Collusive Price Floors and Bounded Rationality: Evidence from the Chinese Movie Industry

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Abstract

This paper examines the impact of explicit collusive price floors on firms' pricing behavior, market structure and welfare in the Chinese movie industry, a market characterized by product differentiation and highly elastic demand. We employ a structural model to estimate demand and extend the Nash-Bertrand supply model, introducing a minimum bound mechanism that incorporates both price floors and two forms of boundedly rational behavior: overconfident cinema-specific add-ons and performance-based weighting. We find that while collusive price floors significantly boost profits, they substantially reduce consumer surplus, underscoring the need for regulations. However, given the specific context, effective regulation is complicated by the regulator's own stake in the industry. As an alternative, we propose enhancing social welfare under a price floor by eliminating cinema-specific add-ons and focusing solely on performance-based pricing. This second-best approach achieves a Pareto improvement, increasing both profits and consumer surplus, under inter-cinema agreements.

Keywords: Collusive price floor, Oligopoly pricing competition, Bounded rationality, Add-on pricing, Weights on performance, Overconfidence.

1. Introduction

Price floors are a common practice in Resale Price Maintenance (RPM) and are applied across various industries to achieve specific economic and social objectives, particularly in labor markets and agriculture. Typically, price floors aim to protect low-income producers and stabilize their income, though they often lead to excess supply (Gardner, 1987; Loertscher and Muir 2024; Sumner and Alston, 1986). Ippolito (1991) notes that the impact of RPM is context-dependent—potentially harmful to competition if misapplied but beneficial in some cases. For instance, Card and Krueger

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(1994) found that increasing the minimum wage did not adversely impact employment. Prior studies on price floors generally focus on inelastic markets with homogeneous products. However, how do price floors affect market structure and welfare in industries characterized by product differentiation and highly elastic demand, such as the movie industry?

In the Chinese movie market, an explicit collusive price floor is enforced through release contracts between exhibitors and distributors, mandating that exhibitors sell tickets above a set minimum price. Similar to practices in labor and agricultural sectors, this agreement aims to shield producers from intense low-price competition among exhibitors. However, in a market with differentiated products and highly elastic demand, the impact of such a price floor remains an open question.

Specifically, in markets with inelastic demand, price floors reduce consumer surplus by raising prices, as consumers generally remain in the market despite higher costs. However, in highly elastic markets, the impact diverges: marginal consumers exit the market entirely rather than pay the higher prices, leaving producers unable to capture their surplus. Thus, price floors in these settings only appropriate surplus from those intra-marginal consumers who remain, while the rest of the potential consumer base is lost. Additionally, the limited price variation in an elastic demand market raises general price levels but diminishes the effectiveness of prices in signaling product quality. High-quality movies are "constrained" by the price floor as they cannot fully differentiate themselves through premium pricing. As a result, consumers with lower willingness-to-pay exit the market, reducing the quantity sold for low-quality movies; this reduction might be offset by the higher price. However, for high-quality movies, the quantity sold may also decline, and given the constraints on price increases, this reduction in sales may not be fully offset by the higher price, leaving some high-quality producers inadequately protected. Therefore, while price floors may aim to stabilize producer revenues, they do so imperfectly in highly elastic and differentiated markets, with ambiguous overall welfare impacts.

This paper estimates the impact of price floor in the Chinese movie market, focusing on the city of Wuhan. Using a structural model, we

analyze the effects of the price floor on pricing, box office revenue, social welfare, and market competition while considering boundedly rational price-setting behaviors. We also examine the heterogeneous impact of the price floor on both high-quality and low-quality movies.

For demand estimation, we employ a three-level nesting structure (Einav, 2007; Chiou, 2008) to evaluate the effects of new movie entries on market expansion, business stealing, and cannibalization. . Our estimates reveal substantial market expansion effects, with new movies attracting approximately 65.1% of consumers from other leisure activities. Business stealing is also notable, with 27.6% of consumers drawn from other cinemas, compared to 7.3% from other movies within the same cinema — the cannibalization.

Movie demand is highly elastic, amplifying market expansion in general. The extents of business stealing and cannibalization are heterogenous across cinema chains. Cross-price elasticities across cinemas and chains indicate that Dadi Cinemas' lowest-price strategy achieves minimal cannibalization but substantial business stealing, while Wanda's higher prices result in lower business stealing and higher cannibalization. Zhong Ying, a fixed-price player, experiences the least business stealing. Additionally, our analysis based on movie characteristics shows that Hollywood movies contribute to market expansion, albeit less than expected due to their higher prices. High-quality movies are the primary drivers of market expansion, while low-quality movies have a negligible impact.

On the supply side, we use a Nash-Bertrand model with product differentiation to simulate cinemas' pricing strategies, assuming zero marginal cost per additional ticket (de Roos and McKenzie, 2014). During our observation period, a price floor of 20 CNY is imposed across all movies. We extend the model to incorporate this price floor constraint and calculate revenue-maximizing prices for non-sold-out movie sessions under Nash-Bertrand equilibrium conditions. However, our simulated prices do not align with observed data, suggesting that cinemas may adjust prices based on additional criteria rather than adhering strictly to the price floor. This raises a key question: what additional factors influence cinema

managers' pricing decisions other than the rigid price floor, within the profit-maximizing considerations?

Experimental evidence from Dufwenberg, Gneezy, Goeree, and Nagel (2007) suggests that price floors can prompt boundedly rational behavior, motivating us to explore behavioral factors that may influence cinemas' pricing decisions. Recent studies on behavioral firms find that managers' biases, influenced by personal skills and expectations of future outcomes, can affect strategic choices. For instance, Huffman, Raymond, and Shvets (2023) note that "motivated beliefs" often lead individuals to persist in overconfident expectations. Huffman and Liu (2024) highlight that low-skill managers may overestimate the profitability of aggressive pricing strategies (e.g., price wars).

In practice, managers at prominent cinemas, such as Wanda, often expect higher box-office performance and believe they merit higher ticket than competitors, even for the same movie. This overconfidence is reflected in their pricing through cinema-specific add-ons. Moreover, exhibitors often use past experience to anticipate demand fluctuations, adjusting prices based on day and movie characteristics in addition to the fixed price floor and any add-on fees.

Drawing from theoretical literature and anecdotal evidence, we incorporate two behavioral factors that cinemas incorporate beyond Nash-Bertrand equilibrium pricing under a rigid price floor of 20 CNY: cinema-specific add-on pricing and weights based on expected box-office performance. Specifically, we model cinema ticket pricing p with four components: $p = (\,pf^{20} + a_m) * w_{j,t} + \Delta$. The first component, pf^{20}, represents the common price floor of 20 CNY mandated by the existing distribution contracts. The second component, a_m, is a cinema-specific add-on, enabling larger firms to arbitrarily price above the common price floor pf^{20}, driven by managers' overconfidence in "expected outcomes" tied to their market advantages. The third component, $w_{j,t}$, is a weighting factor, allowing cinemas to scale the baseline price ($pf^{20} + a_m$) according to expected box-office performance, adjusting for day t and movie j. The final component, Δ, fine-tunes prices to reach the optimal equilibrium level dictated by the Nash-Bertrand competition.

In summary, we extend the traditional Nash-Bertrand supply model by incorporating both the price floor and bounded rational pricing behavior, providing a better empirical fit than the standard supply model. To our knowledge, this is the first study that empirically captures bounded rationality in pricing within a price floor setting and assesses its impact on various market outcomes.

Our first counterfactual analysis simulates prices in the absence of price floors and compares them with the observed prices. We find that the price floor of 20 CNY raises the average ticket price by 26 CNY, resulting in significant losses of 72.78% in consumer surplus and 55.85% in total social welfare. Conversely, the price floor boosts overall industry profits by 82.89%, creating a profit incentive to keep prices above the floor. Price floors have heterogenous impacts on cinemas. While exhibitors with advantages, such as Wanda and Jin Yi, experience tremendous profit gains from the market expansion in the presence of price floors, those with market disadvantages, like Dadi, would see reduced profits at equilibrium prices.

Exploring alternative pricing strategies, we find that a mix of add-on and performance-based pricing helps sustain this collusive price floor. For advantaged cinemas, market expansion driven by the performance-based weights offsets potential losses from the business-stealing effects of add-on pricing.

Furthermore, we find that when only add-on pricing is applied, disadvantaged cinemas like Dadi benefit from the general price hikes of other market-advantaged cinemas due to their overconfidence. However, these price increases harm the overall industry profit due to the reduced market size, with consumer surplus dropping by 60.85%. In contrast, adjusting prices solely based on performance weighting leads to gains in both profits and consumer surplus compared to the price floor alone. Though the consumer surplus increases modestly by 1.32%, it at least avoids further deterioration.

Our results suggest that collusive price floors should be regulated, as substantial profit gains come at the expense of consumer surplus. However, such regulation may be challenging, given the existing revenue-sharing

mechanism between market players and the government. As a second-best alternative, we propose focusing solely on performance weighting under the current price floor and forbidding add-on pricing, which could yield a Pareto improvement, raising the total surplus by 26.35%. This approach, however, requires inter-cinema coordination, as lower-performing cinemas, like Dadi, may have strong incentives to deviate from this equilibrium.

This paper contributes to several literature. Our findings contribute to the literature on price regulation by examining the effects of price floors in markets with differentiated products and highly elastic demand—contrasting with traditional applications in inelastic markets like agriculture and labor, where price floors aim to meet social welfare objectives (Breza, Kaur, and Shamdasani, 2021; Renkin, Montialoux, and Siegenthaler, 2022; Loertscher and Muir, 2024).

Our analysis also addresses the debate on uniform pricing versus price dispersion for differentiated goods. In various movie markets, such as the U.S., EU, and Australia, uniform pricing of varying extents is common, though research suggests it may be inefficient, with movie-specific or day-specific discounts shown to stimulate demand and increase profit (Einav, 2007; Chiou, 2008; Davis, 2006b; De Roos and McKenzie, 2014; Ho, Liang, Weinberg, and Yan, 2018). The Chinese mainland movie industry, however, stands out for its significant and widespread price variations across screening times, cinemas, and movies—even under a price floor. Our analysis reveals that, without bounded rationality, equilibrium prices for different movies within the same cinema on a given day are quasi-uniform, regardless of the presence of a price floor, which is a form of uniform pricing. Thus, our study allows us to compare the implications of uniform pricing against those of price dispersion driven by bounded rationality. We examine the shifts in profit, consumer surplus, and incentives when cinemas deviate from near-uniform price equilibria and apply bounded rational pricing, with and without a price floor. Our analysis highlights the strong profit incentives for cinemas to deviate from uniform pricing and underscores the economic impacts of bounded rationality in pricing decisions.

Furthermore, our research complements studies on bounded rationality. In parallel to Han, Huffman, and Liu's (2024) findings on overconfidence in price cuts under a price ceiling, we observe overconfident managers raising prices under a price floor. Unlike lab-based studies (e.g., Huffman, Raymond, and Shvets, 2022), our work empirically identifies boundedly rational pricing by decomposing the minimum bound of Nash equilibrium pricing into two components: (1) overconfident add-on pricing based on cinema-specific advantages and (2) subjective weights on box-office performance adjusted for day and movie characteristics.

Finally, our study contributes to the traditional literature on entry and price-setting strategies. While many economists examine the effects of firm entry into markets (Berry and Waldfogel, 1999; Davis, 2006a; Seim and Waldfogel, 2010), our research shifts focus to the entry of new products. Although Einav (2007) and Chiou (2008) estimate the impact of new movie entries, they ignore business stealing and cannibalization effects. In contrast, we leverage detailed auditorium-title-screening data to estimate market expansion, business stealing, and cannibalization when new products enter. Additionally, we assess how these effects vary across market players by estimating elasticities. This approach is particularly valuable for sectors with frequent differentiated product entries, such as smart transportation, supermarkets, finance, and creative industries like music, books, and TV series.

The remainder of the paper is structured as follows: Section 2 describes the Chinese movie industry and the data. Section 3 presents the demand and supply model. Section 4 details the empirical estimation and results. Section 5 discusses counterfactual analysis. Section 6 concludes.

2. An exhibitor dominated market

As in many other countries such as the US (Einav 2007) and Australia (de Roos & McKenzie 2014), China's movie industry has three divisions: production, distribution, and exhibition. Major studios have integrated production and distribution, and the exhibitors are not vertically integrated with producers or distributors. However, it distinguishes itself from other countries by being predominantly exhibitor-driven,[3] whereas producers

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

hold more influence elsewhere. We begin by providing an overview of the formation of market power of exhibitors and the constraints present in the Chinese movie industry. Following this, we examine the pricing behavior of exhibitors with heterogenous market power under these constraints, with particular attention to price floors.

