Heterogeneity in Vertical Foreclosure: Evidence from the Chinese Film Industry*

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Abstract

How do vertically integrated firms' pricing and product provision decisions change with upstream and downstream competition? We answer this question in the context of the Chinese film industry, where vertical integration is pervasive. Weekly variation in the set of available films generates changes in the vertical structure of local markets. We exploit this variation to measure the effect of vertical integration on prices and showings, finding that theaters allocate significantly more showings to vertically integrated films. This effect is particularly pronounced in two scenarios: when an integrated theater faces limited spatial competition in the downstream retail sector, allowing it to divert demand to its own films; and when an integrated film is similar to competing independent films, making foreclosure profitable. We then estimate a model of demand and supply that accounts for potential direct effects of integration on consumer utility. Preliminary results suggest that our findings are driven by theaters internalizing the upstream revenue share for integrated films.

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1. Introduction

The potential effects of vertical integration on consumer welfare have long been a source of debate in antitrust circles. Legal commentators often point to the reduction in double marginalization as the first-order effect of vertical mergers, and argue that the efficiencies generated by vertical integration largely outweigh the potential harms. However, recent empirical work has pushed back against this consensus, emphasizing the negative effects of vertical foreclosure on consumer welfare (see Beck and Scott Morton (2021) for a summary).

This debate has come into sharper focus since the recent update and subsequent withdrawal for revision of the Vertical Merger Guidelines. Compared to the 1984 Non-Horizontal Merger Guidelines, the 2020 draft guidelines recognize the competitive harm from full foreclosure (denying rivals' access to inputs or consumers) and partial foreclosure (raising rivals' costs), emphasizing the importance of market structure in determining a firm's *ability* and *incentive* to foreclosing rivals (Ross and Winter, 2021; Shapiro, 2021). In particular, the guidelines recognize that the potential for a vertically integrated firm to foreclose rivals depends on the horizontal market structure in both the upstream and downstream markets.

Although there is growing recognition that the potential harms of vertical foreclosure should be taken seriously in antitrust analysis, empirical evidence on when and where vertical integration is harmful to consumers continues to be in short supply. Much of the empirical work evaluating the welfare effects of vertical integration focuses on ex-post analyses of one or several vertical mergers (e.g., Koch et al., 2017) or structural analyses of specific markets (e.g., Cuesta et al., 2019). The findings of these studies are mixed, suggesting that the welfare effects of vertical integration are highly context-dependent. In particular, there is limited systematic empirical evidence of how vertical foreclosure varies with downstream and upstream market structures within an industry.

In this paper, we document the heterogeneity in the effects of vertical integration on downstream pricing and product provision decisions using data from the Chinese film industry. We focus on how the magnitude of *customer foreclosure* varies with market structure. In the context of the film industry, this occurs when a theater (the downstream firm) that is vertically integrated with a producer or distributor has an incentive to divert consumers away from films produced by upstream rivals and towards vertically integrated films. This can be achieved through pricing and showings decisions – for instance, by raising the price or reducing the showings of non-integrated films.[1] This distortion does not necessarily reduce welfare: Just

[1] This form of foreclosure, termed the *Edgeworth-Salinger* effect, and has been documented by Luco and

as theaters face an incentive to raise the price or reduce the showings of non-integrated films, they may lower the price or increase showings for integrated films. The net effect of this distortion combined with the elimination of double marginalization has an ambiguous effect on consumer welfare.

Following the language of the draft vertical merger guidelines, we characterize the magnitude of these foreclosure effects as depending on the firm's *ability* and *incentive* to foreclose, which we think of conceptualize as expressions of upstream and downstream market power. A downstream firm's ability to foreclose is the extent to which its pricing and product availability choices can reduce upstream rivals' product market shares. The ability to foreclose depends on downstream market power. For instance, monopoly retailers have the ability to foreclose upstream rivals by choosing not to stock non-integrated products, whereas retailers in perfect competition do not. A firm's incentive to foreclose refers to the profitability of foreclosing rivals. Customer foreclosure of upstream rivals is profitable when rival products are close substitutes.

The Chinese film industry differs from the U.S. film industry in several key respects that make it well-suited for quantifying the effects of vertical integration that are of concern to regulators.[2] First, vertical integration between downstream exhibitors and upstream distributors and producers is common but not universal, with significant variation in vertical structure across local markets. Second, vertical contracts are standardized across the industry, with all films using the same revenue-sharing scheme to divide box office receipts between downstream and upstream firms. Third, the distribution of films is centrally coordinated by an industry association. Each film is released in all cinema chains on the same nationwide release date, and the window during which a film is available for exhibition is the same for all downstream cinemas.

In this setting, theaters make pricing and showings decisions given the set of films available each week. We argue that variation in the set of available films allows us to measure the effect of vertical integration on equilibrium pricing and showings decisions. Unlike in retrospective vertical merger analyses, in our setting ownership is relatively fixed over time, but the set of available products changes. In particular, the national release schedule generates variation in

Marshall (2020) in the soft drinks industry.

[2] In United States v. Paramount Pictures (1948), the U.S. Supreme Court ordered Hollywood film studios to divest from their film theater operations due to concerns about customer foreclosure. The issue of integration of content production and exhibition companies has come under renewed scrutiny in recent years, as online platforms such as Netflix and Amazon have begun to produce films. In 2020, The Department of Justice suspended the "Paramount Decree," citing the increased competition from online platformswhich has weakened the potential foreclosure ability of cinemas.

the vertical structure of each market such that a theater may be vertically integrated with one of the available films in week t and not integrated with any of the available films in week $t + 1$. Interacting this variation in vertical integration with cross-market differences in the competitive environment allows us to examine the heterogeneity of the effects of vertical integration by upstream and downstream market structure.

We combine several data sources to measure these effects. We use theater-film-week level data that records showings, ticket sales, and revenue for the universe of Chinese theaters from 2011 to 2015. To measure the spatial competition between theaters, we geocode the theaters' locations based on a manual search. We complement the data with hand-collected ownership information from the administrative establishment-level registration database. Finally, to measure the similarity between films distributed, we collect consumer-level viewership and review records for 847 films from more than 80,788 users on the largest online film rating website.

Our descriptive results suggest that any measurable vertical foreclosure is likely to come through changes in the allocation of showings to films, rather than through price. There are no significant differences in prices between vertically integrated and non-integrated films. Indeed, there is little residual variation in prices conditional on theater and film-city fixed effects. On the other hand, we find that the number of weekly showings of a given film is 8% to 10% higher in vertically integrated theaters than in non-integrated theaters in the same city-week. Within a theater, vertically integrated films are shown about 4% more than non-integrated films available simultaneously. These results are statistically significant and robust to various alternative specifications.

These average differences in showings mask significant heterogeneity. We examine this heterogeneity along two dimensions. First, we show how the effect of vertical integration on showings varies with downstream competition. We find that the showings differential between integrated and non-integrated films is significantly decreasing in the number of rival theaters and screens within 5 km. This finding is consistent with downstream competition diminishing the theater's *ability* to distort showings allocations.

Next, we examine how the effect of vertical integration varies with upstream market conditions. We construct a measure of films' locations in a latent attribute space using a matrix factorization algorithm applied to consumer review data. Films with correlated reviews are closer together in this latent space. We show that the effect of vertical integration on showings is greatest when there are more close competitors to the vertically integrated film in this latent space. To the extent that review correlation predicts substitution patterns between films, this finding can be explained by theaters having a greater *incentive* to distort showings when the non-integrated film is a close substitute for the integrated film.

These results jointly display patterns consistent with vertically integrated theaters internalizing upstream revenue when making showings decisions and suggest that the magnitude of the customer foreclosure effect depends on upstream and downstream market structure. However, they do not account for the possibility of synergies between theater and film ownership, such as increased promotion at vertically integrated theaters, which could have a direct effect on demand. In other words, it may be that showings for integrated films are higher because demand for these films is higher at vertically integrated theaters.

To account for this possibility, we develop and estimate a model of consumer demand for films that allows a direct effect of integration of consumer utility. The model also allows for flexible substitution across theaters based on distance and across films based on the latent characteristics. This approach to using latent characteristics obtained from auxiliary data to measure substitution patterns is similar to the Magnolfi et al. (2022)'s use of embeddings derived from a consumer survey, Bajari et al. (2021)'s use of embeddings derived from products' images and text descriptions on Amazon.com, and Armona et al. (2021)'s use of Bayesian Personalized Ranking from consumers' web-browsing histories. However, to our knowledge this is the first paper to estimate a demand model using latent characteristics generated from correlations in consumer reviews.

To test for vertical foreclosure, we use the estimated model to compute the marginal revenue of showings for each film-theater-week. As we show theoretically in Section 2, if a theater internalizes upstream revenue for vertically integrated films, the marginal revenue of showings should be lower for integrated films and higher for non-integrated films, when an integrated film is available. We find patterns consistent with this prediction: in markets with limited downstream competition vertically integrated films have 41% lower marginal revenue, and non-integrated films have 9.5% higher marginal revenue when an integrated film is available.

Finally, we estimate a supply model in which firms choose showings optimally given an internalization parameter which measures how much weight they place on upstream revenue for integrated films. Across multiple specifications, we find bounds on this internalization parameter that are greater than the downstream revenue share and cover 1, consistent with 100% internalization of upstream revenue.

1.1. Related Literature

A large literature has studied the competitive effects of vertical integration. The elimination of double marginalization (Spengler, 1950) and the alignment of investment incentives (Grossman and Hart, 1986; Ciliberto, 2006; Yang, 2020) have been widely recognized as welfare-enhancing efficiency gains from vertical integration.

On the other hand, vertical foreclosure has attracted increasing attention since the release of the 1984 Guidelines. Prominent studies on input foreclosure, which occurs when an integrated upstream firm reduces the supply of inputs to downstream competitors, include Salop and Scheffman (1983), Salinger (1988), Ordover et al. (1990), Chipty (2001), Hortaçsu and Syverson (2007), Lee (2013) and Crawford et al. (2018). Customer foreclosure, which occurs when an integrated downstream firm reduces the demand for inputs from upstream rivals, has received less attention but has recently been documented in the soft drinks industry by Luco and Marshall (2020).

