	3301.93	1498	10.08
Week six	1250.46	660	0	8450	1530.83	304	2.24
Week seven	2132.43	780	0	15300	2917.22	173	2.02

Table 10 List of time-varying dummy variables

	Variable	Mean	Std. Dev.	Min	Max
School holiday	Not school holiday*	0.791	0.407	0	1
	School holiday	0.209	0.407	0	1
Seasonality	Autumn	0.206	0.404	0	1
	Spring	0.403	0.49	0	1
	Summer	0.202	0.402	0	1
	Winter*	0.189	0.392	0	1
Public holiday	Holiday	0.085	0.279	0	1
	Weekday	0.657	0.475	0	1
	Weekend*	0.258	0.438	0	1

Table 11 Results of "First stage" instrument regressions

	(1)	(2)	(3)	(4)
Dependent Variable	Price	Screen allocation	Inside share j	Inside share m
No. of screens of rival cinemas	-0.011*	0.003**	0.007***	-0.002***
	(-1.701)	(1.987)	(13.624)	(-6.271)
Mean screen allocation	-0.156***	0.636***	0.055***	-0.003**
	(-5.314)	(89.057)	(23.676)	(-2.453)
No. of movies	-3.117***	-0.765***	0.211***	-0.259***
	(-4.093)	(-4.138)	(3.523)	(-7.315)
Mean ln (inside share j)	-0.366**	0.728***	0.520***	0.032***
	(-2.188)	(17.930)	(39.521)	(4.133)
Mean ln (inside share m)	0.654	0.266*	0.078*	0.577***
	(1.164)	(1.945)	(1.769)	(22.061)
R-squared	0.573	0.770	0.618	0.856
r2_a	0.567	0.767	0.613	0.854
F	99.71	248.4	120.1	441.8

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 12 Estimation result[29]

	(1) Main	(2)	(3)	(4) OLS
Price	-0.082***	-0.082***	-0.082***	0.001***
	(-2.708)	(-2.708)	(-2.708)	(2.808)
ln(inside share j)	0.485***	0.485***	0.485***	0.914***
	(10.232)	(10.232)	(10.232)	(309.688)
ln(inside share m)	0.349**	0.349**	0.349**	0.945***
	(2.422)	(2.422)	(2.422)	(186.542)
Movie variables				
Allocation of screens	0.048***	0.048***	0.048***	0.011***
	(6.448)	(6.448)	(6.448)	(14.009)
Week of run	-0.135***	-0.135***	-0.135***	-0.093***
	(-4.845)	(-4.845)	(-4.845)	(-23.743)
Demographics				
Pop [0, community]	-0.0000004		0.000008***	0.0000001***
	(-0.421)		(2.911)	(4.838)
Pop (community, suburb]	-0.000008***		0.000008*	0.00000004
	(-2.979)		(1.913)	(1.387)
No. of rival cinemas [0, community]	-0.001***	0.003***		-0.00002***
	(-3.003)	(6.870)		(-2.843)
No. of rival cinemas (community, suburb]	-0.0001***	0.001***		0.000002
	(-3.713)	(6.507)		(0.482)
Day and date variables				
Autumn	0.061	0.061	0.061	-0.090***
	(0.582)	(0.582)	(0.582)	(-3.036)
Spring	0.368***	0.368***	0.368***	0.263***
	(4.918)	(4.918)	(4.918)	(11.180)
Summer	0.287***	0.287***	0.287***	0.070**
	(3.338)	(3.338)	(3.338)	(2.482)
Weekday	-1.019***	-1.019***	-1.019***	-0.910***
	(-17.964)	(-17.964)	(-17.965)	(-86.759)
Weekend	-0.297***	-0.297***	-0.297***	-0.288***
	(-7.191)	(-7.191)	(-7.191)	(-25.395)
School holiday	0.510***	0.510***	0.510***	0.201***
	(6.468)	(6.468)	(6.468)	(15.745)
Length of run[30]				
Two weeks	-0.883***	-0.883***	-0.883***	-2.258***
	(-3.594)	(-3.594)	(-3.594)	(-11.989)
Three weeks	-1.039***	-1.039***	-1.039***	-2.012***
	(-4.425)	(-4.425)	(-4.425)	(-10.787)
Four weeks	0.025	0.025	0.025	-0.592
	(0.136)	(0.136)	(0.136)	(-1.432)
Five weeks	-1.052***	-1.052***	-1.052***	-0.784***
	(-4.703)	(-4.703)	(-4.703)	(-12.259)
Six weeks	-0.618***	-0.618***	-0.618***	-0.148***
	(-5.175)	(-5.175)	(-5.175)	(-3.564)
Seven weeks	-0.126	-0.126	-0.126	-0.123***
	(-0.75)	(-0.75)	(-0.75)	(-3.85)
Constant	4.792*	-6.024***	-5.964**	0.931***
	(1.959)	(-4.312)	(-2.529)	(18.094)
R-squared	0.687	0.687	0.687	0.947
Robust z-statistics in parentheses				
*** p<0.01, ** p<0.05, * p<0.1				

[29] I report the results using three decimal places. However, the parameters of the Baidu Index, number of seats, population count, and number of competing cinemas are extremely small; therefore, I use higher decimal places for these four parameters.