Operating License and Quantitative Restrictions for Exhibitors

The development of a 'cinema chain-centered' distribution and screening mechanism in China has been actively promoted by the State Administration of Radio, Film, and Television (SARFT) since 2001[4]. During the period from 2001 to 2002, 30 cinema chains were established. Subsequently, new chains were required to apply for an operating license, and in 2015, the application channel for establishing new cinema chains was closed after 46 chains had been established. As a result, cinemas are now concentrated under a limited number of chains.

In contrast, establishing a movie production company is relatively easier. Table 2.1 shows that the number of registered producers grew significantly, from 1,982 at the end of 2013 to 25,570 by the end of 2019, leading to intensified competition among producers. A notable issue is the high rate of unreleased movies in the Chinese mainland market. As detailed in Table 2.1, over 500 local movies (approximately 70%) fail to secure public release each year, with a peak of 746 unreleased films in 2018. Despite cinemas and screens operating at full capacity, many films cannot secure projection resources, resulting in their exclusion from the market.[5]This striction has created a high barrier to entry, benefiting exhibitors, and intensifying competition among producers.

Different cinema chains wield varying degrees of market power in the industry. Among 46 cinema chains operating in the market[6], Wanda emerged as the most prominent with a substantial 14.89% market share as shown in Table 2.2. The top five cinema chains collectively contribute to

[4] State Administration of Radio, Film and Television (SARFT) of China issued *Detailed Implementing Rules of Reformation of Film's Distribution and Screening Mechanism* at 18th Dec 2001, and mentioned establishment of "cinema chain-centered" mechanism of distribution and screening.
For more details:Yun Shen, 'The System of Theatre Chains in China: a Perspective of Film Distribution', *Contemporary Cinema*, 2006 (6), P19-26, https://www.docin.com/p-255707950.html

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

[6] Lizheng Fan, 'Chinese movie market insights in 2014' (27/02/2015), *CHINA FILM NEWS*, http://www.dmcc.org.cn/mainSite/xw/zxgz/612777/index.html

half of the domestic box office revenue, while the top ten chains exert control over more than 70% of the market. Larger cinema chains, such as Wanda, which holds the top position in China, enjoy advantages like superior locations and projection equipment, enabling them to attract larger audiences and secure a greater market share. [7] In addition, these larger chains benefit from economies of scale through shared facilities, such as popcorn stands, and reduced per-screen staffing costs, including shared ushers and auditorium-cleaning teams. Furthermore, larger cinema chains own a greater number of cinemas and screens, providing them with the flexibility to make crucial decisions regarding pricing, the allocation of screens to specific films, and screening schedules. The ability to flexibly allocate auditoriums plays a pivotal role in cinema operations, impacting the introduction of new movies, pricing variations at different times, and the choice of auditoriums for screening. Having a greater number of screens at their disposal allows cinemas to offer a wider array of combinations of both old and new movies.

As a result, exhibitors, including individual cinemas and cinema chains, play a key role in determining ticket prices, seat and screen allocations, and the timing of film releases or discontinuations. Moreover, they typically receive a larger share of the box office revenue compared to producers and distributors.

Role of cinema chain on process of release

First of all, the distributor must submit the film to SARFT for examination and obtain a release permission certificate. Subsequently, negotiations with cinema chains take place, encompassing discussions on revenue-sharing ratios and release dates. Simultaneously, applications are made to China Film Group Corporation (CFGC) and Huaxia Film Distribution for a projection key[8]—an encryption code specific to a movie, granting cinemas the right to screen that particular movie within a defined

[7] '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

[8] How does encryption work in digital cinema? https://baike.baidu.com/reference/2223956/533aYdO6cr3_z3kATPWIzvv1MSvGYIyq67OBU7FzzqIPmGapB4rsXYEm4dty_f5pEQbK_ZVjc8IQhOGkXVUWsaoPJLMqFux1xDKuDy6RkOCzoogszIAFvNIcH7BD2KSyqxGigWHDmfSM6WP-0zvfvZixcXdC9RBl4IHDM_fXuI

screening period, which typically spans around 30 days.[9] If a film earns exceptional performance and the distributor wishes to extend its exhibition period, they must reapply for the new projection key.

Distributors hold the authority to determine the scale of a movie's release in the United States, offering three release types: wide release, platform release, and limited release (Einav, 2007). However, there is no precise definition for the scale of new movie release in China, and once the projection key is secured for a movie, movie becomes eligible for nationwide release. The exhibitors employ considerable influence over the scale of release.[10] Following their contractual agreements with distributors, cinema chains furnish their cinemas with lists of forthcoming movies along with their release dates. Subsequently, each individual cinema enjoys the autonomy to decide whether to screen a specific movie, the number of screens and seats to allocate on a given day, and when to conclude the screening. As depicted in Table 2.3, some films may only be shown for a single day, while others enjoy 50 days run.

Cinema's expectation about box office performance is essential in shaping exhibitors' decisions of introducing a movie and screen allocation.[11] Cinema managers typically base these decisions on three key factors: 1) movie characteristics, including reviews, production origins, and the reputation of the movie stars; 2) the specific attributes of their own cinema, such as the total number and size of screens, and local demand; and 3) the long-standing relationships between cinema chains, producers, and distributors.

Blockbusters, in particular, follow a common pattern. They are typically released simultaneously across various cinema chains and venues. There are several key reasons for this uniformity. First, blockbusters are usually supported by influential distributors. Second, as profit-driven entities, no cinema is willing to let another to release a popular movie a day before them, and none want to risk falling behind in releasing a promising movie with high revenue potential. However, the situation is more challenging for

[9] More details about projection keys in China
https://baijiahao.baidu.com/s?id=1651548212625520732&wfr=spider&for=pc
[10] Insight Media, 'Mysteries of allocation of screens and seats' (28/09/2016), *Huxiu*, 28/09/2016, http://m.huxiu.com/article/165514.html
[11] In one of Chun's series paper, Entry, Exit, Expectations, and Performance over the Product Life Cycle, she demonstrate dynamic interaction among movie's performance and cinema's expectation.

lesser-known art movies, as they struggle to gain exposure in front of consumers. Even though a few larger cinemas may attempt to screen them when they have vacant auditoriums during low-demand days, it remains a formidable challenge for these films to reach their intended audience.

Monopsony, Revenue-sharing quota and one-time buyout contract

For foreign (imported) movies in China, where there are three methods of import. First, a revenue-sharing model is employed to import a select number of foreign movies into mainland China (Excluding 3D and IMAX movies), initially 34 movies and later expanding to 39 movies since 2016, as indicated in Table 2.1. The producer receives 35%, while two distributors, the China Film Group Corporation (CFGC) and Huaxia Film Distribution, enjoying a monopoly on foreign movies, secure 17%. The exhibitor takes home the remaining 48% (Zheng, 2013), with the producer covering the advertising costs. It's noteworthy that Hollywood blockbusters constitute approximately 90% of the revenue-sharing quota.

Other foreign movies follow a one-time buyout contract. Distributors make a single, fixed payment to producers for exclusive rights to screen the film in the mainland market. In a manner akin to wholesale transactions, distributors essentially purchase the movie from the producer and subsequently resell it within a specific market. Consequently, distributors shoulder full responsibility for both profits and risks in the mainland Chinese market. The number of one-time-buyout movies surpasses the quantity of revenue-sharing imports. A significant portion of buyout movies originate from regions like Europe, Japan, and South Korea, while others include smaller Hollywood productions. These films play a vital role in diversifying content and intensifying competition within the Chinese market. Oversight of movie importation and the choice between the revenue-sharing model and one-time buyouts is overseen by the state-owned CFGC.

In the exceptional case mentioned above, co-produced movies created in collaboration with a Chinese company are released in the Chinese market. Producers, whether they are Chinese or foreign companies, are entitled to 39.43% of the net revenue, mirroring the allocation for domestic

movies. To qualify for this category, more than one-third of the main cast must originate from mainland China.[12]

Local mainland China producers and distributors receive a smaller portion of the net revenue, amounting to 39.43%, while exhibitors claim a larger share at 52.27% following government and China Film Special Fund levies, which account for 8.3% of the total box office revenue.[13] In contrast, in the United States, the distributor and producer are entitled to the majority of the fixed share, either 90% of net revenues or a 70% share of gross revenues (Einav, 2007). The revenue distribution in China typically remains constant regardless of the movie's length.

Collusive Price floor and differentiated pricing strategy

Before a movie is released, an exhibition contract between distributor and exhibitor establishes a 'minimum price' at the city levels. The minimum price serves as a safeguard against overly aggressive pricing strategies between exhibitors and protects the interests of the producers. Any form of discounted ticket, whether for students or promotions, must be priced above this minimum threshold. If a cinema sells a ticket below the minimum price, they are obligated to compensate for the shortfall (Fu, 2014). This price is mainly determined by three factors: the city's size and gross domestic product (GDP), the movie's production origin (imported or local), and the screen's size and characteristics, such as IMAX, CINITY, Atmos, and more. Minimum resale prices are permitted by Chinese law[14]. This stands in contrast to the United States and Australia, where such practices are considered illegal and categorized as anti-competitive behavior (Einav, 2007). In these countries, suppliers are prohibited from exerting pressure on businesses to charge their recommended retail prices[15].

After the establishment of a minimum price, each cinema chain formulates its pricing strategy at the city level, taking into account the varying market dynamics and market power across different cities. To illustrate, consider Dadi, which was founded in Guangdong. They hold a

[12] How to produce a co-production movie? http://news.mtime.com/2016/02/08/1552287.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.

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

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

more advantageous position in Guangdong, boasting superior locations, a larger number of cinemas, and a more experienced workforce compared to other provinces. In Guangdong, Dadi adopts a broader approach to price discrimination by offering a wider range of prices for different movies, screening times, and cinemas. On the other hand, when operating in cities like Wuhan, where their market influence is less pronounced, Dadi, as a new entrant during our observation period, employs a competitive low-price strategy to compete with other cinema chains. Evidently, cinemas under the same chain work collaboratively.

Ultimately, the cinema manager determines the final retail ticket price by considering both the cinema chain's overarching pricing strategy and local demand fluctuation. [16] Managers possess the most intimate knowledge of the demand shocks and consumer behaviors in the vicinity where their cinema is located.

Through the three stages of price determination outlined above, the Chinese mainland movie industry exhibits an uncommon degree of price variation, with significant differences across screening times, cinemas, and movies. Notably, my research uncovers that cinema chains pursuing distinct marketing goals employ entirely different pricing strategies, including price leadership, differentiated pricing, and fixed pricing. This unique setting, akin to a natural experiment, provides an excellent opportunity to investigate how the market responds to the entry of new products for firms with differing pricing strategies.

Data and Key variables

The core dataset comes from the Chinese Box Office Database[17], which contains detailed information about film characteristics: the real-time number of seats, the rate of occupation and ticket price per auditorium. The data source includes around 50% of market size by revenue in China. In total, we collect 8,458,892 observations across 191 cities of all sizes from March 12, 2013 to May 16, 2014.

We choose data in Wuhan for this paper. Wuhan's 2014 GDP was about 1.0069 trillion RMB (163.769 billion USD), the eighth highest in mainland

[16] Chao Fu, Ticket price of movie has become cheaper. What happened?, *Gui Quan*, http://ent.qq.com/original/guiquan/g150.html
[17] Chinese box office database: http://58921.com/

China and with 10.22 million residents; the city has the 13th largest urban population in China. The dataset contains 194,397 observations covering 307 movies from 20 cinemas and five cinema chains. Throughout the analysis, relatively small movies are removed, and we 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 2.3 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. We 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.

The data sample used in this study covers 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.

[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/

Price variation and relatives

As exhibitors has quite strong influence over the process of releasing and pricing, we further describe the price variation across cinemas and cinema chains in Table 2.4. Wanda, the largest cinema chain, shows the highest average price and standard deviation. Zhong Ying, a state-owned cinema chain, fixes their ticket prices. Da Di always charge the lowest price in the Wuhan market. Cinemas adjust the final retail price based on the overall pricing strategy of the cinema chain. We selected these typical three cinemas from three cinema chains—Zhong Ying, Wanda, and Dadi—in order to examine the detailed variation pattern in Figures 1-3 for price, revenue, number of running movies, and new movies daily. Figures 1 to 3 demonstrate a clear weekend-pattern in daily revenue. Additionally, it is evident that cinemas usually release new movies on Fridays.

Panel (1) of all three figures gives the daily average price. The cinema of Wanda, the largest cinema chain, has the highest average price and degree of dispersion. In contrast, ZhongYing cinema in Figure 2 keeps ticket prices constant and displays the least amount of dispersion in price. The cinema from Dadi, taking the role of a price leader, always charges the lowest price in the Wuhan market, as depicted in Figure 3.