Existing empirical studies on vertical integration have found mixed evidence of competitive harms and benefits, even within narrowly defined industries. Beck and Scott Morton (2021) conclude in their literature review that there is limited evidence supporting the dominance of either the efficiency or foreclosure effect, as their relative magnitudes "depend on market structure and incentives."

Our study contributes to the literature by investigating how market structure affects the behavior of vertically integrated firms. While this question has been theoretically studied in Hart et al. (1990) and Rey and Tirole (2007), it has received limited empirical attention. Hortaçsu and Syverson (2007) examine whether price-integration and quantity-integration relationships differ across markets with varying "foreclosure potentials," such as concentration in the upstream bottleneck segment. They find that while the difference is sizable, it is statistically weak, suggesting that the competitive effects of vertical integration exhibit significant heterogeneity. Additionally, Luco and Marshall (2021) provide a numerical example demonstrating that foreclosure incentives are more pronounced when products are more substitutable.

Our paper is also related to the vast literature on vertical integration in the media industry (e.g., Suzuki, 2009; Gil, 2009, 2015; Gil et al., 2024; Chen et al., 2022). Among these papers, this paper is most closely related to two contemporaneous papers, Gil et al. (2024) and Chen et al. (2022), both of which examine the effect of vertical integration in the Chinese film industry using similar sales data. Our paper differs these studies in the scope of the data used and the focus of the empirical exercises.

Gil et al. (2024) use daily data from February and March 2013, while this paper uses weekly data covering the years 2011–2015. They find differences in outcomes across films distributed by vertically integrated distributors and independent distributors, but the differences are not large enough, given differences in revenue-sharing terms, support claims of anticompetitive foreclosure motives. We find similar differences in showings across films distributed by different distributors and investigate how such differences vary with upstream film substitutability and downstream retail competition.

Chen et al. (2022) use weekly data from 2014 to 2018 and find evidence of vertical foreclosure. Our paper differs from theirs in explicitly modeling two sources of heterogeneity in vertical foreclosure: (1) the geographic configuration of theaters in a city, and (2) the differentiation in film content perceived by consumers (i.e., latent attributes). We estimate the importance of these dimensions using novel consumer film rating datasets, and our results highlight how this variation in upstream and downstream competition affects vertical foreclosure and consumer welfare, with implications for targeted antitrust policy. We therefore consider our findings to be complementary to Gil et al. (2024) and Chen et al. (2022).

From a policy perspective, our paper makes two contributions to the ongoing debate on vertical merger enforcement. First, we show that vertically integrated firms may use non-price strategies, such as product provision, to foreclose their rivals, even when price strategies are also available (Salinger, 2021; Conlon and Mortimer, forthcoming). Second, our analysis of how foreclosure behavior varies with horizontal market structures provides insights into potential structural presumptions in future vertical merger reviews. As highlighted by Lafontaine and Slade (2021) and Moresi and Salop (2021), the lack of a rebuttable presumption poses a higher burden of proof for the antitrust authorities in vertical mergers compared to horizontal mergers. We use our estimated structural model to evaluate previously proposed anticompetitive presumptions, including diversion ratios (Luco and Marshall, 2021), gross upward pricing pressures (Moresi and Salop, 2013), and concentration (Moresi and Salop, 2021). Our results support the extensive evidence that vertical mergers should not be presumed to enhance efficiency (Beck and Scott Morton, 2021; Lafontaine and Slade, 2021) and highlight the usefulness of presumptions in detecting competitive harms.

The rest of this paper is structured as follows. In Section 2, we provide a theoretical discussion of the relevant effects of vertical integration. In Section 3, we describe the setting and data. Section 4 presents descriptive evidence of heterogeneous vertical foreclosure. In Section

5, we develop a structural model of film demand. We present results from the structural model in Section 6, and Section 7 concludes.

2. Theoretical Framework

Consider a setting in which a single theater sets prices and showings for two films, A and B. Let p_j be the price of film j and S_j be the number of showings of film j. For now, assume no capacity constraints on showings. The theater's objective function is given by

$$\Pi = R_A p_A q_A(p_A, p_B, S_A) - cS_A + R_B p_B q_B(p_B, p_A, S_B) - cS_B,$$

where $q_A(p_A, p_B, S_A)$ is demand for film A as a function of both prices and showings and c is the marginal cost of an additional showing. Notice that the marginal cost of an additional admission to either film, fixing showings, is zero, and that the theater retains a share $R_j \in [0, 1]$ of revenue from film j. Assume that the two films are substitutes so $\frac{\partial q_B}{\partial p_A} > 0$, $\frac{\partial q_A}{\partial p_B} > 0$, and that q_j is increasing and concave in S_j.

First, consider a setting in which $R_A = R_B = R^0$, meaning the theater internalizes the same share of revenue from both films, as would be the case if the theater is not vertically integrated with upstream firms for either film. Holding S_j fixed, the theater's optimal prices (p_A^*, p_B^*) are given by the solution to the first-order conditions:

$$\begin{aligned} p_A^* \frac{\partial q_A}{\partial p_A} + q_A + \frac{R^0}{R^0} p_B^* \frac{\partial q_B}{\partial p_A} &= 0 \\ p_B^* \frac{\partial q_B}{\partial p_B} + q_B + \frac{R^0}{R^0} p_A^* \frac{\partial q_A}{\partial p_B} &= 0. \end{aligned} \tag{1}$$

Now suppose that the theater becomes integrated with the upstream firms for film A and internalizes a higher revenue share for A, with $R_A = R^1 > R^0$. The derivatives of the firm's profit function with respect to p_A and p_B evaluated at the non-integrated prices (p_A^*, p_B^*) are

$$\begin{aligned} p_A^* \frac{\partial q_A}{\partial p_A} + q_A + \frac{R^0}{R^1} p_B^* \frac{\partial q_B}{\partial p_A} &< 0 \\ p_B^* \frac{\partial q_B}{\partial p_B} + q_B + \frac{R^1}{R^0} p_A^* \frac{\partial q_A}{\partial p_B} &> 0. \end{aligned} \tag{2}$$

When film A becomes integrated the theater will, all else equal, want to increase p_B and decrease p_A. These inequalities are a result of what Luco and Marshall (2020) term the *Edgeworth-Salinger effect*. When the theater internalizes a higher revenue share for film

A relative to B, it has an incentive to direct consumers towards film A by raising p_B and lowering p_A. Consequently, the differential vertical structure across products may therefore lead to price increases and price decreases relative to a benchmark where R_j is the same for all films.

Notice that the downwards pricing pressure on p_A is *not* a result of the elimination of double-marginalization. Indeed, unlike in the wholesale pricing model studied by Luco and Marshall (2021), a revenue-sharing model with zero marginal cost of admissions does not induce double marginalization. A downstream theater that sells a single film will set the same revenue-maximizing price for any R_j. Likewise, a theater that sells two films will price according to equation (1) as long as $R_A = R_B$. Prices deviate from this benchmark when $R_A \neq R_B$ and the theater has an incentive to direct customers towards the film with the higher revenue share.

Equation (2) also indicates that the downwards/upwards pricing pressure on p_A and p_B is a function of the cross-derivatives $\frac{\partial q_B}{\partial p_A}$ and $\frac{\partial q_A}{\partial p_B}$. When these cross-price effects increase in magnitude, the left-hand side of the inequalities in equation (2) becomes larger. Although not a formal proof, this observation indicates that when films are closer substitutes we might expect greater distortion of prices away from the non-integrated levels. On the other hand, increased downstream competition could reduce $\frac{\partial q_B}{\partial p_A}$ through greater consumer diversion to alternative theaters, lessening the price distortion from vertical integration.

Consider now the theater's showings decision. The first-order conditions for showings are given by

$$R_A p_A \frac{\partial q_A}{\partial S_A} = R_B p_B \frac{\partial q_B}{\partial S_B} = c.$$

As before, suppose that the theater becomes integrated with the upstream firm for film A, such that $R_A = R^1 > R^0$. The derivatives of the theater's profit function with respect to S_A and S_B, evaluated at the non-integrated optimal showings (S_A^*, S_B^*), are

$$R_A p_A \frac{\partial q_A}{\partial S_A} > R_B p_B \frac{\partial q_B}{\partial S_B} = c. \tag{3}$$

This increase in the theater's revenue share from film A from R^0 to R^1 will lead to upwards pressure on the number of showings of film A (the efficiency effect) and downward pressure on the number of showings of film B (the *Edgeworth-Salinger* effect). These effects on showings are analogous to the effects on price described above. The source of downward pressure on film

B's showings is the cross-derivative $\frac{\partial q_A}{\partial S_B^*}$ – firms have an incentive to reduce the showings of non-integrated films only if this leads to substitution towards integrated films. The magnitude of this distortion is therefore a function of these cross-derivatives which depend on upstream and downstream competition, as discussed above.

In the new equilibrium, the theater will choose S_A to equalize the marginal return to an additional showing across films. Fixing (p_A, p_B) it is clear that an increase in R_A will lead to a reallocation of showings towards film A and away from film B. Further, if $R_A > R_B$, then it must be that $p_A \frac{\partial q_A}{\partial S_A} < p_B \frac{\partial q_B}{\partial S_B}$. That is, the total marginal revenue in showings of the integrated film should be lower than the marginal revenue of the non-integrated film. This observation will form the basis of our tests of vertical foreclosure in Section 6.

3. Industry Background and Data

3.1. Industry Structure

3.1.1. Upstream Production and Distribution: Government Regulation and Coordination

The film industry consists of four key segments: producers, distributors, theater chains, and film theaters. Producers create and revise films based on feedback from film censors. Distributors, upon obtaining distribution licenses, assume responsibility for vertical contracting and marketing.