[30] The base case for length of run dummy is “eight weeks” movie. As I removed relatively small movies (screening less than one week in cinema), the variable starts from “two weeks” movie.

Table 13 Own-price elasticities

Cinema chain/Cinema	median	Mean	Std. Dev
Dadi (Chain)			
Huan Feng Shang Ye	-4.384	-4.354	0.592
Hankou Yan Jiang Yi Hao	-3.924	-3.927	0.482
Jiangxia Yijia Gouwu Guangchang	-3.939	-4.140	0.551
Xiang Long Shi Dai	-3.923	-3.991	0.463
Wuhan Xin Shi Jie	-3.942	-4.033	0.513
UA (Chain)			
Huanyi Xinmingzhong	-4.761	-5.478	1.296
Jin Yi (Chain)			
Jin Yi Nanhu	-7.557	-7.579	0.936
Jin Yi Wang Jia Wan	-6.051	-6.884	1.269
Jin Yi Wu Jia Shan	-6.046	-6.330	0.727
Jin Yi Wu Sheng Lu	-6.847	-7.244	0.857
Jin Yi Xiao Pin Mao	-6.793	-7.364	1.541
Jin Yi Yang Cha Hu	-6.820	-6.896	0.551
Jin Yi Zhong Nan	-6.046	-6.336	0.661
Wanda (Chain)			
Jianghanlu Wanda	-6.256	-6.812	2.191
Hanjie Wanda	-7.716	-9.076	4.243
Jing Kai Wanda	-6.793	-8.117	3.411
Leng Jiao Hu Wanda	-6.688	-8.201	3.601
Wanda Chun Shu Li	-6.121	-6.398	2.352
Wanda Hanyang Hanshang	-6.362	-7.860	3.198
Zhong Ying (Chain)			
Zhong Ying Wuhan Donggou	-5.432	-5.367	0.334

Notes: Own-price elasticities are derived from models (1), as reported in Tables 12.

Table 14 Cross-price elasticities of movies within same cinema

Cinema chain/Cinema	Median	Mean	Std. Dev
Dadi (Chain)			
Huan Feng Shang Ye	0.234	0.256	0.104
Hankou Yan Jiang Yi Hao	0.246	0.271	0.124
Jiangxia Yijia Gouwu Guangchang	0.178	0.186	0.069
Xiang Long Shi Dai	0.195	0.207	0.085
Wuhan Xin Shi Jie	0.184	0.193	0.077
UA (Chain)			
Huanyi Xinmingzhong	0.371	0.425	0.281
Jin Yi (Chain)			
Jin Yi Nanhu	0.390	0.405	0.182
Jin Yi Wang Jia Wan	0.329	0.330	0.122
Jin Yi Wu Jia Shan	0.357	0.371	0.185
Jin Yi Wu Sheng Lu	0.296	0.302	0.111
Jin Yi Xiao Pin Mao	0.319	0.333	0.156
Jin Yi Yang Cha Hu	0.311	0.322	0.111
Jin Yi Zhong Nan	0.261	0.268	0.095
Wanda (Chain)			
Jianghanlu Wanda	0.501	0.569	0.276
Hanjie Wanda	0.379	0.418	0.189
Jing Kai Wanda	0.365	0.406	0.190
Leng Jiao Hu Wanda	0.486	0.545	0.276
Wanda Chun Shu Li	0.273	0.314	0.157
Wanda Hanyang Hanshang	0.322	0.352	0.147
Zhong Ying (Chain)			
Zhong Ying Wuhan Donggou	0.258	0.274	0.115

Table 15 Cross-price elasticities of movies disaggregated by cinemas

Cinema chain/Cinema	Median	Mean	Std. Dev
Dadi (Chain)			
Hankou Yan Jiang Yi Hao	0.086	0.041	0.500
Jiangxia Yijia Gouwu Guangchang	0.220	0.261	1.220
Xiang long Shi Dai	0.119	0.248	0.870
Wuhan Xin Shi Jie	0.072	0.103	0.096
UA (Chain)			
Huanyi Xinmingzhong	0.113	0.134	0.407
Jin Yi (Chain)			
Jin Yi Nanhu	0.034	0.040	0.022
Jin Yi Wang Jia Wan	0.029	0.034	0.017
Jin Yi Wu Jia Shan	0.023	0.028	0.014
Jin Yi Wu Sheng Lu	0.024	0.027	0.013
Jin Yi Xiao Pin Mao	0.020	0.023	0.011
Jin Yi Yang Cha Hu	0.018	0.020	0.010
Jin Yi Zhong Nan	0.016	0.018	0.009
Wanda (Chain)			
Jianghanlu Wanda	0.035	0.047	0.053
Hanjie Wanda	0.055	0.070	0.182
Jing Kai Wanda	0.025	0.033	0.027
Leng Jiao Hu Wanda	0.018	0.022	0.017
Wanda Chun Shu Li	0.019	0.022	0.016
Wanda Hanyang Hanshang	0.016	0.019	0.014
Zhong Ying (Chain)			
Zhong Ying Wuhan Donggou	0.013	0.017	0.012