The price variation of Dadi exhibits a clear weekend-pattern, with prices higher from Friday to Sunday, while Wanda's variation appears unrelated to the weekend. This is because the average daily price in Figures is the mean of the price of all movies shown in the specific cinema, which conceals the detailed information about the pricing strategy and allocation of projection resources for different movies. Lengjiahu Wanda has 9 screens and 1686 seats, with the largest screen corresponding to 316 seats and the smallest to only 30. The cinema typically assigns multiple big screens to exhibit a newly-released movie at a lower price, but rearranges incumbent movies to a few small screens and charges a higher price. In comparison, the price variation of Dadi in Figure 3 shows an expected weekend-pattern, with prices significantly higher on weekends. Dadi has only four small screens and no VIP auditoriums, limiting the combination choice of screen allocation and price.

The simple hedonic price model reported in Table 2.5 helps identify which characteristics are key to price variation. Since the explanatory variables are all dummy variables, the parameters are not presented. An R-squared of 0.61 indicates that these variables explain over 60% of the variation in price.

3. The model

We first identify the shape of demand of Chinese movie market. We incorporate differentiation across three dimensions—movie, day, and cinema—using a three-level nesting structure to capture the effects of market expansion, business stealing, and cannibalization. On the supply side, we consider pricing model of Bertrand-Nash competition with differentiated products. Each manager of cinema sets its prices to maximize profits, bounded by three factors: the price floor, add-on pricing, and weights box-office performance across different days and movies. We then examine how changes in the price floor can affect equilibrium profits, consumer surplus and total welfare.

Demand model we build a three-level nested logit model with unobserved consumer heterogeneity, following Berry, Levinsohn, and Pakes (1995), Nevo (2000), 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 $\xi_{j.t.m}$. We 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 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), we use a three-level nesting structure to specify $V_{i,j,t,m}$:

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

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, $\pi_m \in [0, 1]$ 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.

We 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

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

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

$$S_{j,t,m} = \frac{e^{\frac{\delta_{j,t,m}}{\pi_m \pi_j}} \cdot E_J^{\pi_j - 1} \cdot D_G^{\pi_m - 1}}{[1 + \sum_A D_G^{\pi_m}]}, \quad (8)$$

in which the inclusive value terms are

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

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

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

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

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.

We 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, we will study the structural changes in the time series of movie prices and focus on the consumer's time choice.

The own-price elasticities for movie *j* at day *t* in cinema *m* defined by Eq. (12) are as follows:

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

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

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.

The collusive price floor and bounded rationality

Following our demand estimation, we focus on pricing under an exogenously determined allocation of screens. Exhibitors' decisions involve a monthly arrangement of movie screenings and screen allocation per film, as discussed in Section 2; however, we leave this aspect for future research. We assume a zero marginal cost for an additional attendee, allowing cinema managers to focus on maximizing revenue when a session is not expected to sell out. This assumption is reasonable, given the mean and median seat occupancy rates of 18.9% and 9.1%, respectively, shown in Table 2.3. Cinemas make rational pricing decisions within the Bertrand

model of product differentiation, incorporating three additional factors in setting a minimum price bound ($p_{jtm}^{min} = (pf^{20} + a_m) * w_{j,t}$): an explicit collusive price floor (pf), cinema-specific add-on pricing (a_m), and daily price variation based on a movie's box office performance ($w_{j,t}$).

The explicit collusive price floor set by distribution contracts is a primary consideration in exhibitors' pricing strategies. Therefore, we set a price floor of 20[21] (pf^{20}) as the first component of minimum bound p_{jtm}^{min}. If a cinema sells a ticket below pf^{20}, it must compensate for the shortfall. Thus, while concession sales are not factored into our model, the lower bound imposed by the pf^{20} rule is essential to consider.

Second, cinemas from large chains benefit from advantages such as prime locations, superior projection equipment, and economies of scale through shared facilities. They also enjoy greater flexibility in pricing, screen allocation, and scheduling decisions due to their larger networks of cinemas and screens. Anecdotal evidence suggests that managers of prominent cinemas, like Wanda cinemas, expect higher box-office performance and believe they deserve higher ticket prices than other cinemas, even when screening the same movie *j*. In a mirrored scenario of the study by Han, Huffman, and Liu (2024) on 'overconfidence in the profitability of price cuts under a price ceiling,' our analysis focuses on add-on pricing under a price floor. We assume that, similarly, cinema managers exhibit overconfidence in the 'expected outcomes' tied to their market advantages, incorporating this belief into their pricing decisions. They adding an "extra charge a_m" above the price floor of 20, resulting in an raising minimum bound of ($pf^{20} + a_m$).

Third, as shown from figures 1-3, price and revenue of movies tend to follow similar variation patterns across days. We assume that managers of cinemas might don't have foresight about box office performance for each movie and each day, but they do have foresight about demand fluctuation over several key characteristics of day and movie according to the past experience. Drawing on Ellison's (2002) concept of performance-based pricing, we then weight price variations based on the price floor and the cinema's add-on price, $(pf^{20} + a_m) * w_{j,t}$. While the add-on price is

[21] During the observe period, the price floor usually set at 20 RMB for Wuhan market.

associated with each specific cinema, the weights primarily depend on price variation across days and movie characteristics. We use day of the week, month, and holiday to capture effects of day *t*, and Douban scores, length of run, and regions of production to capture effects of movie *j*.

Finally, based on these three restrictions of minimum bound $p_{jtm}^{min} = (pf + a_m) * w_{j,t}$, we consider the profit-maximizing pricing decisions à la Bertrand-Nash. Following the similar simulation method as Davis (2010) and de Roos and McKenzie (2014), we assume that the manager of cinema m seeks to maximise the static profit of cinema *m* and solves the following problem at day *t*:

$$\max_{\{P_{j,t,m}\}_{f=1}^{F_{t,m}}} M \sum_{j=1}^{J_{t,m}} S_{j,t,m} * P_{j,t,m} \tag{14}$$

where M is the market size. This leads to a set of first order conditions for all movies at all cinemas:

$$S_{j,t,m} + \sum_{g=1}^{J_{t,m}} \frac{\partial S_{g,t,m}}{\partial P_{j,t,m}} P_{g,t,m} = 0,$$

$$t = 1, \dots, T, h = 1, \dots, H_t, f = 1, \dots, F_{ht} \tag{15}$$

Re writing Eq. (15) in matrix notation, we have

$$S_t + \aleph_t *. D_p S_t P_t = 0 \tag{16}$$

where $\aleph_t$ is an ownership matrix corresponding to cinema competition. We consider the possibility outlined above that cinemas seek to simply maximise profits of their own cinema: $\aleph_t(j, g) = 1$ if movies *j* and g are exhibited at the same cinema *m* at time *t*, and 0 otherwise; $[X *. Y]$ indicates element-by-element multiplication; and $D_p S_t$ represents a matrix of partial derivatives of market shares with respect to prices with typical element $D_p S_t(a, b) = \frac{\partial S_{b,t}}{\partial P_{a,t}}$. We can rewrite Eq. (16) to form the basis of a simple recursive algorithm to simulate profit-maximising prices:

$$p_t^{k+1} = -(\aleph_t .* D_p S_t(P_t^k))^{-1} S_t(P_t^k) \tag{17}$$

Initialising p_t^0 to be a $J_{t,m} \times 1$ zero vector, we iterate Eq. (17) until convergence.

4. Empirical estimation and results

We first describe how we use the dataset to estimate our demand model with differentiated products and identify consumer's substitution patterns by calculating demand elasticities. Then the estimated demand parameters are subsequently used to uncover markups and replication the complex pricing behaviors of exhibitors.

For estimation of demand model in previous section, we first treat the entire city of Wuhan as the market and the market size M is around 10.22 million people. 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.

$$S_{j,t,m} = \frac{q_{j,t,m}}{M}, \quad (1)$$

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

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

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*.

We 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.

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

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

We calculate the weight of the daily price, WT_t, by first using the seats sold for each screening time ($Seats\ sold_{j,st,m}$) divided by the seats sold during day *t,* $\sum(Seats\ sold_{j,st,m})$. Subsequently, we obtain the weighted daily price by summing the product, $WT_t * P_{j,st,m}$.

Endogeneity 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 we do while choosing price $P_{j,t,m}$ and product characteristics. One such source of endogeneity arises because we could not collect data on advertising spending. Cinemas may set higher prices and arrange more screens for movies with big advertising budgets. We 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. We also control for time-varying effects by including school and public holidays, seasonality, and weekend and weekday dummies, as shown in Table 2.3. Thus, we consider endogenous problems through unobservable that are not absorbed by these effects, which affect the variation in prices and allocation of screens.

We instrument for price using the total number of screens across rival cinemas.[22] We 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. We 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, we 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.

We 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. We 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. We assume that demand shocks,

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

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 cinemas 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, control movies, cinemas, and time-varying fixed effects first. We 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. We 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.

The first-stage results in Table 4.1 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 4.2 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. We consider this a sign that the instruments are working as expected.

The parameter estimates of demand in Eq. (11) are presented in Table 4.2. 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.

Market expansion, business stealing, and cannibalisation

Column (1) of Table 4.2 presents the parameters of $(1-\pi_m\pi_j)$ and $(1-\pi_m)$, equaling 0.485 and 0.349, respectively, in our main demand model. Therefore, π_m equals 0.651 while π_j equals 0.791, which reveals 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.

Own-price elasticities

Table 4.3 presents own-price elasticities disaggregated by cinema. Our demand estimates generate high mean own-price elasticities of 6.319[23]

[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).

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?

We 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 4.3, 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. We review the differentiated pricing strategy among cinemas in Figure 1-3 and note that of all cinemas, Dadi, the price leader, shows the smallest elasticities. JinYi 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.

Business stealing and Cannibalisation effects with differentiated pricing strategies

When cinema introduce a new movie, they need to decide the price for the movie as well. Especially our sample provides evidence for firms with

three typical pricing strategies: price leader, price variation and fixed price. We conjecture that movie release from firms with different pricing strategy leads to different market results. In this section, we use the cross-price elasticities of movies in the same cinema (within-cinema elasticities) and across different cinemas (cross-cinema elasticities) to discuss the asymmetric patterns of cannibalisation and business stealing across different pricing strategies through Tables 4.4 and 4.5.

Both within- and cross-cinema elasticities, separately shown in Table 4.4 and Table 4.5, are lower than one and presents a highly unbalanced pattern as we expected. In Table 4.4, 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. In Table 4.5, the mean of the JinYi 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. We conjecture that the using of nesting structure enhances the variability of both within- and cross-cinema elasticities. Without the nesting structure, the variability of elasticities would only be affected by $S_{j\prime,t,m\prime}$. However, according to Eq. (13), the variability of elasticities is also affected by both inside shares, $S_{j\prime,t,m\prime|IN,t,m\prime}$ and $S_{IN,t,m\prime|IN,t,A}$.

The within-cinema elasticities reveals that the extent of the cannibalisation effect of movie released from a cinema chain is significantly correlated with the pricing strategy of that chain in Table 4.4. Dadi charges the lowest price in the market and practice a very narrow range of price variation, which leads to the lowest median elasticities and the smallest difference in the median and mean elasticities, namely weak cannibalisation. JinYi 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, which is moderate cannibalisation. 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, namely strong cannibalisation. ZhongYing cinema chain's fix the ticket

price for almost all movies and it shows the second lowest elasticities and standard deviation, the second weak cannibalisation chain.

Table 4.5 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 within-cinema elasticities (cannibalisation) are five times larger than cross-cinema elasticities (business stealing effects) on average. The regression results indicate business stealing among cinemas, whereas cross-price elasticities indicate business stealing among individual movies. In respect of 15 cinemas in our dataset, the model estimation is consistent with the elasticities results.

Cinema chains' pricing tactic also significantly impact on the extent of business stealing effect. 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. JinYi practices moderate price variation, which results in a middle position in respect of stealing business from other cinema chains. ZhongYing, 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 4.4 and in red in Table 4.5, 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. We 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. It is worth to pay attention on Jianghanlu Wanda, which is in the business center area. According to the standard economic intuition of a geographically differentiated product market, it face more competitors than other cinemas. Therefore, It makes sense that Jianghanlu Wanda lower the price to steal business from other cinemas or prevent their consumers be attracted by other cinemas. It can be observed that the average level and range of price variation of Jianghanlu Wanda are significantly lower than other Wanda cinemas from Appendix 1. As a result, cross-cinema elasticities (business stealing) of Jianghanlu Wanda as set out in Table 4.5, is 0.035, the second highest among all Wanda cinemas. Moreover, it is even higher than JinYi WuShengLu cinema's cross-cinema elasticities, located in the same area as Jianghanlu Wanda, which means the business stealing of Jianghanlu Wanda is quite high comparing to others. However, we conjecture that the increase of consumers is not so significant when they reduce the price to release new movies. It is because the cannibalisation of Jianghanlu Wanda soars, as it exhibits the highest within-cinema elasticities, highlighted in red in Table 4.5.