Vertical contracting between distributors and exhibitors is centrally coordinated by *China Film Distribution and Exhibition Association*, a government-supervised industry association. Most domestic firms are members of the association and use standardized exhibition contracts. These contracts have the following features: a film-specific nationwide release date for each film and the same revenue-sharing scheme. According to the scheme, SARFT collects taxes and fees amounting to 8.3% of gross revenue. Theater chains and theaters receive 57% of the post-tax revenue, while producers and distributors receive 43%. Table A3 provides a summary of the details.

Finally, encrypted digital films are transmitted to theater chains and subsequently to their affiliated theaters. The government controls the encryption and decryption technology and therefore the set of films that all theaters have access to.

3.1.2. Downstream Exhibition: Ownership, Pricing, and Screening

In 2002, a mandate was enforced, requiring theaters to affiliate with one of over 40 theater chains. By 2015, franchises accounted for over 80% of theaters, while the remaining theaters were owned by chains. In addition to distributing film copies, chains also guide film screenings at their affiliated theaters.[3] However, pricing decisions are made at the individual theater level and nearly 65% of the variation in the average theater-film-week level admission fee is at the theater-week level.

3.2. Vertical Ownership

Vertical integration in the Chinese film industry originated from government control over the planned economy when there were significant overlap in state ownership between upstream and downstream firms. After the 2002 reform, private motion picture conglomerates entered the industry, further increasing vertical integration. For a detailed overview of revenue and vertical integration status among top distributors and theater chains, interested readers can refer to Table A1 in Appendix A.1.

Moreover, films have been nationally distributed since 2002, while theater chains often remain regional, resulting in cross-region variation in the vertical structure of films exhibited by vertically integrated firms. Figure 1 shows the geographic distribution of downstream revenue from integrated theaters for four upstream distributors during the 2011-2015 sample period. The upper two graphs represent national distributors, while the lower left graph is for *Shanghai Film*, a Shanghai-based production, distribution, and exhibition company, with nearly 50% of its downstream revenue coming from Shanghai and a nearby province. The lower right graph is for *Pearl River*, with over 50% of its downstream revenue generated by integrated theaters in the Guangdong province.

3.3. Data, Sample Restrictions, and Variable Construction

3.3.1. Box Office Data

We use film box office data from EntGroup China, a leading film industry consulting firm. The data are sourced from the administrative box-office system.[4] We construct the following

[3] Theater managers actively track film popularity to allocate screening capcity. See the report from *Tencent Entertainment* at https://ent.qq.com/a/20120811/000248.htm, retrieved on May 26, 2021. See also the report from *Beijing Times* on August 24, 2012: "The Inner Workings of the Film Scheduling" at https://sports.qq.com/a/20120824/000113.htm, retrieved on May 26, 2021.

[4] The SARFT maintains a national film ticketing information system that collects retail prices and admissions for each screening. This data is then used for splitting revenue among industry participants.

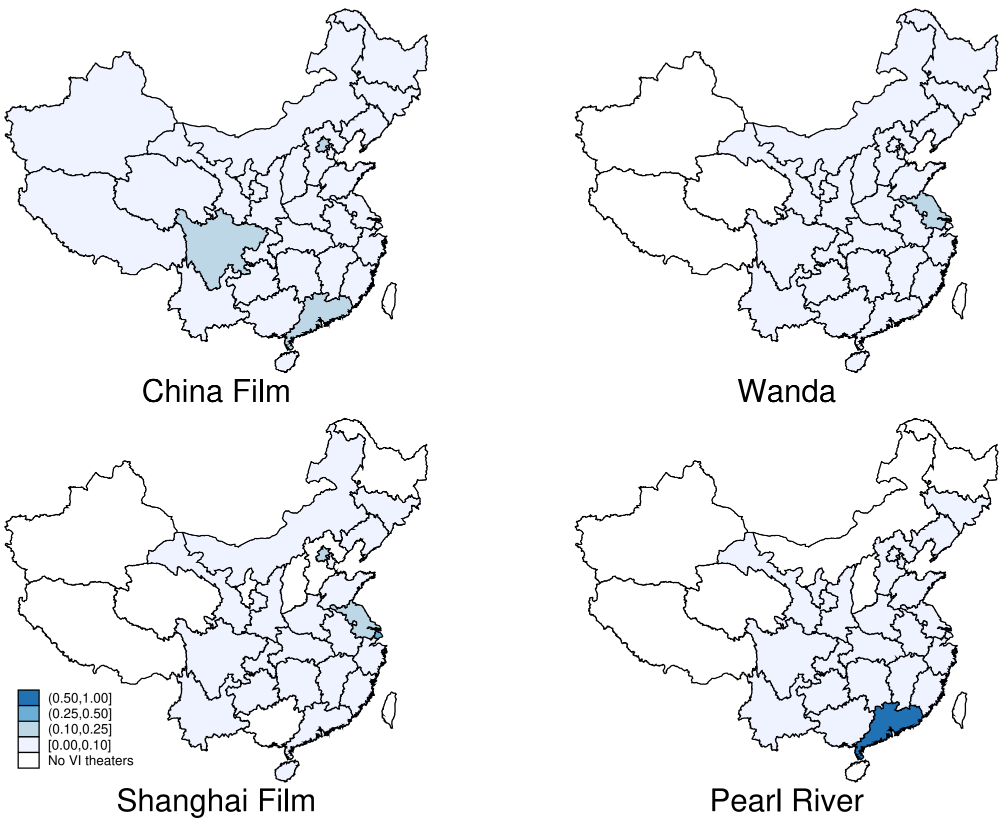


Figure 1: Locations of Integrated Theaters

Note: This figure plots, for four upstream distributors, the geographic distribution of their downstream integrated theaters revenue during the 2011-2015 sample period.

theater-film-week level variables from this dataset: box-office revenue, average admission fee, admissions, and the number of showings. We exclude observations for propaganda films, niche films, nonprofit theaters, and small cities showing 20% fewer films.[5]

We augment this dataset with hand-collected information on film genre, release date, exhibition format, and producers and distributors. Additionally, we gather data on each theater's affiliated chain, number of screens, number of enhanced screens, and seating capacity. Theaters' locations are geocoded based on a manual search.

3.3.2. Consumer Rating Data

We obtain our consumer-film-level rating data from Douban, China's largest online platform for rating films, books, music, and games. Launched in 2005, Douban is often regarded as the Chinese counterpart to IMDb or MovieLens in the United States.[6] On Douban, users rate films on a scale from 1 to 5 stars. As of September 2012, the platform reported 66 million registered users and over 100 million monthly visitors, a figure comparable to the 40 million monthly in-theater moviegoers in China at the time.[7] By 2019, Douban's user base had grown to 200 million registered users, with 100 million active on a monthly basis.[8]

Aggregate user ratings and review data from Douban have been widely used to evaluate the prospects of upcoming films, assess audience sentiment toward films in release, and analyze customer perceptions across various film types, genres, and origins. These aggregate data have also been cited in industry reports by media consulting firms, in news coverage of China's media industry,[9] and in previous papers on the Chinese film industry (Chen et al., 2022; Gil et al., 2024).

To obtain a representative and reliable sample of film consumers, we first restrict our sample to users who have written at least one review ranked among the top 300 most useful for the reviewed film. This criterion results in a final sample of 11,047 users. For all 628 films in our box office data, we only keep their ratings posted on the platform during our box office data sample period (2011–2015). We also include 916 additional films that ranked in

[5]Propaganda films often have unusually long release windows, while niche films are typically released in one or two provinces for non-commercial purposes, such as promoting the cultures of ethnic minorities.

[6]See, for example, BBC's report at https://www.bbc.com/news/world-asia-china-54241734, accessed August 25, 2021.

[7]Source: https://jobs.douban.com/about/, accessed August 25, 2021.

[8]Source: http://column.iresearch.cn/b/202003/885318.shtml, accessed August 25, 2021.

[9]See, for example, reports by the *Hollywood Reporter* (https://www.hollywoodreporter.com/movies/movie-news/china-box-office-dune-2-20-million-1235849021/), *Variety* (https://variety.com/2020/film/asia/why-china-hates-disney-mulan-1234770198/), and *Deadline* (https://deadline.com/2024/08/alien-romulus-china-global-international-box-office-1236042797/), all accessed August 25, 2021.

the top percentile by the number of star ratings. Following these steps, our dataset comprises 1,798,305 star rating records.

3.3.3. Spatial Distribution of Consumers

We obtain the spatial distribution of consumers from Brinkhoff (2022), which reports population size at the census tract level from the 2010 population census. To our knowledge, this is the most granular available data on population distribution.[10]

3.3.4. Ownership Data

We obtain firm ownership information from Qichacha, an online government-sponsored enterprise information system. Qichacha provides administrative establishment registration information, including owners, registration dates, and addresses. Following La Porta et al. (1999), we collect data on the *ultimate* owners of theaters, theater chains, distributors, and producers. Vertical integration is defined as common ownership between a distributor and a theater chain.

3.4. Descriptive Statistics

Table 1 provides summary statistics for the data used in our empirical analysis. Panel A presents statistics for price, showings, share of showings, admissions, and admissions per showing at the theater-film-week level in the box office data. The dataset consists of 2,019,234 observations for 2,070 theaters, 628 films, 112 cities, and 210 weeks. All the reported statistics are conditional on the theater exhibiting the film. Admissions and showings are weekly totals, with an average of 600.01 and 23.77, respectively. Inflation-adjusted price is calculated as sales per admission measured in 2015 US dollars, with an average of nearly five dollars.

Panel B summarizes theater characteristics, with the average theater size being 6.18 screens and 907.96 seats, with 2.39 enhanced format screens on average.

Panel C provides film-level characteristics, with 14% of the 628 films in our sample being imported under the revenue-sharing contract, and 30% in enhanced formats (3D/IMAX). In terms of film genres, the proportions of action, adventure, romance, science fiction, and comedy films are 36%, 15%, 28%, 10%, and 24%, respectively.

Panel D presents summary statistics of the film rating data, which consists of 1,798,305 star rating records from 11,047 users. On average, users give 162.79 star ratings, with a

[10] A Chinese city is divided into counties, which are further subdivided into census blocks. For example, in the 2010 census, urban Beijing comprised 6 districts and 97 census blocks.

minimum of 1, a maximum of 1,215, and a median of 110 ratings. Films in our dataset receive an average of 1,164.71 ratings, with a minimum of 63, a maximum of 5,958, and a median of 780 ratings.

Finally, Panel E provides tabulations of the vertical integration status at three different levels: film-theater, film, and theater. Among the 707,954 film-theater pairs in our box-office data, 17% of observations are associated with vertical integration. The percentages of producer- and distributor-theater chain integration are 5% and 15%, respectively. Additionally, 67% of films are produced (21%) or distributed (63%) by an integrated firm, and 86% of theaters are integrated with either a distributor (71%) or a producer (67%).

4. Descriptive Evidence

4.1. Baseline Regression Analysis

In this subsection, we examine the effect of vertical integration between distributors and theater chains on pricing and showings decisions.[11] We estimate two regression models The first specification is at the film-theater level:

$$y_{ft} = \beta VI_{ft} + \delta_{f,c(t)} + \delta_{w(f)} + \delta_t + \varepsilon_{ft} \tag{4}$$

where y_{ft} is the outcome variable for film f in theater t. VI_{ft} is an indicator variable that is equal to 1 if the distributor of film f is vertically integrated with theater t. We denote the week of release for film f as $w(f)$ and the city where theater t is located as $c(t)$. The terms $\delta_{fc}, \delta_{w(f)}$ and δ_t represent film-city, week-of-release and theater fixed effects, respectively.

We include film-city fixed effects $\delta_{f,c(t)}$ to control for overall film quality and local demand for film f, and week-of-release fixed effects $\delta_{w(f)}$ to capture time-specific market conditions. Theater fixed effects δ_t control for attributes such as capacity, screen types, and local demand.

The second specification is at the theater-film-week level:

$$y_{ftw} = \beta VI_{ft} + \delta_{f,c(t)} + \delta_{fw} + \delta_{tw} + \varepsilon_{ftw} \tag{5}$$

[11] This focus is motivated by two key factors. First, as discussed in Section 3.1, China's film industry has a vertically structured distribution process: once a film is produced and receives a distribution permit, the distributor manages all subsequent marketing strategies and directly coordinates with theater chains. Second, as shown in Panel E of Table 1 (which presents the vertical integration status in our box office data) and Table A2 (which details the contractual relationships between producers and theaters), most producers select their own distributors, if any, and the variation in vertical integration primarily occurs at the distributor-theater chain level. Additional regression results using alternative definitions of vertical integration are reported in Appendix B.

Table 1: Summary Statistics

Panel A: Theater-Film-Week Sales

	N	Mean	Std. Dev.	Min	Median	Max
Price	2,019,234	5.15	1.422	0.575	4.89	32.10
Showings	2,019,234	23.77	25.156	1.000	15.00	467.00
Showings (share)	2,019,234	0.13	0.122	0.001	0.10	1.00
Admissions	2,019,234	600.01	1,277.056	1.000	154.00	68038.00
Admissions/showing	2,019,234	18.00	22.539	0.015	11.14	1,365.00

Panel B: Theaters

	N	Mean	Std. Dev.	Min	Median	Max
Number of screens	2,070	6.18	2.712	1	6.00	20
Number of seats	2,070	907.96	484.470	32	838.00	5,000
Number of enhanced screens	2,070	2.39	2.600	0	1.00	14

Panel C: Films

	N	Mean	Std. Dev.	Min	Median	Max
Imported	628	0.14	0.346	0	0	1
Enhanced format	628	0.30	0.459	0	0	1
Action	628	0.36	0.479	0	0	1
Adventure	628	0.15	0.355	0	0	1
Romance	628	0.28	0.449	0	0	1
Science Fiction	628	0.10	0.305	0	0	1
Comedy	628	0.24	0.428	0	0	1

Panel D: Film Ratings

	N	Mean	Std. Dev.	Min	Median	Max
Star rating	1,798,305	3.39	1.074	1	3	5
At user level						
Number of ratings	11,047	162.79	174.282	1	110	1,215
p25	11,047	2.75	0.899	1	3	5
Median	11,047	3.38	0.944	1	4	5
p75	11,047	3.99	0.982	1	4	5
p75-p25	11,047	0.61	0.627	0	1	4
At film level						
Number of ratings	1,544	1,164.71	1,000.007	63	780	5,958
p25	1,544	2.73	0.885	1	3	5
Median	1,544	3.25	0.916	1	3	5
p75	1,544	3.75	0.864	1	4	5
p75-p25	1,544	0.50	0.504	0	0	2

Panel E: Vertical Integration

	Film-Theater		Film		Theater	
	N	Mean	N	Mean	N	Mean
Vertical Integration	707,954	0.17	628	0.67	2,070	0.86
Distributor-theater	707,954	0.15	628	0.63	2,070	0.71
Producer-theater	707,954	0.05	628	0.21	2,070	0.67

Notes: In Panel A, all rows use observations at the theater-film-week level. All the reported statistics are conditional on the theater exhibiting the film. Admissions and showings are weekly totals. Price is CPI deflated and calculated as sales per admission measured in 2015 US dollars. Panels B and C summarize theater- and film-level variables. Panel D summarizes film rating data. Lastly, Panel E provides tabulations of the vertical integration status at three different levels: film-theater, film, and theater.

where y_{ftw} is the outcome variable for film f in theater t during week w. The terms δ_{fw} and δ_{tw} denote film-week and theater-week fixed effects, respectively. Film-week fixed effects control for variations in demand decay across films, while theater-week fixed effects account for theater-week-specific unobserved demand shocks. This helps isolate the impact of vertical integration on prices and showings, separating it from differences in overall temporal demand faced by integrated and non-integrated theaters.

The coefficient of interest is β, which measures the effect of vertical integration. Our identification assumption is that, after accounting for the fixed effects in equations (4) and (5), VI_{ft} is mean independent of the idiosyncratic factors affecting a theater's supply decisions. A potential violation of this assumption is that integrated distributors selectively distribute films to cater to the demand of downstream theaters.

The identification assumption is reasonable in our context for two reasons. First, vertical integration between distributors and theater chains remains stable throughout the sample period, largely due to historical provincial government ownership of theaters and distributors (see Section 3.2); Second, films are distributed nationally with predetermined release dates, and distributors are likely to select films based on overall quality rather than regional appeal.

Table 2 reports estimation results. We look at three variables: log price, log showings, and log number of weeks in release (duration). In Columns (1) and (2), we report the estimates of equation (4) using the subsample of the first week observations. Therefore, this specification abstracts away from dynamics in price and screening, and looks at the most important strategic variables: first-week price and showings. Vertical integration increases first-week showings by 3.5% but has no economically significant effects on pricing. In Columns (3) and (4), we report the estimates of the same model using film-theater totals sample. Vertical integration increases initial run duration by 0.7% and total showings by 4%. Lastly, we use the full film-theater-week sample and control for the full set of fixed effects in equation (5). The results are reported in Columns (5) and (6): vertical integration increases weekly showings by 2.9%.

4.2. The Efficiency and Foreclosure Effects of Vertical Integration

In the previous subsection, we demonstrated the net impact of vertical integration on supply decisions by comparing integrated and non-integrated films. The estimated difference captures both efficiency gains (better utilization of theater capacity) and foreclosure (shifting capacity from non-integrated to integrated films). In this subsection, we employ a more saturated model to shed light on both effects (similar to Luco and Marshall, 2020).

Table 2: Baseline Results

	First-week sample		Film-theater totals sample		Full sample	
	log(price)	log(showings)	log(duration)	log(showings)	log(price)	log(showings)
	(1)	(2)	(3)	(4)	(5)	(6)
VI_{ft}	-0.002*	0.035***	0.007***	0.040***	-0.002***	0.029***
	(0.001)	(0.004)	(0.002)	(0.004)	(0.000)	(0.002)
Week FE	Yes	Yes	Yes	Yes		
Theater FE	Yes	Yes	Yes	Yes		
Film-city FE	Yes	Yes	Yes	Yes	Yes	Yes
Film-week FE					Yes	Yes
Theater-week FE					Yes	Yes
N	650,755	650,755	650,755	650,755	2,013,804	2,013,804
R^2	0.742	0.771	0.732	0.789	0.798	0.757
Residual variance	0.017	0.265	0.069	0.366	0.013	0.313

Notes: This table presents regression estimates of the impact of vertical integration between distributors and theater chains on pricing and showing decisions. Columns (1)–(4) are at the movie-theater level, following equation (4). Columns (5)–(6) are at the movie-theater-week-showtime level, following equation (5). Standard errors, clustered at the market level, are shown in parentheses. *** p <0.005, ** p <0.01, * p <0.05.

A key prediction from the theoretical framework in Section 2 is that, compared to a no-integration equilibrium, integrated films should be cheaper and/or more frequently screened, while non-integrated films in theaters exhibiting their own integrated films may become more expensive and/or less screened. The film-theater level regression model is:

$$y_{ft} = \beta_1 VI_{ft} + \beta_2 1\{VI_{ft} = 0, VI_{-f,t} > 0\} + \delta_{f,c(t)} + \delta_{w(f)} + \delta_t + \varepsilon_{ft} \tag{6}$$

and the film-theater-week level regression model is

$$y_{ftw} = \beta_1 VI_{ft} + \beta_2 1\{VI_{ft} = 0, VI_{-f,t,w} > 0\} + \delta_{f,c(t)} + \delta_{fw} + \delta_t + \varepsilon_{ftw} \tag{7}$$

where $VI_{-f,t,w}$ denotes the number of newly released integrated rivals of film f in week w for theater t, and $VI_{-f,t}$ is the number of integrated rivals during film f's initial run. Indicator variables $1\{VI_{ft} = 0, VI_{-f,t} > 0\}$ and $1\{VI_{ft} = 0, VI_{-f,t,w} > 0\}$ equal one if film f is non-integrated and screened alongside integrated films. The control group (omitted category) represents films where neither the film's distributor nor its rivals' distributors are integrated with a theater. The coefficient β_1 captures the impact of vertical integration on supply decisions for integrated films, while β_2 measures the effect on non-integrated films.