Heterogeneity in demand

In this section, we examine potential variations in consumer's response to type of new product entry: production regions and quality. We use Douban rating to present the quality of movie in mainland. The ratings for movie reviews are from Douban,[24] 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. Anyone could apply account in this website and leave reviews and rating to any movie. Douban rating can be treated as a window to express the taste and preference of Chinese audiences about the soundtrack, special effect, sets, storyline etc. of a movie. As Douban is very

[24] Link to Douban movie: https://movie.douban.com/

popular and the high rating is usually considered as a signal of "good" movie. Therefore, some distributors try to manipulate the rating of their movie, but Douban developed a machine learning method to identify these "faked" accounts and ratings.

Table 4.6 shows the number of movies released during the observed period by Douban rating and production regions. We can observe d that the Douban rating, for 49 out of 55 movies from U.S., are above 5.5, while only 57 out of 202 Chinese mainland movies reach that level of rating. We conjecture that Hollywood movie might be the main source of market expansion and business stealing. Therefore, we begin by comparing the effect of new movies entry on locally produced movies and Hollywood movies.

According to the results presented in Column (1) and (2) of Table 4.7, Hollywood movies still exhibit strong and pronounced market expansion effects, with a $1-\pi_m$ of 0.503, however the parameter for price is less negative than the main result and is not statistically significant. We conjecture that the Hollywood movies are well-received in the Chinese market, leading cinemas to increase prices for these movies, [25] resulting in the insignificant parameter. On the contrary, market expansion of local movies is not as significant as expected. This could be attributed to the release of a substantial number of poorly rated local movies, accounting for 70% during the observation period, which strongly influences $1-\pi_m$, the market expansion parameter.

Next, we explore potential heterogeneity arising from product quality by categorizing movies into acclaimed and poorly rated ones. The non-linear entry effect of both groups of movies is presented in Columns (3) and (4) of Table 4.7, revealing a discernible pattern. $1-\pi_m$ is not significant for poorly rated movies, while $1-\pi_m$ and $1-\pi_m\pi_j$ of acclaimed movies are closely aligned with the main result in Table 4.2. Consequently, we can conclude that the introduction of acclaimed Hollywood movies has a positive effect on the market expansion of the Chinese movie industry. When combined with local high-quality movies, they contribute to the overall market expansion of the movie industry.

[25] We could also find the evidence in Appendix 1, which shows that the price for Hollywood movies is higher than local movies.

Decomposition of minimum bound of price setting

Combining both the process of price decision discussed in section 2 and the model in section 3, We use the traditional Bertrand model of price competition with product differentiation to simulate the price, but with three extra considerations on minimum bound ($p_{j,t,m}^{min}$): price floor of 20 (pf^{20}), manager's add-on pricing behavior (a_m), and weights ($w_{j,t}$) on performance of movie *j* on day *t*.

We first take consider of the price floor of 20 CNY (pf^{20}) setting on the distribution contract and restrict the minimum bound above 20 CNY ($p_{jtm}^{min} \geq 20$) when we use Bertrand pricing model to imitate the manager's rational pricing decision. However, both mean and deviation of simulated price under pf^{20} are far away the observed price. It is clear evidence that beside the price floor, there are more considerations for managers to price beyond traditional Bertrand-Nash equlibirum.

From anecdotal evidence we know that managers of supreme cinemas believes that the advantages of their cinema bring positive effect on performance of all movies shown in their cinema. Therefore, we add a linear additive term a_m on common pf^{20} according to the expectation to obtain a cinema-specific minimum bound ($pf^{20} + a_m$). However, we do not have specific data about the cinema-specific term a_m. Besides, we do not have data on those cinema-specific minimum prices so we cannot directly back out the value of a_m. We tried to calibrate the value of a_m to maximize the model fitness by matching the mean of the simulated prices and the observed prices. As the additive term a_m depends on the cinema's characteristics (e.g., quality of the service, size of cinema). As for multiplicative term ($w_{j,t}$), we assume that cinemas have pass experience and gain perfect foresight about movie's performance over characteristics over days and movie. So we can back out the $w_{j,t}$ they used from the actual ticket sale data. The multiplicative term ($w_{j,t}$) depends on the movie *j*'s characteristics—Douban scores, length of run, and regions of production, and day *t*'s characteristics—day of the week, month and holiday. It is reasonable to assume that both terms do not vary with respect to the value of the price floor. We hence keep them fixed across our counterfactual exercises.

We present detailed information about the price replication in Table 4.8 and Figure 4. We believe this simulation successfully mirrors the observed prices in reality, as the shapes of the distributions are quite similar. While the differences in density between the real and simulated prices are noticeable in both graphs, we consider this acceptable because the function used to simulate prices is continuous, resulting in very small unit price variations, such as 0.001. In reality, however, price variations typically occur in whole units, usually by increments of 1.

5. Counterfactual policy experiments

We then conduct regulatory counterfactuals to estimate the effect of removing the price floor. What is the impact of a price floor on the profitability of the entire industry? Additionally, we investigate which types of firms benefit the most from this collusive price floor.

We first examine the overall impact of the price floor. Columns (1) to (4) of Table 5.1 list the price and revenue data when the price floor is set at 20 (pf^{20}), with cinemas employing four different pricing strategies: (1) No bounded rationality, (2) cinema specific add-on pricing only, (3) weights on box office performance only, and (4) combination of the add-on and weights on performance pricing. Columns (5) to (7) present the results after removing the price floor pf^{0}, showing three scenarios: (5) no bound, (6) add-on pricing only and (7) combination of Add-on and performance weights.

Comparing columns (1) and (5) reveals that the price floor raises the overall industry equilibrium price by approximately 26 CNY. The primary goal of the price floor—preventing fierce pricing competition among exhibitors—is achieved. The mean of overall profit of the industry increases, indicating that the collusive price floor contract indeed provides profit incentives for all exhibitors to defend it.

In addition to the overall increase in industry profit, we also aim to estimate the impact of the price floor on individual cinemas with varying levels of market power. First, we summarize the variation in price and profit for each cinema across the seven simulation scenarios outlined in

Table 5.1. Then, we conduct paired comparisons between groups and present the results in Table 5.2.

Column (1) of Table 5.2 presents a paired comparison between pf^{20} and pf^{0}—assuming all cinemas aim for maximum profit without additional price variation. Prices increase by approximately 26 CNY for nearly all cinemas when moving from pf^{0} to a pf^{20}, but the revenue patterns reveal some interesting shifts. Cinemas like Dadi, which are at a market disadvantage, experience even lower profits when setting prices at equilibrium levels under pf^{20}. In contrast, cinemas like Wanda and Jin Yi, which have idiosyncratic advantages, see a significant increase in average profit with pf^{20} in place, even though their median revenue decreases. This suggests that the price floor drives up overall prices, leading to higher profits during periods of high demand, but during periods of low demand, the increased prices further reduce demand, resulting in lower profits.

Therefore, we expect that exhibitors have a strong incentive to adjust cinema-specific prices based on their unique advantages, rather than adhering strictly to the Nash equilibrium, especially for cinemas facing competitive disadvantages, such as Dadi. Column (2) of Table 5.2 shows the changes in equilibrium price and revenue when cinemas take their idiosyncratic advantages into account in their pricing decisions ($pf^{20} + a_m$).

This leads to a price decrease of around 6.5 CNY in Dadi cinemas, a slight increase in UA cinemas, and a 10 CNY increase in "overconfident" Wanda and Jin Yi cinemas, while Zhong Ying continues to follow a fixed pricing strategy. The revenue for each cinema changes as expected: revenue increases for all Dadi cinemas, while the "overconfident" Wanda and Jin Yi cinemas face a significant loss in revenue. Surprisingly, the fixed-price cinema Zhong Ying and the slight price-raising UA see a significant increase in revenue. This makes sense, as business stealing accounts for over 30% in our demand estimation.

Column (3) of Table 5.2 compares revenue and pricing between no price floor (pf^{20}) and a price floor plus cinema-specific add-on $(pf^{20} + a_m)$. It highlights how cinemas adjust their add-on prices based on advantage heterogeneity. This comparison offers insight into the profit incentives driving cinemas like Wanda and Jin Yi to raise their average prices, even

at the risk of reduced profits. Although column (3) shows that Wanda and Jin Yi cinemas experience some profit loss due to adding relatively higher a_m under pf^{20}, their overall profit remains higher than in a scenario pf^{0}. This suggests that if all cinemas collude to adhere to a price floor, they can still collectively benefit from it.

Social welfare

Table 5.3 shows the welfare effect of price floor on total profits, consumer surplus and total welfare. Apparently, cinemas have collective profit incentive to collusively maintain price above price floor. The Table 5.3 shows that the overall profit would have a tremendous increase of 82.89% under pf^{20}, but the total social welfare of 55.85% was lost. As we mentioned in session 2, government is also part of revenue sharing. Therefore, we consider this result is reasonable. Consumer would gain from a ban of collusive price floor, in which consumer and total surplus rise by 72.78% and 55.98%.

6. Extension

To better understand the incentives and welfare effects of a price floor, we now explore several extensions. The counterfactual results reveal that firms have strong profit incentives to deviate from the equilibrium under pf^{20}. In this session, we examine how the outcomes change under alternative pricing strategies, focusing on two key forms of bounded rationality: add-on pricing (a_m) and performance-based pricing ($w_{j,t}$).

Profit incentives in bounded rationality under price floor

We first discuss the different pricing strategies when price floor exists, which is shown in Table 6.1. For easy comparison, we replicate the comparation of pf^{20} and $(pf^{20} + a_m)$ from column (2) of Table 5.3 as the column (1) of Table 6.1 here. As previously discussed, with a price floor of 20, "overconfident" cinemas like Wanda and Jin Yi face revenue losses due to add-on pricing. In contrast, lower-priced cinemas like Dadi gain a competitive edge, while UA benefits from slight price increases.

Column (2) of Table 6.1 illustrates the effects when cinemas adjust prices using only performance-based weights, accounting for daily demand fluctuations and movie characteristics $(pf^{20} * w_{j,t})$. We observe that

prices tend to decrease for most cinemas, with the median price declining more rapidly and significantly than the mean price. This trend is reasonable, given the generally low demand in the Chinese movie market, where median seat occupancy is approximately 9.1%, as noted in Section 2. Alongside this price reduction, we see a notable increase in profits, as shown in column (2) of Table 6.1. This can be attributed to the overall price reduction across cinemas stimulating market expansion, especially considering the substantial market expansion effect estimated at 65.1% in our demand analysis. Therefore, these results align well with market expectations.

Column (3) shows change of equilibriums from pure Add-On Pricing to pure Weights on Performance Pricing. If Dadi does not account for its market disadvantage but only adjusts prices weights on demand fluctuations, it may find itself in a worse profit situation. On the other hand, Jin Yi and Wanda do not apply additional cinema-specific add-on prices but instead follow demand fluctuations, which could boost their profits. Apparently, if cinemas use single strategy, regardless of the pricing strategy they choose, some cinemas will inevitably suffer the loss of profit and have incentive to change the situation. In contrast, Column (4) demonstrates that using combination of add-ons and weights under a price floor is a better option for all players. For Wanda and Jin Yi, which have a market advantage, the market expansion driven by weights on box office performance offsets the profit loss from business being stolen due to overconfident add-on pricing. For Dadi, which faces market disadvantages, lower prices can attract additional customers to the cinema.

Alternative pricing-setting behaviors in the absence of price floor

The market results for alternative pricing-setting behaviors in the absence of a price floor is presented in Table 6.2. Column (1) shows the comparison if cinemas exert add-on pricing or stick on basic equilibrium price. Cinema-specific add-on pricing results in a slight increase in both price and profit for all cinemas. Notably, cinemas like Jing Kai Wanda and Leng Jiao Hu Wanda, which raised prices relatively higher than other cinemas, experienced the highest profit increases.

Column (2) shows the comparation between an unbounded pricing and pricing on combination of add-ons and weights on day/movie performance, while Column (3) compares prices with add-ons only to those with combination of add-ons and weights. Evidently, by further considering price variation across days and movies, cinemas could achieve higher profit increases compared to using add-ons alone. In this case, the profit growth is not driven by price increases to avoid competition, but by price reductions across all cinemas during periods of low demand, leading to significant market expansion. Without a price floor, the equilibrium price tends to be low. Consequently, raising prices can lead to higher profits for cinemas, whether the motivation is add-on pricing or performance-based strategies.

Welfare Change for Different Price-setting Behaviours

In the session 5, we discussed the welfare changes resulting from the removal of the price floor. Here, we further explore the changes in social welfare under different price-setting behaviors, both in the presence and absence of a price floor, as shown in Tables 6.3 and 6.4.

Column (5) in Table 6.3 shows that both box office profits and consumer surplus decrease when cinemas exert add-on pricing (a_m). In our previous analysis of Table 6.1, we found that Dadi cinemas with market disadvantages actually benefits from the price increases by overconfidence of cinemas with market advantages. However, here we see that price hikes by overconfident cinemas harm the overall industry profit, shrinking the total market size. Consumer surplus hit even harder, dropping by 60.85%.