Our identification strategy is similar to that of the baseline regression models in the previous subsection. We leverage within-theater variation in vertical structure, as some films are distributed by integrated distributors and others by non-integrated ones. Notably, all theaters show non-integrated films, which allows us to isolate the effects of vertical integration.

Table 3 presents estimates for this analysis. The results align with the theoretical predictions and the net effects shown in Table 2. Columns (1) and (5) report estimated effects on price, though the effect has a small magnitude economically.

Columns (2)–(6) report estimated effects on showings. Column (2) presents the regression results for the impact of vertical integration on first-week showings. An integrated film receives 2.7% more first-week showings in its own downstream theater compared to being screened in a non-integrated theater where all rival films are also non-integrated. Conversely, a film receives 3.8% fewer first-week showings if its distributor is not integrated with the theater, but at least one rival film is integrated. Similar patterns are present in Column (5), where we examine the total showings in the first run. In Column (3), we examine the duration of the first release. The results show that a film's weeks in release are 2.8% fewer if it is screened alongside a film owned by the theater. However, vertical integration does not give a film longer duration.

Lastly, for the film-theater-week sample in Column (6), we find evidence of increased showings for integrated films and decreased showings for a non-integrated film shown alongside a rival film integrated with the theater, although the latter is not statistically significant. This is partly due to the analysis being conditional on a film being exhibited in the theater, and similar patterns are found by Gil et al. (2024).

To sum up, the estimates reported in Table 3 suggest that an integrated theater reallocates screening capacity from non-integrated to integrated films and shortens non-integrated films' initial runs when they are screened alongside integrated films. The effect works both on the extensive and intensive margins.

4.3. Market Structure and the Effect of Vertical Integration

In this subsection, we extend the analysis in Tables 2 and 3 to examine how the effects of vertical integration vary with product competition across films and downstream inter-theater competition.

4.3.1. Downstream Competition

We first investigate how the impact of vertical integration changes with downstream spatial competition between theaters. In line with Chen et al. (2022) and Gil et al. (2024), we measure downstream theater competition theater t faced in week w by $\log(\text{Theater}_{tw})$, which is log

Table 3: The Equilibrium Effects of Vertical Integration

	First-week sample		Film-theater totals sample		Full sample	
	log(price)	log(showings)	log(duration)	log(showings)	log(price)	log(showings)
	(1)	(2)	(3)	(4)	(5)	(6)
VI_{ft}	-0.003***	0.027***	0.002	0.029***	-0.005***	0.024***
	(0.001)	(0.004)	(0.002)	(0.004)	(0.001)	(0.004)
$1\{\mathrm{VI}_{ft} = 0,\ \mathrm{VI}_{-f,t} > 0\}$	-0.004***	-0.038***	-0.028***	-0.058***	-0.004***	-0.007
	(0.001)	(0.004)	(0.002)	(0.005)	(0.001)	(0.004)
Week FE	Yes	Yes	Yes	Yes		
Theater FE	Yes	Yes	Yes	Yes		
Film-city FE	Yes	Yes	Yes	Yes	Yes	Yes
Film-week FE					Yes	Yes
Theater-week FE					Yes	Yes
N	650,755	650,755	650,755	650,755	2,013,804	2,013,804
R^2	0.742	0.771	0.732	0.790	0.798	0.757

Notes: This table presents regression estimates of the impact of vertical integration between distributors and theater chains on pricing and showing decisions. Columns (1)–(4) are at the movie-theater level, following equation (4). Columns (5)–(6) are at the movie-theater-week-showtime level, following equation (5). Standard errors, clustered at the market level, are shown in parentheses. *** p <0.005, ** p <0.01, * p <0.05.

number of theaters (self-included) within 5 km radius. In Table 4, we present estimates of a regression model including the interactions between the two key explanatory variables in equations (6) and (7) with $\log(\mathrm{Theater}_{tw})$.

The variation in the scope of new theater entry across cities and over time provides us with a clean identification of how foreclosure behaviors are restrained by downstream competition. In addition to the discussion of identification in Section 4.2, another important identification assumption is that theater chains do not base the expansion of new theaters on the popularity of their own integrated films. This assumption is reasonable, as most theater expansion is driven by the broader growth of commercial centers.

Column (1) reports the heterogeneity in the effects of vertical integration for first-week observations. Both the efficiency and foreclosure effects are statistically significant and economically meaningful. Notably, the foreclosure effect is smaller for theaters facing greater local competition. Columns (2) and (3) examine the heterogeneity in effects for the duration of a film's initial run and the total number of showings at each theater. The results are consistent with those in Column (1). On average, if a theater has four rivals within a 5 km distance, then there is no difference in its showings in the downstream theaters owned by the film's distributor and in other theaters.

These results are consistent with the idea that downstream competition limits a theater's *ability* to distort showings allocations and foreclose non-integrated films. With greater downstream competition, the substitution between different films within a single theater (i.e.,

$\partial q_A / \partial S_B^*$ in equation (3)) is mitigated by substitution between films across competing theaters.

Table 4: Heterogeneous Foreclosure Effects by Downstream Competition

	First-week sample	Film-theater totals sample		Full sample
	log(showings)	log(duration)	log(showings)	
	(1)	(2)	(3)	(4)
VI_{ft}	0.038***	0.003	0.038***	0.042***
	(0.007)	(0.003)	(0.008)	(0.005)
$1\{\text{VI}_{ft} = 0,\, \text{VI}_{-f,t} > 0\}$	-0.052***	-0.038***	-0.084***	-0.015***
	(0.007)	(0.003)	(0.008)	(0.004)
$\text{VI}_{ft} \times \log(\text{Theaters}_{tw})$	-0.006	-0.000	-0.005	-0.010***
	(0.004)	(0.002)	(0.004)	(0.002)
$1\{\text{VI}_{ft} = 0,\, \text{VI}_{-f,t} > 0\} \times \log(\text{Theaters}_{tw})$	0.009**	0.007***	0.016***	0.003
	(0.003)	(0.002)	(0.004)	(0.002)
Week FE	Yes	Yes	Yes	
Theater FE	Yes	Yes	Yes	Yes
Film-city FE	Yes	Yes	Yes	Yes
Film-week FE				Yes
N	650,755	650,755	650,755	2,017,381
R^2	0.771	0.732	0.790	0.706
Median(Theaters_{tw})	5.000	5.000	5.000	5.000

Notes: This table presents regression estimates of the heterogeneous impact of vertical integration between distributors and theater chains on showing decisions by downstream theater market competition. Columns (1)–(3) are at the movie-theater level. Column (4) is at the movie-theater-week-showtime level. Variable $\log(\text{Theaters}_{tw})$ is log number of theaters (self-included) within 5 km radius. Standard errors, clustered at the market level, are shown in parentheses. *** $p < 0.005$, ** $p < 0.01$, * $p < 0.05$.

4.3.2. Upstream Competition

To investigate the effect of upstream competition - that is, competition between films - on vertical incentives, we develop an empirical measure of "closeness" for films, analogous to the distance measure used for theaters in Section 4.3.1. Films are complex products not easily described by a finite set of characteristics, and it is therefore difficult to determine a priori (in the absence of e.g. a structural model of demand) which films are similar, and therefore likely to be close substitutes.

To make progress in this direction, we adopt a procedure for eliciting *latent attributes* of films using review data. The idea behind this approach is that films with correlated reviews—where people who like film A also tend to like film B—should be close together in a latent attribute space. To recover these latent attributes, we use a matrix factorization algorithm (Koren et al., 2009; Mnih and Salakhutdinov, 2007), which has been applied to several economic problems (see Athey and Imbens (2019) for a review). Tellingly, this algorithm was originally developed for the Netflix Challenge and is likely similar to methods currently used in the industry for film recommendations.

Suppose the set of films rated by consumer i is denoted by $\mathcal{F}_i$, and the star rating for film $f \in \mathcal{F}_i$ is r_{if}. The algorithm estimates the parameter vector $(b_i, b_f, \tau_{kf}, \nu_{ik})$ by minimizing the mean squared error:

$$\sum_i \sum_{f \in \mathcal{F}_i} \left(r_{ij} - b_i - b_f - \sum_{k=1}^{K} \nu_{ik} \tau_{kf} \right)^2 + \lambda \left(b_i^2 + b_f^2 + \sum_{k=1}^{K} (\tau_{kf}^2 + \nu_{ik}^2) \right),$$

where b_i is the individual rating "bias," which accounts for systematic tendencies of some users to rate higher or lower than others, b_f is the film "bias," which accounts for the tendency of high-quality films to receive higher ratings overall, $\{\tau_{kf}\}_{k=1}^K$ are the K-dimensional latent attributes of film f, and $\{\nu_{ik}\}_{k=1}^K$ are the K-dimensional preferences for latent attributes.

We minimize this objective function using stochastic gradient descent, an iterative optimization method. Due to the high dimensionality of the parameters $(b_i, b_f, \tau_{kf}, \nu_{ik})$ in our problem (I, F, $K \times F$, and $I \times K$, respectively, with $I = 11,047$ and $F = 1,544$), it is computationally infeasible to use standard algorithms such as Nelder-Mead or BFGS.

To avoid overfitting, we employ the cross-validation method proposed in Owen and Perry (2009) to determine the appropriate number of latent characteristics (K) and the regularization parameter (λ), which penalizes the norm of the preference and characteristic vectors. The technical details are provided in Appendix C.

With the latent attribute measures in hand, we estimate a regression model similar to that in Section 4.3.1, interacting vertical integration with the standardized distance in latent attributes to a rival film of different ownership status. According to the theoretical model, the greater the distance between two films, the lower their substitutability, which in turn reduces a theater's *incentive* to divert consumers to its own integrated film. The results of the regression are presented in Table 5.

Column (1) examines the heterogeneity in the effects of vertical integration for first-week observations. As expected, both the efficiency and foreclosure effects are statistically significant and economically meaningful. Importantly, the foreclosure effect diminishes when films face less competition from integrated rivals. For instance, the median standardized distance between a focal non-integrated film and a rival film integrated with the theater is 0.369. At this distance, the showings of the focal film in an integrated theater are 3.5% higher than in a non-integrated theater, consistent with the findings in Table 3. Additionally, when a non-integrated film faces less competition—specifically, when the nearest integrated film is one standard deviation farther—the foreclosure effect decreases by 0.7 percentage points (16%), *ceteris paribus*.

Columns (2) and (3) further explore this heterogeneity by examining the effects on the duration of a film's initial run and the total number of showings in each theater. The findings are in line with those reported in Column (1).

Overall, these results support the theoretical predictions outlined in Section 2: foreclosure behaviors become more pronounced when an integrated film faces close substitutes owned by the same theater. In particular, when a vertically integrated film, A, competes with a highly similar non-integrated film, B, the cross-elasticity $\partial q_A/\partial S_B^*$ is high, increasing the *incentive* to distort showings in favor of the integrated film.

Table 5: Upstream Film Competition and Heterogeneous Effects of Vertical Integration

	First-week sample	Film-theater totals sample		Full sample
	log(showings)	log(duration)	log(showings)	
	(1)	(2)	(3)	(4)
VI_{ft}	0.030***	0.008***	0.032***	0.023***
	(0.005)	(0.003)	(0.006)	(0.004)
$1\{\text{VI}_{ft}=0,\ \text{VI}_{-f,t}>0\}$	-0.042***	-0.031***	-0.064***	-0.011*
	(0.004)	(0.002)	(0.005)	(0.005)
$\text{VI}_{ft}\times \min_{f':VI_{f'}=0} d_{f,f'}$	0.003	0.000	0.007	-0.004
	(0.003)	(0.001)	(0.003)	(0.003)
$1\{\text{VI}_{ft}=0,\ \text{VI}_{-f,t}>0\}\times \min_{f':VI_{f'}=1} d_{f,f'}$	0.007***	0.006***	0.011***	-0.001
	(0.002)	(0.001)	(0.002)	(0.001)
Week FE	Yes	Yes	Yes	
Theater FE	Yes	Yes	Yes	Yes
Film-city FE	Yes	Yes	Yes	Yes
Film-week FE				Yes
N	650,755	650,755	650,755	2,013,806
R^2	0.771	0.732	0.790	0.757
$\text{Median}(\min_{f':VI_{f't}=1} d_{f,f'} \mid VI_{ft}=0)$	0.369	0.369	0.369	0.094
$\text{p90}(\min_{f':VI_{f't}=1} d_{f,f'} \mid VI_{ft}=0)$	2.448	2.448	2.448	2.368

Notes: This table presents regression estimates of the heterogeneous impact of vertical integration between distributors and theater chains on showing decisions by upstream competition between films in release. Columns (1)–(3) are at the movie-theater level. Column (4) is at the movie-theater-week-showtime level. Variable $\min_{f':VI_{f'}=0} d_{f,f'}$ is the minimum standardized distance between film f and its non-integrated rival f', and variable $\min_{f':VI_{f'}=1} d_{f,f'}$ is the minimum standardized distance between film f and its integrated rival f', both in the latent attribute space shown in Figure C2. Standard errors, clustered at the market level, are shown in parentheses. *** $p<0.005$, ** $p<0.01$, * $p<0.05$.

5. Structural Model

To separate the strategic effects of vertical integration of theaters' showings decisions from the potential direct effect of vertical integration on consumer utility, we build and estimate a model of consumer demand and theater showings decisions in which the vertical integration status of a film-theater pair enters utility directly. The estimated model will allow us to test for vertical foreclosure by asking whether theaters' showing choices can be rationalized without appealing to vertical incentives.

5.1. Demand

The demand model follows the discrete choice demand framework of Berry et al. (1995). We follow Chen et al. (2022) and define a market as a county-week, indexed by m. A consumer, i obtains the following utility from seeing film f at theater t,

$$\begin{aligned} u_{imft} &= p_{mft}\beta_1 + VI_{ft}\beta_2 + \log(S_{mft})\beta_3 + \gamma_{imf} + \delta_{it} + \xi_{mft} + \epsilon_{imft} \\ &= \tilde{u}_{imft} + \epsilon_{imft} \end{aligned} \tag{8}$$

Consumer utility is given by individual-specific taste for film f, γ_{if}, individual-specific taste for theater t, δ_{it}, and observable film characteristics that vary across theaters and over time within a market. Specifically, p_{mft} is the ticket price, VI_{ft} is an indicator for whether film f is vertically integrated with theater t, and S_{mft} is the number of showings of film f in theater t in market m. The term ξ_{mft} captures a film-theater-market specific unobservable, and ϵ_{imft} is a preference shock, assumed to be independently and identically distributed (i.i.d.) extreme value type 1.

The taste of consumer i for film f is given by:

$$\gamma_{if} = \gamma_{w(m)f} + \gamma_m + \sigma_1 \left(\sum_{k=1}^{K} \hat{\nu}_{ik}\hat{\tau}_{kf} \right) + \sigma_0 \hat{b}_i,$$

where $\gamma_{w(m)f}$ denotes film-week fixed effects, γ_m denotes market fixed effects that absorb county-week specific demand shocks common to all films in release, and $\left(\sum_{k=1}^{K} \hat{\nu}_{ik}\hat{\tau}_{kf}\right)$ captures the interaction between the K latent attributes of film f and individual i's preferences for those attributes, as estimated in Section 4.3.2.[12]

Similarly, consumer i's taste for theater t is composed of a theater fixed effect and a

[12] This interaction term can be interpreted as a bias-adjusted rating that individual i would assign to film f. Recall that the collaborative filtering algorithm predicts ratings using the formula:

$$\hat{r}_{if} = \hat{b}_i + \hat{b}_f + \sum_{k=1}^{K} \hat{\nu}_{ik}\hat{\tau}_{kf},$$

where $\hat{b}_i$ and $\hat{b}_f$ represent the estimated user and film biases, respectively, while $\hat{\tau}_{kf}$ and $\hat{\nu}_{ik}$ are the latent attributes of the product and the consumer's preferences for those attributes.

consumer-specific component,

$$\delta_{it} = \delta_t - \eta \|X_t - X_i\| \tag{9}$$

where $\|X_t - X_i\|$ is the distance between consumer i's home location, X_i, and theater t's location, X_t, in kilometers. Consumers prefer to visit theaters closer to their homes, and theaters that are near each other are therefore closer substitutes than theaters that are far from each other.

We normalize the consumer's means utility from the outside good to zero. The expected market share of a film-theater pair is then given by integrating choice probabilities over the distribution of consumer preferences,

$$s_{mft} = \int \frac{\exp\left(\tilde{u}_{imf't'}\right)}{1 + \sum_{(f',t') \in \mathcal{F}_m} \exp(\tilde{u}_{imf't'})} dF(\boldsymbol{\nu}_i, X_i), \tag{10}$$

where the integrand is the probability of choosing film and theater pair (f, t). This expression follows from the assumption that ϵ_{imft} is i.i.d. type-1 extreme value. The integral is taken over the joint empirical distribution of consumers' idiosyncratic preferences for film attributes, $\boldsymbol{\nu}_i$—as computed in Section 4.3.2—and consumer locations, X_i, collected from the geocoded population census data described in Section 3.3.3.

5.2. Supply

We assume that theater t in market m chooses the number of showings, S_{mft} for each available film $f \in \mathcal{F}_m$ to maximize static profit (suppressing the m subscript),

$$(p_t^*, S_t^*) = \arg \max_{p_t, S_t \in \mathbb{R}_{\geq 0}^{|\mathcal{F}|}} \sum_{f \in \mathcal{F}} M \lambda_{ft} p_{ft} s_{ft} \left(p_t, S_t, p_{-t}, S_{-t}\right) - C_t(S_t)$$

where M is the population in the market, and $s_{ft}\left(p_t, S_t, p_{-t}, S_{-t}\right)$ is the market share of film f at theater t, as defined in equation (10). This market share is a function of four vectors: p_t and S_t, which have a length of $|\mathcal{F}|$ with non-negative entries p_{ft} and S_{ft} that respectively record the price and the number of showings for film $f \in \mathcal{F}$ at theater t, and p_{-t} and S_{-t}, which record the prices and showings for all other film-theater pairs in the market.[13]

$M p_{ft} s_{ft}\left(p_t, S_t, S_{-t}\right)$ is the gross sales, and $C_t(S_t)$ is the fixed cost of allocating screening capacity as S_t. The revenue weight that theater t places on the gross sales of film f when it

[13]Recall that $\mathcal{F}$ denotes the set of all films available in a market. The vector S_t represents the showings for films that theater t chooses to exhibit as well as those dropped from exhibition.

allocates showings is given by

$$\lambda_{ft} = \lambda_0 + \lambda_1 R_{ft}. \tag{11}$$

Here, $\lambda_0 = (1 - 8.5\%) \times 57\%$ represents the revenue share from downstream film exhibition, per the standard revenue sharing rules described in Appendix Table A3. R_{ft} denotes the ownership share that theater t's chain holds in the upstream producers and distributors, and λ_1 measures the extent to which a downstream theater internalizes the profits from its ownership of upstream production and distribution. If theater t internalizes all upstream revenue from integrated films, then $\lambda_1 = 1$ and $\lambda_{ft} = 1, \forall f : VI_{ft} = 1$.