In contrast, adjusting prices based solely on performance weighting, as shown in column (6), produces the opposite effect, leading to increases in both profit and consumer surplus compared to the price floor alone. While consumer surplus rises only modestly by 1.32%, it at least does not deteriorate, marking an important finding. Previous counterfactual analysis indicates that collusive price floors should be regulated, as substantial profit gains often come at the expense of a significant reduction in consumer surplus. However, such regulation may be challenging, considering the regulator's role in this game. Here, we identify a second-best alternative to improve social welfare. By avoiding add-on pricing and

focusing purely on performance weighting, a Pareto improvement may be achievable. Yet, this requires a higher degree of collusion, with inter-cinema transactions, as cinemas with lower performance, like Dadi, may have a strong incentive to deviate from this equilibrium.

Column (7) shows the effects of combining add-ons with performance-based pricing, reflecting real-world pricing. In this case, the two opposing effects largely offset each other, resulting in a net increase in industry profits but at a cost to social welfare. This approach resembles a compromise due to the practical challenges of achieving higher-level collusion.

In the absence of a price floor, as shown in Table 6.4, where prices are already very low, both add-ons and the combination of add-ons with performance weighting increase firms' profits, but at the cost of consumer surplus.

Price Floors Favor High-Quality Films, While Performance-Based Pricing Benefits Low-Quality Films

We want to further examine whether the price floor and different price-setting behaviors affect movies of different quality differently. In the heterogeneity analysis of demand, we divided movies into low-quality [0, 5.5) and high-quality (5.5, 10] based on Douban scores. Here, we further divide the movies into six groups: [0, 3.5], (3.5, 4.5], (4.5, 5.5], (5.5, 6.5], (6.5, 7.5], and (7.5, 10] for more detailed insights.

Table 6.5 presents comparison of profit changes for different price setting behavior across Douban score groups. The first row of Table 6.5 shows the heterogeneous effects of the price floor on movies of different quality. As expected, the price floor significantly boosts profits for high-quality movies (last three columns), with increases of 81.3%, 111.3%, and 136.8%, respectively. For low-quality movies (first three columns), the profit increases are much smaller, at 32.8%, 46.9%, and 29.9%, respectively.

Rows 2 to 4 of Table 6.5 present profit changes under different price-setting behaviors with a price floor. The pure add-on strategy (a_m) has a negative effect on all movies, shown in row 2, while the weights on performance pricing strategy ($w_{j,t}$) have a positive effect on profits for all

movies, shown in row 3. The positive effect of $w_{j,t}$ on low-quality movies is almost twice as large as on high-quality movies. This is because demand for high-quality movies is often high, leading cinemas to raise prices based on performance. In contrast, low-quality movies tend to see price drops due to their relatively poor box office performance, resulting in a strong business-stealing effect. This is further supported by the results in Appendix 5, where the mean price for high-quality movies (>5.5) is slightly higher than for low-quality movies (<5.5), with the maximum price for high-quality movies being 10 units higher than for low-quality movies.

Uniform pricing and price dispersion

In our analysis, the standard deviations of equilibrium price without bounded rationality, whether or not a price floor is present, are quite small, highlighted in red in Table 5.2. Upon further investigation, we found that the prices for different movies in the same cinema on the same day are identical, which is a form of uniform pricing practice. Therefore, our analysis can also be treated as a comparison between uniform pricing and price dispersion caused by bounded rationality. Our research shows that, without external forces, cinemas have clear profit incentives to deviate from this near-uniform price equilibrium. We present the changes in profit, consumer surplus, and incentives when cinemas do not adhere to this uniform pricing and instead apply bounded rationality pricing, both with and without a price floor. This sheds light on the long-standing debate about uniform pricing for differentiated goods.

7. Conclusion and implications

This paper evaluates the impact of a collusive price floor between producers and exhibitors in the Chinese movie market using a structural model. We analyze how the price floor affects pricing, box office revenue, social welfare, and market competitiveness while considering boundedly rational price-setting behaviors. We further extend the analysis of price-setting behaviors in absence of price floor.

We first identify the shape of demand and estimate three key effects of new movie releases: market expansion (65.1% of consumers drawn from other leisure activities), business stealing (27.6% from other cinemas), and

cannibalization (7.3% from other movies within the same cinema). These effects significantly influence the impacts of the price floor and different pricing strategies on profits and consumer surplus.

On the supply side, we reveal that cinemas employ two behavioral strategies beyond the Nash-Bertrand equilibrium under price floor: cinema-specific add-on pricing out of manager's overconfidence and weighting based on expected box office performance. By setting the minimum bound out of these three factors, we extend the traditional Bertrand-Nash model to achieve a better fit.

Our counterfactual analysis indicates that the price floor raises the average ticket price by 26 CNY, resulting in significant losses of 72.78% in consumer surplus and 55.85% in total social welfare. Conversely, the price floor boosts overall industry profits by 82.89%, creating a shared profit incentive to keep prices above the floor. While exhibitors with heterogenous advantages, such as Wanda and Jin Yi, experience tremendous profit gains, those with market disadvantages, like Dadi, would see reduced profits at equilibrium prices and have strong profit incentive to adjust prices rather than strictly following the Nash equilibrium.

In examining alternative pricing strategies, we find that the combination of add-on pricing and performance-based pricing may be a factor in maintaining this delicate collusive price floor. For market-advantaged cinemas, performance-driven market expansion offsets potential profit losses from the business-stealing effects of add-on pricing. Conversely, for disadvantaged cinemas like Dadi, lower prices help to attract additional customers.

Furthermore, we discovered that when cinemas exert add-on pricing only, Dadi cinemas with market disadvantages benefits from the price increases by overconfidence of cinemas with market advantages. However, price hikes by overconfident cinemas harm the overall industry profit, shrinking the total market size. Consumer surplus drop by 60.85%. In contrast, adjusting prices based solely on performance weighting, leads to increases in both profit and consumer surplus compared to the price floor alone. While consumer surplus rises only modestly by 1.32%, it at least does not deteriorate, marking an important finding.

Our findings highlight that collusive price floors should be regulated, as substantial profit gains often come at the expense of a significant reduction in consumer surplus. However, such regulation may be challenging, considering the regulator's role in this game. Here, we identify a second-best alternative to improve social welfare when price floor exists: by avoiding add-on pricing and focusing purely on performance weighting, a Pareto improvement may be achievable. Yet, this requires a higher degree of collusion, with inter-cinema transactions, as cinemas with lower performance, like Dadi, may have a strong incentive to deviate from this equilibrium.

Our analysis compares uniform pricing with price dispersion resulting from bounded rationality, providing insights into the long-standing debate on pricing strategies for differentiated goods. The findings emphasize the complex interplay between regulatory measures and pricing behaviors, revealing significant implications for market dynamics and policy in the Chinese cinema industry.

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Tables

Table 2.1 Total number of produced and unreleased movies during 2002–2015

	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
No. of local movies (produced)[26]	558	621	689	893	824	758	888	992	1,018	1,139	1,087
No. of local movies (released)			158	227	247	256	296	381	355	393	412
No. of local movies (unreleased)			531	666	577	502	592	611	663	746	675
Unreleased rate of local movies			77%	75%	70%	66%	67%	62%	65%	65%	62%
No. of imported movies (released)-revenue sharing			34	34	34	34	34	39	39	39	39
No. of imported movies (released)-one time buyout			36	41	25	33	28	51	70	83	83
No. of total movies (released)			228	303	305	323	358	471	464	515	534
No. of registered producers[27]			1,335	1,677	1,982	4,377	8,212	15,362	18,428	21,724	25,570
No. of cinema chain	37	37	39	40	42	45	46	48	48	48	50

Table 2.2 China's top ten cinema chains[28]

Rank	Cinema chain	Number of showings (million)	Number of viewers (million)	Box office revenue (USD million)	Market share[29]
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%

[26] The Data from National Bureau of Statistics of China: http://www.stats.gov.cn/.
[27] The data from QCC https://www.qcc.com/, a database including detailed information registered in China.
[28] Data source: *China Film News 2013*, Vol. 1222, p. 25.
[29] Market share is defined by the share of the revenue.

Table 2.3 Summary statistics[30]

		Mean	Median	Std. Dev.	Min	Max	Skewness
Movie characteristics							
Price (RMB)		44.425	40	18.228	15	200	2.16
Screen allocation (Daily)		7.226	6	5.647	1	52	1.577
Seat allocation (Daily)		1258.828	819	1272.501	22	13671	2.008
Rate of seat occupation		0.189	0.091	0.247	0	1	1.995
Length of run (Day)		24.818	26	9.047	1	50	0.035
Cast appeal (Baidu Index)		17334.07	5861	31392.1	10	148280	2.995
Review (Douban score)		6.368	6.4	1.384	2.2	8.9	-0.678
Cinema characteristics							
No. of screens per cinema		8.477	9	2.506	4	15	0.685
No. of seats per cinema		1419.536	1371	540.956	350	2400	0.164
No. of seats per screen		169.594	155	73.439	22	648	1.119
time-varying dummy variables							
School holiday	Not school holiday*	0.791	1	0.407	0	1	-1.431
	School holiday	0.209	0	0.407	0	1	1.431
Seasonality	Autumn	0.206	0	0.404	0	1	1.456
	Spring	0.403	0	0.49	0	1	0.397
	Summer	0.202	0	0.402	0	1	1.481
	Winter*	0.189	0	0.392	0	1	1.588
Public holiday	Holiday	0.085	0	0.279	0	1	2.975
	Weekday	0.657	1	0.475	0	1	-0.66
	Weekend*	0.258	0	0.438	0	1	1.105

Table 2.4 Variation of price by cinema and cinema chain

Cinema chain	Cinema	Obs.	Median	Mean	Std.Dev.
Da Di	Huan Feng Shang Ye	8126	30	29.22	4.19
	Hankou Yan Jiang Yi Hao	212	25	26.56	3.70
	Jiangxia Yijia Gouwu Guangchang	8714	25	27.72	3.85
	Xiang Long Shi Dai	8849	25	26.72	3.12
	Wuhan Xinshijie	5795	25	27.09	3.34
UA	Huanyi Xinmingzhong	3401	30	37.86	10.73
	Jin Yi Nanhu	2716	53	50.23	5.54
	Jin Yi Wang Jia Wan	3074	38	45.20	7.64
	Jin Yi Wu Jia Shan	2499	46	42.47	4.09
Jin Yi	Jin Yi Wu Sheng Lu	3207	43	47.83	5.02
	Jin Yi Xiao Pin Mao	4204	43	48.93	10.76
	Jin Yi Yang Cha Hu	3211	43	45.56	2.69
	Jin Yi Zhong Nan	3714	38	41.67	4.07
Wanda	Jianghanlu Wanda	23378	40	46.73	14.87
	Hanjie Wanda	13500	50	56.51	25.44
	Jing Kai Wanda	21104	40	51.93	20.99
	Leng Jiao Hu Wanda	21830	40	53.24	22.24
	Wanda Chun Shu Li	20140	40	42.12	15.19
	Wanda Hanyang Hanshang	23191	40	49.31	18.72
Zhong Ying	Zhong Ying Wuhan Donggou	13526	35	35.63	1.71

[30] Number of observations is 194,391 for all variables.