Theaters play a pure strategy Nash equilibrium in pricing and showings. That is, their pricing and showings vectors, (p_t^*, S_t^*), are mutual best responses to each other. We assume that theaters know all attributes of the available films in advance, including the relevant information on unobservable quality ξ_{mft} under the assumptions on the information structure.[14]

A theater's optimal pricing and showings decisions are characterized by the following first-order conditions:

$$\lambda_{ft} s_{ft} + \sum_{f' \in \mathcal{F}_t} (\lambda_{f't} p_{f't} - mc_{f't}) \frac{\partial s_{f't}}{\partial p_{ft}} = 0, \tag{12}$$

$$\underbrace{M \sum_{f' \in \mathcal{F}_t} (\lambda_{f't} p_{f't} - mc_{f't}) \frac{\partial s_{f't}}{\partial S_{ft}}}_{\text{Marginal profit of showing}} = \frac{\partial C_t(S_t)}{\partial S_{ft}} \quad \text{if } S_{ft} > 0, \tag{13}$$

$$\underbrace{M \sum_{f' \in \mathcal{F}_t} (\lambda_{f't} p_{f't} - mc_{f't}) \left. \frac{\partial s_{f't}}{\partial S_{ft}} \right|_{S_{ft}=1}}_{\text{Marginal profit of one showing}} \leq \frac{\partial C_t(S_t + \iota_f)}{\partial S_{ft}} \quad \text{if } S_{ft} = 0. \tag{14}$$

We also explore an alternative model where marginal costs ($mc_{f't}$) are assumed to be zero, and theaters use a reduced-form pricing rule and make decisions solely on the number of showings.[15] The estimates of fixed costs remain robust under this alternative assumption regarding theater pricing practices.

[14] A detailed description of these assumptions is provided in Section 6, with the corresponding estimation results presented in Section 7.

[15] Under this assumption, the first-order conditions simplify to:

$$\underbrace{M \sum_{f' \in F_t} \lambda_{f't} p_{f't} \frac{\partial s_{f't}}{\partial S_{ft}}}_{\text{Marginal profit of showing}} = \frac{\partial C_t(S_t)}{\partial S_{ft}} \quad \text{if } S_{ft} > 0,$$

$$\underbrace{M \sum_{f' \in F_t} \lambda_{f't} p_{f't} \left. \frac{\partial s_{f't}}{\partial S_{ft}} \right|_{S_{ft}=1}}_{\text{Marginal profit of one showing}} \leq \frac{\partial C_t(S_t + \iota_f)}{\partial S_{ft}} \quad \text{if } S_{ft} = 0.$$

5.3. Discussion

The inclusion of weekly showings in the individual utility function reflects how an increased number of showings can boost overall demand for a film within a week. This specification can be micro-founded using a discrete choice model over a shorter time horizon for individual showing slots: the greater the number of showings allocated to a film, the more opportunities consumers have to select it, thereby increasing its likelihood of being chosen. As shown in Train (2009), aggregating consumer choices over a weekly period produces the functional form specified in equation (8). Similar approaches are adopted in Hastings et al. (2017) and Chen et al. (2022), which highlight the demand-side rationale for manipulating showings allocation to foreclose rival films.

The inclusion of vertical integration (VI_{ft}) in the utility function captures effects beyond price and total showings, such as local promotional efforts and preferential scheduling, which can directly influence demand under vertical integration.[16]

The model allows for heterogeneity in upstream and downstream competition, and therefore in the theater's *ability* and *incentive* to distort showings towards integrated films. In particular, films are horizontally differentiated by their latent attributes τ_{kf}. Because consumers have heterogeneous preferences over these attributes, films that are closer in the latent attribute space will be closer substitutes than films that are distant in this space. A theater will therefore have a greater incentive to reduce showings for a non-integrated film if it is also showing an integrated film that is close in latent attribute space. We call the degree to which the films in particular a market horizontally differentiated the level of "upstream competition".

Theaters are also horizontally differentiated based on geographic location, leading to differing degrees of "downstream competition". Consumer-specific preferences for theaters, δ_{it}, are spatially correlated, so theaters in closer proximity are stronger substitutes than those farther apart. The degree of substitution across theaters affects the theater's ability to foreclose upstream rivals by distorting showings - a local monopolist needs to worry less about substitution to other theaters than a theater operating in a more competitive local market.

On the supply side, theaters set showings in Nash equilibrium, taking into account substitution across films within theater and across theaters. Firms differentially weight revenue from integrated and non-integrated films. This allows for the distortionary effects discussed

[16] A similar specification is used in Gil et al. (2024), which includes a binary indicator for theaters showing a vertically integrated movie, and in Chen et al. (2022), which employs an index of vertical ownership.

above in Section 2. In particular, if $\lambda_1 > 0$ theaters have an incentive to allocate more showings to integrated films..

Finally, note that vertical integration has a direct effect on utility. If $\beta_2 > 0$, a vertically integrated theater would still allocate more showings to integrated films, even without internalizing upstream revenue, due to the direct demand-expansion effect of vertical integration.

6. Estimation and Identification

This section begins by outlining our empirical specification for estimating the structural parameters of the model. We then discuss the assumptions required to identify the key parameters.

We use the same sample employed in the descriptive analysis in Section 4. Before estimating the structural models, we estimate the four-dimensional latent attributes, $\{\tau_{kf}\}_{k=1}^{4}$, and the empirical distribution of consumer latent tastes for these attributes, $\{\nu_{ik}\}_{k=1}^{4}$. These estimates are derived from review data, as outlined in Section 4.3.2.

6.1. Demand

The vector of demand parameters to be estimated is $\theta_D = (\beta_1, \beta_2, \beta_3, \sigma, \eta)$. The model is estimated following the GMM approach of Berry et al. (1995). For a given parameter vector θ_D, we solve the BLP fixed-point algorithm to recover a vector of unobservables $\xi_{mft}(\theta_D)$ that rationalizes the observed market shares.

We include film-week fixed effects, market fixed effects, and theater fixed effects in the utility specification given in equation (8). Consequently, $\xi_{mft}(\theta_D)$ captures the *transitory* unobservable demand shock at the film-theater-week level. Following Schiraldi (2011), Sweeting (2013) and Hodgson (2023), we assume that $\xi_{mft}(\theta_D)$ evolves according to a first-order autoregressive process:

$$\xi_{mft} = \rho_\xi \xi_{mf,t-1} + \omega_{mft},$$

where ω_{mft} is mean-zero and independent of $\xi_{mf,t-1}$.

6.1.1. Demand Moments

We assume that VI_{ft} is econometrically exogenous for the the same reason we described in Section 4.2. Accordingly, the coefficient β_2 is identified under the assumption that VI_{ft} is uncorrelated with $\xi_{mft}(\theta_D)$:

$$E(\xi_{mft}(\theta_D) \times VI_{ft}) = 0.$$

The remaining parameters are identified using three sets of instrumental variables: the opening of new theaters, the variation in film release schedules, and lagged market shares. The key identifying assumption is that these instruments are uncorrelated with the transitory unobservable demand shock ξ_{mft} or its innovation ω_{mft}.

The first set of instrumental variables, Z_1^D, measures changes in downstream competition in theater markets, including the number of rival theaters within 2 kilometers, the number within 2 to 5 kilometers, and their interaction with VI_{ft}. The exogeneity assumption of theater openings is plausible if these decisions are driven by time-invariant unobserved location characteristics (captured by theater fixed effects) and long-term trends in film quality (captured by market fixed effects), rather than temporary demand fluctuations (similar to the empirical strategy in Nevo, 2001; Houde, 2012).[17]

The second set of instrumental variables, Z_1^D, measures changes in upstream competition between films. This includes differences between a focal film and competing films shown in the same theater in terms of latent attributes (b_f, τ_{kf}) and observable attributes (such as vertical integration with theaters, weeks since release, and whether the film is foreign).[18] The exogeneity assumption of the release schedule is supported by institutional practices: films are released nationwide in all theaters on their designated release dates, and release schedules are coordinated by the industry association months in advance, making them orthogonal to temporary regional demand shocks.

Note that Z_1^D is constructed based on the films shown alongside the focal film within a theater. Therefore, it is correlated with the extensive margin film supply decisions (i.e., whether the theater drops a film from release in a given week). We report estimates under two alternative assumptions regarding the information structure available to theaters when making these extensive margin film provision decisions:

Assumption 1. Following Chen et al. (2022) and Gil et al. (2024), the extensive margin

[17]Two factors support the exogeneity assumption of theater openings. First, historical theater entry has been primarily driven by urbanization and the initial scarcity of theaters in certain areas. Second, entering a local market involves substantial sunk costs and a lengthy construction period, prompting theater chains to base entry and exit decisions on long-term profitability rather than short-term demand fluctuations, especially given the pronounced seasonality of the industry.

[18]Specifically, the instruments $Z_{2,fmt}^D$ associated with film f in theater t, market m include: (1) the number of new releases; (2) $1\{f \text{ is foreign}\}$ – share of foreign rival films; (3) $\sum_{f' \in \mathcal{F}_{mt}} (b_f - b_{f'}) \times \sqrt{\sum_k (\tau_{kf} - \tau_{kf'})^2}$, where $\mathcal{F}_{mt}$ is the set of films shown in theater t, market m; (4) $\sum_{f' \in \mathcal{F}_{mt}} (b_f - b_{f'}) \times 1\{weeks_{mf'} \leq 4\} \times \sqrt{\sum_k (\tau_{kf} - \tau_{kf'})^2}$, where $weeks_{mf'}$ is the number of weeks since the release of film f' as of week $w(m)$; (5) $1\{\mathrm{VI}_{ft} = 0, \mathrm{VI}_{-f,t} > 0\}$ and $1\{\mathrm{VI}_{ft} = 0, \mathrm{VI}_{-f,t} > 0\} \times \min_{f':\mathrm{VI}_{f'}=1} d_{f,f'}$ as defined in Section 4.

decision is independent of ξ_{fmt}:

$$E(\xi_{fmt}(\theta_D) \times Z^D_{2,fmt}) = 0.$$

Assumption 2. Following Schiraldi (2011), Sweeting (2013), and Hodgson (2023), the extensive margin decision is contingent on $\xi_{fm,t-1}$ but orthogonal to ω_{fmt} (innovation to demand shocks):

$$E(\omega_{fmt}(\theta_D, \rho_\xi) \times Z^D_{2,fmt}) = 0.$$

The last instrumental variable, Z_3, measures how local demand shocks persist over time. Following Schiraldi (2011) and Sweeting (2013), we use lag market share to identify ρ_ξ. Lag market share is a valid instrument if Assumption 2 is satisfied: theaters set prices and showings without information of $\omega_{fmt}(\theta_D, \rho_\xi)$.