Table 2.5 Price relatives

Simple Hedonic price model	
lndailyprice	
cinema fixed	**
movie characteristics	
Week of run	
regions	**
Douban	**
Day charactersistics	
Day of week	**
School holiday	**
month	**
R2	0.61
N	28,316
* p<0.05; ** p<0.01	

Table 4.1 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 4.2 Estimation result[31]

	(1)Daily	(2)Daily	(3)Daily	(4)Weekly	(5)OLS
Price	-0.097***	-0.097***	-0.097***	-0.097***	0.001***
	(-2.895)	(-2.895)	(-2.895)	(-2.896)	(3.430)
Nesting structure					
$1-\pi_m\pi_j$ (bottom level)	0.542***	0.542***	0.542***	0.542***	0.924***
	(10.477)	(10.478)	(10.477)	(10.437)	(366.186)
$1-\pi_m$ (upper level)	0.359**	0.359**	0.359**	0.359**	0.893***
	(2.399)	(2.399)	(2.399)	(2.395)	(205.947)
Movie variables					
Allocation of screens	0.036***	0.036***	0.036***	0.036***	0.010***
	(4.492)	(4.492)	(4.492)	(4.474)	(13.678)
Week of run	-0.092***	-0.092***	-0.092***	-0.093***	-0.080***
	(-3.057)	(-3.057)	(-3.057)	(-3.061)	(-23.956)
Demographics					
Pop [0, community]	-0.000		0.000***	-0.000	0.000***
	(-0.375)		(2.769)	(-0.365)	(5.617)
Pop (community, suburb]	-0.000***		0.000*	-0.000***	0.000
	(-2.853)		(1.811)	(-2.844)	(1.187)
No. of rival cinemas [0, community]	-0.001***	0.003***		-0.001***	-0.000***
	(-2.925)	(6.772)		(-2.915)	(-4.374)
No. of rival cinemas (community, suburb]	-0.000***	0.001***		-0.000***	0.000
	(-3.704)	(6.382)		(-3.694)	(0.026)
Day and date variables					
Autumn	0.059	0.059	0.059	0.060	-0.073***
	(0.508)	(0.508)	(0.508)	(0.511)	(-2.891)
Spring	0.379***	0.379***	0.379***	0.384***	0.255***
	(4.604)	(4.604)	(4.604)	(4.653)	(12.681)
Summer	0.280***	0.280***	0.280***	0.282***	0.087***
	(2.997)	(2.997)	(2.997)	(3.016)	(3.612)
Weekday	-0.871***	-0.871***	-0.871***	-0.873***	-0.759***
	(-13.855)	(-13.856)	(-13.855)	(-13.839)	(-84.856)
Weekend	-0.242***	-0.242***	-0.242***	-0.244***	-0.230***
	(-5.378)	(-5.379)	(-5.378)	(-5.399)	(-23.709)
School holiday	0.525***	0.525***	0.525***	0.529***	0.189***
	(6.170)	(6.170)	(6.170)	(6.194)	(17.312)
Length of run					
Two weeks	-0.598**	-0.598**	-0.598**	-0.600**	-1.473***
	(-2.255)	(-2.255)	(-2.255)	(-2.257)	(-10.032)
Three weeks	-0.710***	-0.710***	-0.710***	-0.711***	-0.847***
	(-2.752)	(-2.753)	(-2.752)	(-2.750)	(-10.921)
Four weeks	0.228	0.228	0.228	0.227	-0.542***
	(1.133)	(1.133)	(1.133)	(1.126)	(-11.405)
Five weeks	-0.749***	-0.749***	-0.749***	-0.751***	-0.568***
	(-3.276)	(-3.276)	(-3.276)	(-3.278)	(-10.225)
Six weeks	-0.525***	-0.525***	-0.525***	-0.528***	-0.004
	(-4.037)	(-4.037)	(-4.037)	(-4.043)	(-0.122)
Seven weeks	0.018	0.018	0.018	0.019	-
	(0.099)	(0.099)	(0.099)	(0.109)	
movie fixed effect	Y	Y	Y	Y	Y
cinema fixed effect	Y	Y	Y	Y	Y
Constant	-1.783	-12.872***	-12.787***	-6.473***	-1.774
	(-0.669)	(-8.901)	(-5.135)	(-148.418)	(-0.664)
Observations	28,316	28,316	28,316	28,316	28,316
R-squared	0.580	0.580	0.580	0.957	0.578
r2_a	0.574	0.574	0.574	0.957	0.572

Robust z-statistics in parentheses

[31] We 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, we use higher decimal places for these four parameters.

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

Table 4.3 Own-price elasticities

Cinema chain/Cinema	Median	Mean	Std. Dev
Dadi (Chain)			
Huan Feng Shang Ye	-3.705	-3.747	0.596
Hankou Yan Jiang Yi Hao	-3.924	-3.305	0.476
Jiangxia Yijia Gouwu Guangchang	-3.558	-3.613	0.551
Xiang Long Shi Dai	-3.482	-3.452	0.486
Wuhan Xin Shi Jie	-3.519	-3.502	0.539
UA (Chain)			
Huanyi Xinmingzhong	-4.305	-4.659	1.163
JinYi (Chain)			
JinYi Nanhu	-6.556	-6.608	1.066
JinYi Wang Jia Wan	-5.559	-6.030	1.317
JinYi Wu Jia Shan	-5.483	-5.475	0.911
JinYi WuShengLu	-6.286	-6.368	1.006
JinYi Xiao Pin Mao	-6.065	-6.492	1.428
JinYi Yang Cha Hu	-6.157	-6.037	0.758
JinYi Zhong Nan	-5.526	-5.581	0.763
Wanda (Chain)			
Jianghanlu Wanda	-5.627	-5.928	1.994
Hanjie Wanda	-6.534	-8.022	3.910
Jing Kai Wanda	-5.843	-7.148	3.173
Leng Jiao Hu Wanda	-5.843	-7.193	3.369
Wanda Chun Shu Li	-5.352	-5.619	2.116
Wanda Hanyang Hanshang	-5.788	-6.940	2.980
Zhong Ying (Chain)			
Zhong Ying Wuhan Donggou	-4.851	-4.693	0.538

Table 4.4 Cross-price elasticities of movies within same cinema

Cinema chain/Cinema	Median	Mean	Std. Dev
Dadi (Chain)			
Huan Feng Shang Ye	0.449	0.492	0.199
Hankou Yan Jiang Yi Hao	0.512	0.556	0.245
Jiangxia Yijia Gouwu Guangchang	0.349	0.365	0.145
Xiang Long Shi Dai	0.383	0.409	0.173
Wuhan Xin Shi Jie	0.365	0.385	0.162
UA (Chain)			
Huanyi Xinmingzhong	0.666	0.765	0.445
JinYi (Chain)			
JinYi Nanhu	0.699	0.729	0.305
JinYi Wang Jia Wan	0.602	0.599	0.213
JinYi Wu Jia Shan	0.647	0.684	0.337
JinYi WuShengLu	0.556	0.566	0.205
JinYi Xiao Pin Mao	0.567	0.582	0.264
JinYi Yang Cha Hu	0.581	0.596	0.203
JinYi Zhong Nan	0.477	0.488	0.171
Wanda (Chain)			
Jianghanlu Wanda	0.762	0.860	0.388
Hanjie Wanda	0.653	0.709	0.325
Jing Kai Wanda	0.628	0.690	0.311
Leng Jiao Hu Wanda	0.767	0.850	0.392
Wanda Chun Shu Li	0.484	0.555	0.270
Wanda Hanyang Hanshang	0.559	0.612	0.245
Zhong Ying (Chain)			
Zhong Ying Wuhan Donggou	0.460	0.491	0.199

Table 4.5 Cross-price elasticities of movies shown in different cinemas

Cinema chain/Cinema	Median	Mean	Std. Dev
Dadi (Chain)			
Hankou Yan Jiang Yi Hao	0.257	0.255	0.646
Jiangxia Yijia Gouwu Guangchang	0.258	0.299	1.220
Xiang long Shi Dai	0.137	0.255	0.770
Wuhan Xin Shi Jie	0.083	0.113	0.100
UA (Chain)			
Huanyi Xinmingzhong	0.124	0.149	0.437
JinYi (Chain)			
JinYi Nanhu	0.033	0.036	0.017
JinYi Wang Jia Wan	0.029	0.031	0.013
JinYi Wu Jia Shan	0.025	0.027	0.010
JinYi WuShengLu	0.024	0.025	0.009
JinYi Xiao Pin Mao	0.021	0.021	0.007
JinYi Yang Cha Hu	0.018	0.019	0.006
JinYi Zhong Nan	0.017	0.017	0.006
Wanda (Chain)			
Jianghanlu Wanda	0.039	0.052	0.075
Hanjie Wanda	0.060	0.075	0.156
Jing Kai Wanda	0.030	0.037	0.025
Leng Jiao Hu Wanda	0.020	0.025	0.015
Wanda Chun Shu Li	0.021	0.025	0.014
Wanda Hanyang Hanshang	0.017	0.021	0.012
Zhong Ying (Chain)			
Zhong Ying Wuhan Donggou	0.015	0.019	0.011

Table 4.6 Number of released movies by reviews groups

	Number of movies			
Douban rating	USA	Mainland	Others	Total
(0, 5.5]	6	145	14	165
(5.5, 7]	22	44	25	91
(7, 8.5]	26	13	12	51
(8.5, 10]	1	0	0	1
Total	55	202	51	308

Table 4.7 Heterogeneity in regions and quality

	(1) USA	(2) Local	(3) Douban>5.5	(4) Douban<5.5
Price	-0.026	-0.060***	-0.086***	0.092
	(-1.055)	(-2.893)	(-3.331)	(1.246)
Nesting structure				
$1-\pi_m\pi_j$	0.640***	0.540***	0.547***	0.555***
	(13.781)	(8.727)	(11.030)	(5.280)
$1-\pi_m$	0.503**	0.099	0.376**	-0.243
	(2.076)	(0.649)	(2.474)	(-0.785)
Movie variables				
Allocation of screens	0.040***	0.042***	0.031***	0.101***
	(3.092)	(5.559)	(4.061)	(3.498)
Week of run	-0.141***	-0.108***	-0.107***	-0.257***
	(-9.225)	(-3.044)	(-4.115)	(-3.929)
Demographics				
Pop [0, community]	-0.000	0.000	-0.000	-0.000
	(-0.124)	(1.195)	(-1.138)	(-0.131)
Pop (community, suburb]	-0.000	-0.000**	-0.000***	-0.000
	(-0.976)	(-2.097)	(-3.261)	(-0.691)
No. of rival cinemas [0, community]	-0.000	-0.000**	-0.001***	-0.000
	(-0.859)	(-2.433)	(-3.229)	(-0.844)
No. of rival cinemas (community, suburb]	-0.000	-0.000***	-0.000***	-0.000*
	(-0.915)	(-4.001)	(-3.673)	(-1.661)
Day and date variables				
Autumn	-0.059	-0.220	0.053	0.060
	(-0.462)	(-1.418)	(0.431)	(0.234)
Spring	-0.121	0.380***	0.370***	0.382**
	(-0.621)	(5.763)	(4.432)	(2.146)
Summer	-0.091	0.235**	0.227**	0.099
	(-0.592)	(2.326)	(2.383)	(0.324)
Weekday	-0.970***	-0.748***	-0.877***	-0.402**
	(-13.508)	(-14.668)	(-16.125)	(-2.227)
Weekend	-0.340***	-0.201***	-0.217***	-0.062
	(-8.217)	(-4.192)	(-4.750)	(-0.457)
School holiday	0.217***	0.629***	0.536***	0.046
	(5.424)	(7.248)	(7.329)	(0.261)
Length of run				
Two weeks	-0.948***	-0.414*	-0.601	-0.190
	(-7.562)	(-1.829)	(-0.413)	(-0.384)
Three weeks	-0.910***	-0.706***	-0.820***	0.961
	(-5.708)	(-3.664)	(-3.769)	(0.840)
Four weeks	-0.289**	-0.344**	0.180	0.920
	(-2.052)	(-2.322)	(1.027)	(1.014)
Five weeks	-0.371***	0.474**	-0.826***	-
	(-4.405)	(1.972)	(-3.729)	
Six weeks	0.171	-	-0.452***	-
	(0.619)		(-3.910)	
Seven weeks	-0.083	-	-0.040	-
	(-0.530)		(-0.278)	
movie fixed effect	Y	Y	Y	Y
cinema fixed effect	Y	Y	Y	Y
Constant	-4.793	-6.308***	-0.793	-12.829***
	(-1.405)	(-3.305)	(-0.310)	(-2.758)
Observations	6,571	8,596	12,947	4,454
R-squared	0.912	0.749	0.658	0.422
r2_adjusted	0.911	0.745	0.654	0.408

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.8 Observed price and simulation price

	Price floor = 20	
	(1)	(2) P_sim
Price	observed	(PF20+cid)*w
median	40.00	38.07
mean	41.31	41.64
Min	15.00	18.15
Max	150.00	172.85
std.dev	15.03	16.28
skewness	2.19	2.37
kurtosis	11.17	11.83
Revenue		
median	3526.34	2474.76
mean	11709.48	11421.72
Min	19.99	18.23
Max	366056.30	354237.10
std.dev	22289.52	25485.79
skewness	4.68	5.06
kurtosis	36.05	37.82

Table 5.1 Overview of simulation results

	Price floor of 20 (pf^{20})				No price floor (pf^{0})		
	(1)	(2)	(3)	(4) P_sim	(5)	(6)	(7)
Price	pf^{20}	$pf^{20} + a_m$	$pf^{20} * w_{j,t}$	$(pf^{20} + a_m) * w_{j,t}$	No bound	$pf^{0} + a_m$	$(pf^{0} + a_m) * w_{j,t}$
median	33.36	46.50	31.56	38.07	6.72	7.61	7.65
mean	33.08	42.32	33.13	41.64	8.23	11.70	9.57
Min	24.30	24.26	13.98	18.15	6.63	6.63	6.63
Max	40.00	55.42	109.96	172.85	20.00	40.00	48.38
std.dev	1.45	9.87	9.57	16.28	2.88	8.50	4.10
skewness	0.13	-0.48	2.11	2.37	2.04	2.21	2.11
kurtosis	9.56	1.78	11.54	11.83	6.34	6.61	9.92
Revenue							
median	865.67	804.81	2795.51	2474.76	1674.56	1343.00	2807.25
mean	11437.41	9720.50	19475.92	11421.72	6146.19	7043.45	8667.54
Min	0.08	0.05	0.48	18.23	0.01	0.02	0.26
Max	446762.50	432621.40	487547.60	354237.10	103211.40	143868.10	205452.60
std.dev	30060.20	30944.52	41519.81	25485.79	9995.26	12819.78	13868.30
skewness	4.35	5.83	3.93	5.06	2.67	3.07	2.99
kurtosis	26.06	45.71	23.71	37.82	12.06	15.01	16.32

Table 5.2 Comparison of Price and Profit Between a Price Floor of 20 and No Price Floor[32]

Price		(1) Nobound vs pf^{20}		(2)pf^{20} vs $pf^{20}+a_m$		(3) Nobound vs $pf^{20}+a_m$	
Cinema chain	Cinema	Median	Mean	Median	Mean	Median	Mean
Dadi	Hankou Yan Jiang Yi Hao	26.69	26.67	-7.15	-7.17	19.54	19.50
	Jiangxia Yijia Gouwu Guangchang	26.74	26.74	-5.98	-5.99	20.76	20.75
	Xiang Long Shi Dai	26.74	26.73	-6.70	-6.71	20.04	20.02
	Wuhan Xinshijie	26.74	26.72	-6.74	-6.75	20.00	19.97
UA	Huanyi Xinmingzhong	26.62	25.55	4.20	4.22	30.82	29.78
Jin Yi	Jin Yi Nanhu	26.70	26.65	16.97	16.98	43.67	43.63
	Jin Yi Wang Jia Wan	26.71	26.69	11.87	11.86	38.58	38.54
	Jin Yi Wu Jia Shan	26.73	26.72	8.78	8.78	35.51	35.50
	Jin Yi Wu Sheng Lu	26.72	26.70	14.11	14.11	40.83	40.82
	Jin Yi Xiao Pin Mao	26.61	26.15	16.13	16.15	42.74	42.31
	Jin Yi Zhong Nan	26.73	26.71	8.23	8.21	34.95	34.93
Wanda	Jianghanlu Wanda	26.56	25.98	14.09	13.95	40.65	39.93
	Jing Kai Wanda	25.66	24.74	19.29	19.30	44.94	44.04
	Leng Jiao Hu Wanda	22.00	21.46	23.30	22.86	45.31	44.32
	Wanda Chun Shu Li	26.73	26.70	3.92	3.87	30.65	30.57
	Wanda Hanyang Hanshang	26.64	25.94	14.29	14.14	40.93	40.09
Zhong Ying	Zhong Ying Wuhan Donggou	20.00	19.99	0.00	0.00	20.00	20.00
Revenue							
Dadi	Hankou Yan Jiang Yi Hao	-259.87	-705.14	358.53	648.60	98.66	-56.54
	Jiangxia Yijia Gouwu Guangchang	-104.19	-274.82	260.26	706.33	156.07	431.51
	Xiang Long Shi Dai	-80.55	-195.66	228.48	541.37	147.93	345.71
	Wuhan Xinshijie	-50.90	-130.37	144.18	384.71	93.29	254.34
UA	Huanyi Xinmingzhong	-797.38	11311.19	186.64	5603.49	-610.74	16914.68
Jin Yi	Jin Yi Nanhu	-11.56	7088.84	-2275.84	-6801.07	-2287.41	287.78
	Jin Yi Wang Jia Wan	-1297.14	3732.90	-258.92	-2463.01	-1556.06	1269.88
	Jin Yi Wu Jia Shan	-1075.24	31.20	44.90	-191.62	-1030.34	-160.42
	Jin Yi Wu Sheng Lu	-604.48	2686.81	-633.67	-2768.78	-1238.15	-81.97
	Jin Yi Xiao Pin Mao	-1283.67	11627.32	-769.05	-1071.51	-2052.72	10555.81
	Jin Yi Zhong Nan	-1022.97	-410.94	70.36	-3143.96	-952.61	-3554.90
Wanda	Jianghanlu Wanda	-2955.90	13558.20	-2606.88	-3619.89	-5562.78	9938.31
	Jing Kai Wanda	-1308.27	7039.78	-1383.83	-4394.96	-2692.10	2644.82
	Leng Jiao Hu Wanda	-122.37	10754.89	-2622.95	-5804.64	-2745.32	4950.25
	Wanda Chun Shu Li	-831.10	2023.20	478.48	3499.59	-352.62	5522.79
	Wanda Hanyang Hanshang	-1099.73	3459.09	-694.22	-3990.42	-1793.95	-531.33
Zhong Ying	Zhong Ying Wuhan Donggou	-1106.58	-2462.46	1333.52	3032.38	226.94	569.92

Table 5.3 Welfare Change from No-bound to pf^{20}

	Welfare (CNY million)		Welfare Change
	No Bound	pf^{20}	Percentage (%)
Box office profit	98.86	180.81	82.89%
Consumer Surplus	817.22	222.45	-72.78%
Total Surplus	916.09	403.26	-55.98%

[32] We provide detailed information about the variation in price and profit for each individual cinema in Appendix 4 (a) and (b). These appendices illustrate the impact of a price floor on each exhibitor in the market, considering their varying levels of market power. For convenience, we only present the results of the comparison across different scenario groups.

Table 6.1 Pricing Strategy Comparisons under Price Floor of 20

Price	pf^{20} vs $pf^{20}+a_m$		pf^{20} vs $pf^{20}*w_{j,t}$		$pf^{20}+a_m$ vs $pf^{20}*w_{j,t}$		$pf^{20}+a_m$ vs $(pf^{20}+a_m)*w_{j,t}$	
	(1)		(2)		(3)		(4)	
Cinema/Chain	Median	Mean	Median	Mean	Median	Mean	Median	Mean
Dadi								
Hankou Yan Jiang Yi Hao	-7.15	-7.17	0.59	-0.00	7.74	7.16	0.14	-0.03
Jiangxia Yijia Gouwu Guangchang	-5.98	-5.99	-3.46	-0.00	2.52	5.99	-2.94	-0.03
Xiang Long Shi Dai	-6.70	-6.71	-2.46	-0.00	4.25	6.71	-2.05	-0.01
Wuhan Xinshijie	-6.74	-6.75	-2.43	0.00	4.32	6.75	-2.02	0.00
UA								
Huanyi Xinmingzhong	4.20	4.22	-5.58	0.09	-9.78	-4.14	-5.93	0.08
Jin Yi								
Jin Yi Nanhu	16.97	16.98	1.92	-0.04	-15.05	-17.02	2.63	-0.02
Jin Yi Wang Jia Wan	11.87	11.86	0.25	-0.02	-11.62	-11.88	0.17	-0.06
Jin Yi Wu Jia Shan	8.78	8.78	0.63	-0.01	-8.15	-8.79	0.71	-0.02
Jin Yi Wu Sheng Lu	14.11	14.11	-0.94	-0.02	-15.05	-14.13	0.49	0.04
Jin Yi Xiao Pin Mao	16.13	16.15	-5.14	0.08	-21.27	-16.07	-7.21	-0.15
Jin Yi Zhong Nan	8.23	8.21	-1.86	-0.01	-10.09	-8.22	-2.24	-0.03
Wanda								
Jianghanlu Wanda	14.09	13.95	-5.25	-0.17	-19.34	-14.12	-7.25	-1.17
Jing Kai Wanda	19.29	19.30	-4.42	0.22	-23.70	-19.08	-8.19	-0.65
Leng Jiao Hu Wanda	23.30	22.86	-3.96	0.35	-27.26	-22.51	-9.39	-0.79
Wanda Chun Shu Li	3.92	3.87	-1.29	-0.00	-5.22	-3.87	-1.54	-0.02
Wanda Hanyang Hanshang	14.29	14.14	-1.32	0.12	-15.61	-14.03	-2.22	-0.74
Zhong Ying								
Zhong Ying Wuhan Donggou	0.00	0.00	0.00	-0.00	0.00	-0.01	0.00	-0.01
Revenue								
Dadi								
Hankou Yan Jiang Yi Hao	358.53	648.60	52.51	-38.97	-306.02	-687.56	122.18	-77.70
Jiangxia Yijia Gouwu Guangchang	260.26	706.33	29.16	29.39	-231.10	-676.94	212.46	199.73
Xiang Long Shi Dai	228.48	541.37	27.32	29.27	-201.16	-512.10	191.38	222.68
Wuhan Xinshijie	144.18	384.71	19.61	14.52	-124.58	-370.19	148.06	154.84
UA								
Huanyi Xinmingzhong	186.64	5603.49	1250.02	-4097.61	1063.38	-9701.10	1994.34	-10780.58
Jin Yi								
Jin Yi Nanhu	-2275.84	-6801.07	3861.44	4872.96	6137.28	11674.03	1841.42	1214.97
Jin Yi Wang Jia Wan	-258.92	-2463.01	1340.63	1546.90	1599.55	4009.91	712.93	185.58
Jin Yi Wu Jia Shan	44.90	-191.62	946.56	1921.54	901.66	2113.16	850.39	1693.13
Jin Yi Wu Sheng Lu	-633.67	-2768.78	1392.34	2082.92	2026.01	4851.70	634.29	699.78
Jin Yi Xiao Pin Mao	-769.05	-1071.51	4398.52	4670.05	5167.57	5741.56	1830.00	-8992.83
Jin Yi Zhong Nan	70.36	-3143.96	1070.87	1037.51	1000.51	4181.47	1112.66	4106.07
Wanda								
Jianghanlu Wanda	-2606.88	-3619.89	14820.56	20308.20	17427.43	23928.09	11546.75	10536.59
Jing Kai Wanda	-1383.83	-4394.96	9382.24	14664.36	10766.07	19059.32	4669.41	2645.20
Leng Jiao Hu Wanda	-2622.95	-5804.64	13654.84	17689.96	16277.79	23494.60	5993.54	3883.29
Wanda Chun Shu Li	478.48	3499.59	942.57	-1912.34	464.09	-5411.93	2021.36	-3514.67
Wanda Hanyang Hanshang	-694.22	-3990.42	4148.41	6504.54	4842.64	10494.96	2444.68	3040.74
Zhong Ying								
Zhong Ying Wuhan Donggou	1333.52	3032.38	501.00	664.12	-832.52	-2368.25	1625.57	2133.80

Table 6.2 Pricing Strategy Comparisons Without a Price Floor

Price		(1) Nobound vs $pf^0 + a_m$		(2) Nobound vs $(pf^0 + a_m) * w_{j,t}$		(3) $pf^0 + a_m$ vs $(pf^0 + a_m) * w_{j,t}$	
Chain	Cinema	Median	Mean	Median	Mean	Median	Mean
Dadi	Hankou Yan Jiang Yi Hao	0.00	0.00	0.00	0.00	0.00	0.00
	Jiangxia Yijia Gouwu Guangchang	0.00	0.00	0.00	0.00	0.00	0.00
	Xiang Long Shi Dai	0.00	0.00	0.00	0.00	0.00	0.00
	Wuhan Xinshijie	0.00	0.00	0.00	0.00	0.00	0.00
UA	Huanyi Xinmingzhong	0.04	0.06	0.16	0.12	0.12	0.06
Jin Yi	Jin Yi Nanhu	3.66	3.62	3.62	3.55	-0.05	-0.07
	Jin Yi Wang Jia Wan	0.01	0.01	0.13	0.25	0.12	0.24
	Jin Yi Wu Jia Shan	0.00	0.00	0.01	0.01	0.01	0.01
	Jin Yi Wu Sheng Lu	0.83	0.81	0.37	1.02	-0.46	0.21
	Jin Yi Xiao Pin Mao	2.73	2.29	0.88	2.53	-1.84	0.24
	Jin Yi Zhong Nan	0.00	0.01	0.01	0.02	0.01	0.01
Wanda	Jianghanlu Wanda	0.69	0.59	0.73	1.03	0.04	0.44
	Jing Kai Wanda	4.76	3.97	2.51	3.32	-2.25	-0.65
	Leng Jiao Hu Wanda	4.86	4.07	2.61	3.51	-2.25	-0.55
	Wanda Chun Shu Li	0.00	0.01	0.01	0.02	0.01	0.02
	Wanda Hanyang Hanshang	0.95	0.80	0.81	1.12	-0.15	0.32
Zhong Ying	Zhong Ying Wuhan Donggou	0.00	-0.00	0.00	-0.03	0.00	-0.03
Revenue							
Dadi	Hankou Yan Jiang Yi Hao	31.30	16.42	138.20	92.02	106.89	75.60
	Jiangxia Yijia Gouwu Guangchang	20.36	68.50	94.47	221.50	74.11	153.01
	Xiang Long Shi Dai	18.88	52.12	81.21	157.39	62.34	105.27
	Wuhan Xinshijie	12.69	34.73	51.12	116.01	38.42	81.28
UA	Huanyi Xinmingzhong	168.12	192.17	452.71	503.84	284.59	311.67
Jin Yi	Jin Yi Nanhu	656.30	2712.28	1705.79	3840.25	1049.48	1127.98
	Jin Yi Wang Jia Wan	382.10	210.57	1237.20	1069.46	855.11	858.89
	Jin Yi Wu Jia Shan	42.48	137.65	595.28	502.89	552.80	365.24
	Jin Yi Wu Sheng Lu	233.44	426.48	693.83	1109.13	460.39	682.65
	Jin Yi Xiao Pin Mao	216.91	1622.17	2071.36	4565.90	1854.45	2943.72
	Jin Yi Zhong Nan	110.40	169.60	712.44	656.01	602.04	486.41
Wanda	Jianghanlu Wanda	760.69	1036.54	1619.10	2217.93	858.42	1181.39
	Jing Kai Wanda	401.31	2948.15	2499.29	4846.17	2097.98	1898.02
	Leng Jiao Hu Wanda	702.56	3833.91	3503.77	6263.10	2801.21	2429.19
	Wanda Chun Shu Li	188.95	179.23	641.65	761.71	452.70	582.48
	Wanda Hanyang Hanshang	332.85	775.48	1516.15	1930.61	1183.30	1155.13
Zhong Ying	Zhong Ying Wuhan Donggou	226.54	676.64	1078.90	1758.92	852.36	1082.28

Table 6.3 Welfare Change for Different Price-setting Behaviors under Price Floor Scenario

	Social Welfare (CNY million)				Welfare Change (compare to pf^{20})		
	pf^{20}	$pf^{20}+a_m$	$pf^{20}*w_{j,t}$	$(pf^{20}+a_m)*w_{j,t}$	$pf^{20}+a_m$	$pf^{20}*w_{j,t}$	$(pf^{20}+a_m)*w_{j,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Box Office Profit	180.81	145.12	284.15	209.06	-19.74%	57.15%	15.62%
Consumer Surplus	222.45	87.08	225.39	68.46	-60.85%	1.32%	-69.23%
Total Surplus	403.26	232.20	509.53	277.52	-42.42%	26.35%	-31.18%

Table 6.4 Welfare Change for Different Price-setting Behaviors without Price Floor

	Social Welfare (CNY million)			Welfare Change (compare to No-bound)	
	No-bound	pf^0+a_m	$(pf^0+a_m)*w_{j,t}$	pf^0+a_m	$(pf^0+a_m)*w_{j,t}$
	(1)	(2)	(3)	(4)	(5)
Box Office Profit	98.86	121.11	139.19	40.79%	22.50%
Consumer Surplus	817.22	746.57	598.80	-26.73%	-8.65%
Total Surplus	916.09	867.67	737.99	-19.44%	-5.28%

Table 6.5 Comparison of profit changes across Douban score groups[33]

Comparison Groups	Douban score					
	[0, 3.5]	(3.5, 4.5]	(4.5, 5.5]	(5.5, 6.5]	(6.5, 7.5]	(7.5, 10]
pf^{20} vs No bound	32.8%	46.9%	29.9%	81.3%	111.3%	136.8%
$pf^{20}+a_m$ vs pf^{20}	-5.7%	-9.5%	-33.6%	-23.9%	-12.6%	-20.3%
$pf^{20}*w_{j,t}$ vs pf^{20}	183.4%	299.8%	153.8%	84.1%	71.0%	33.7%
$(pf^{20}+a_m)*w_{j,t}$ vs pf^{20}	84.6%	133.2%	97.9%	20.3%	-0.3%	-7.3%

[33] Appendix 5 presents the detailed information of simulated prices and profits for each quality group (categorized by Douban scores) across different price-setting behaviors. After pairwise comparisons of profit, we obtained Table 6.5.

Figures

Figure 1 Descriptive statistics—Zhong Ying

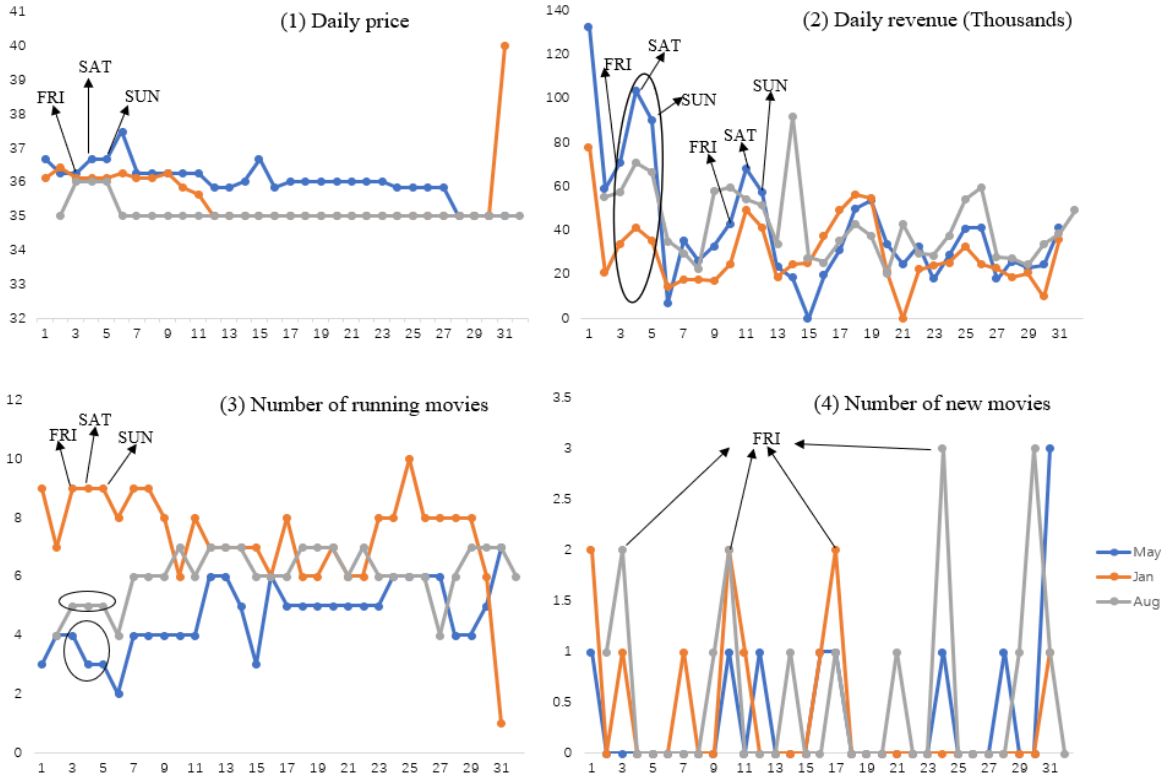


Figure 2 Descriptive statistics—Lengjiahu Wanda

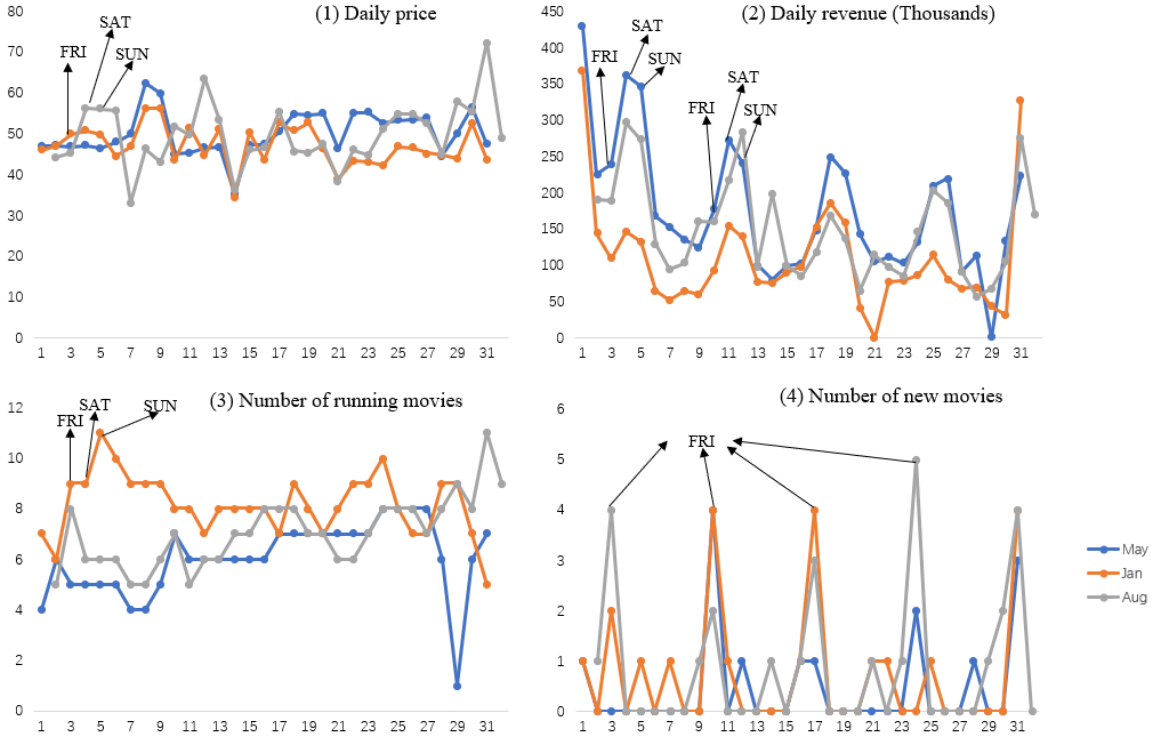


Figure 3 Descriptive statistics—Huanfengshan Da Di

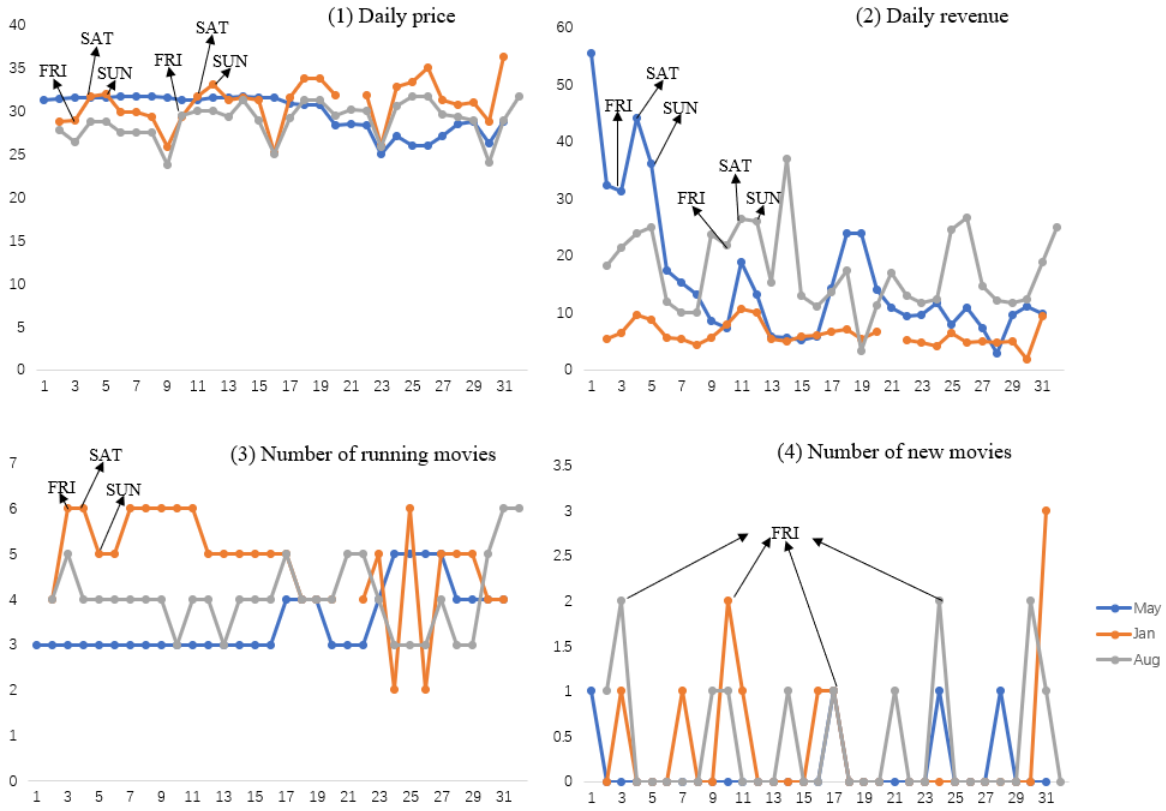


figure 4 simulation price vs observed price