6.1.2. Identification

We assume that price and showings are endogenous, potentially correlated with unobservable demand shocks, and use variation in Z^D_1 and Z^D_1 to identify the coefficients on price (β_1) and showings (β_3). As new releases become available, competition between films within a theater changes. Theaters respond by adjusting prices and reallocating showings, often away from older, low-quality films.

The coefficients on individual taste for film (σ_0, σ_1) is identified using changes in the distribution of latent types among available films. The instrumental variables Z^D_1 described in Section 6.1.1 are constructed following the insights in Gandhi and Houde (2019) that interact distance in latent attributes and observable attributes. If σ is large, films that are closer to competing films in latent attributes $\{\tau_{kf}\}^4_{k=1}$ should face more competition. σ is therefore identified by the correlation between changes in these instruments and market shares.

Finally, the parameter η is identified by substitution patterns between theaters at different distances, and between theaters and the outside option. Specifically, η is identified by the substitution away from a theater when a competitor opens, and the extent to which this substitution diminishes with distance. To rationalize this, we construct instruments in Z^D_1 that measure the number of competing theaters within 2km and 5km for each theater-week.

6.2. Supply

The supply parameters are $\theta_S = (\lambda_0, \lambda_1)$. Notice that we allow the marginal cost of showings, $c_{fmt} \equiv \partial C_{mt}(S_{mt})/\partial S_{fmt}$, to vary at the film-theater-week level, while we fix how theaters internalize their upstream revenue from production and distribution, as defined in equation 11, to be the same across theater-film pairs.

We normalize $\lambda_0 = 0.57$, per the standard revenue sharing contract, and we run two alternative specifications for λ_1: one in which λ_1 is constant across all theaters, and one in which it is allowed to vary at the chain level.

We parametrize fixed costs as $c_{fmt} = c_{mt} + \tilde{c}_{fmt}$, where c_{mt} represents theater-week fixed effects. $\tilde{c}_{fmt}$ thus measures the discrepancy between the marginal revenue of showings for film f and the average marginal revenue across films shown in theater t.

The supply-side moment conditions are

$$E(\tilde{c}_{fmt} \times Z^S) = 0 \text{ if } S_{fmt} > 0$$

$$E(\tilde{c}_{fmt} \times Z^S) \leq 0 \text{ if } S_{fmt} = 0$$

7. Results

7.1. Demand Estimates

Table 6 reports parameter estimates for the demand model. The parameters that enter mean utility are all statistically significant and have the expected sign. Utility is decreasing in price (β_1) and increasing in showings (β_3).

The estimate of parameter β_2 suggests that vertically integration does not generate greater utility. Note that this is an average effect, and the difference in utility from vertical integration can differ across films through estimated film-theater-week level unobservables ξ_{mft}. On average, we do not find statistical evidence of additional utility from vertical integration that could be the result of promotional effort by the integrated theater or other synergies arising from integrated production and exhibition.

The coefficients on individual taste for film (σ_0, σ_1) which control the importance of idiosyncratic film tastes are positive and significant. This means that both latent characteristics and individual overall tastes of films contribute to cross-film substitution patterns observed in the data. To examine whether the latent attributes generate sensible cross-film substitution patterns, we simulate cross-film elasticities for a set of 48 foreign films (selected to be more

Table 6: Demand Estimates

Parameter	Utility component	(1)	(2)	(3)	(4)
Non-linear parameters					
η	Distance	-0.849	-0.880	-1.598	-1.231
		(0.309)	(0.313)	(0.210)	(0.233)
σ_1	Taste for film f	20.185	16.223	11.384	16.047
		(2.646)	(1.771)	(1.439)	(1.599)
σ_0	Overall film tastes		4.093		5.434
			(2.548)		(1.630)
Linear parameters: endogenous product characteristics					
β_1	Price	-0.744	-0.764	-0.798	-1.165
		(0.221)	(0.185)	(0.198)	(0.242)
β_3	Log showings	1.532	1.506	1.490	1.585
		(0.172)	(0.130)	(0.054)	(0.067)
Linear parameters: exogenous product characteristics					
β_2	VI_{ft}	0.007	-0.002	-0.007	-0.0003
		(0.019)	(0.014)	(0.013)	(0.018)
ρ_ξ	AR(1) coefficient of ξ_{fmt}			0.404	0.378
				(0.023)	(0.028)
δ_t	Theater FE	Yes	Yes	Yes	Yes
$\gamma_{w(m),f}$	Movie-week FE	Yes	Yes	Yes	Yes
γ_m	Market FE	Yes	Yes	Yes	Yes

Notes: This table shows the estimated structural parameters in individual demand for a film-theater in equation (8). Standard errors, clustered at the market level, are shown in parentheses.

familiar to an international reader than Chinese films). For this set of films, we simulate demand in a market with a single theater that shows all of these films simultaneously. In this simulation, we set ξ_{mft}, $\gamma_{w(m),f}$, and showings to their average values within each film and δ_t to its average value across all theaters.

Table 7: Cross-Film Showings Diversion Ratios

Interstellar (Sci-Fi)			Despicable Me (Animation)		
Life of Pi	Fantasy	0.037	The Hobbit	Fantasy	0.091
Gravity	Sci-Fi	0.032	Big Hero 6	Animation	0.077
The Hobbit	Fantasy	0.028	How to Train...	Animation	0.074
The Dark Knight	Action	0.019	Night at the...	Fantasy	0.071
X-Men	Sci Fi	0.015	Need For Speed	Action	0.068
Substitution From	Other Films	0.375	Substitution From	Other Films	0.442
	Outside Option	0.625		Outside Option	0.558

Notes: Elasticities are simulated in a market with a single theater showing a set of 48 foreign films. Showings, prices, film, and theater utility are set at their mean level for each film in the set. For two example films, the table records the five largest cross-film showing elasticities, and the share of substitution from other films and from the outside good when shoings are increased by 1 for the target film.

In Table 7 we record the simulated cross-film showings elasticities for the 5 closest substitutes for two focal films. We selected these films – *Interstellar* and *Big Hero 6* – because they exhibit different substitution patterns. *Interstellar* (a science fiction film) has three sci-fi films among its closest 5 substitutes, while *Big Hero 6* (an animated film) has none. Likewise, the two closest substitutes to *Big Hero 6* are animates while there are no animations in the list of close substitutes for *Interstellar*. That these two films are each close substitutes to films that are of the same genre provides some reassurance that the latent attributes derived from review data generate sensible substitution patterns. However, note that if we had included random coefficients observable genre instead of latent attributes, the model would have generated different substitution patterns. For instance, the closest substitute to *Gravity* is *Life of Pi* which is classified as a fantasy film. Likewise, *The Hobbit* and *Ninja Turtles* are live-action films, not animations, but make sense as close substitutes to *Big Hero 6* because they are popular with children. Substitution patterns based only on observable genres would have underestimated this cross-genre substitution relative to the latent attributes.

To illustrate this margin of substitution, the final two lines of Table 7 record the decrease in demand for other films and the outside option as a share of the total change in demand when showings for *Interstellar* or *Big Hero 6* are increased by 1. While the median market share of the outside good is over 99%, on average only 67.05% of substitution goes to the outside good.[19]

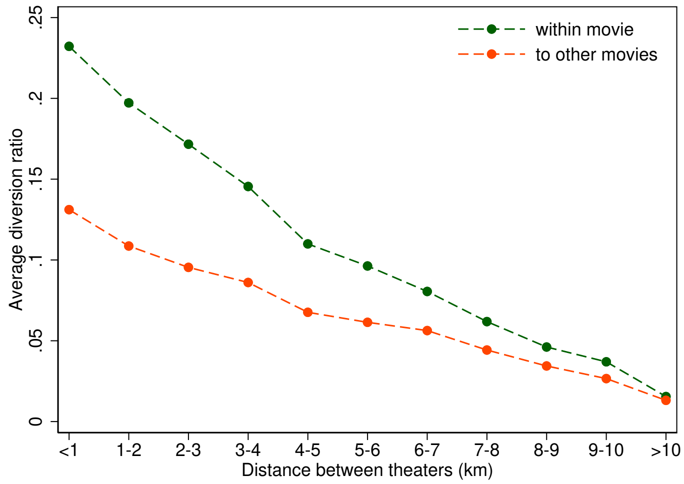
The parameter η controls substitution between theatres at different distances. Figure 2(a) illustrates how cross-theater substitution varies with distance at the estimated parameters. For all film-theater pairs in our dataset, we compute cross-theater diversion ratios for different distances between the pair of theaters. Cross-theater substitution is highest when theaters are within 1km of one another, declines with distance, and is close to zero beyond 4km. The estimated substitution patterns generate meaningful variation in the degree of competition faced by theaters. 63% of theaters in the estimation sample have no competitions within 1km, 19% have no competitors within 2km. This suggests that the extent of downstream competition depends sensitively on the spatial arrangement of theaters, and that taking a geographically large city to be a single market without considering spatial substitution patterns would generate misleading results.

The presence of a significant *direct* effect of vertical integration on utility, captured by the parameter β_2, complicates the interpretation of the results in Section 4. In particular, theaters may allocate more showings to vertically integrated films because demand for vertically integrated films is higher, rather than because they are internalizing upstream revenue. To test whether this is the case, we compute the revenue from the marginal showing for each film-theater-week and regress MR_{mft} on indicators for vertical integration, controlling for film-city and theater fixed effects.

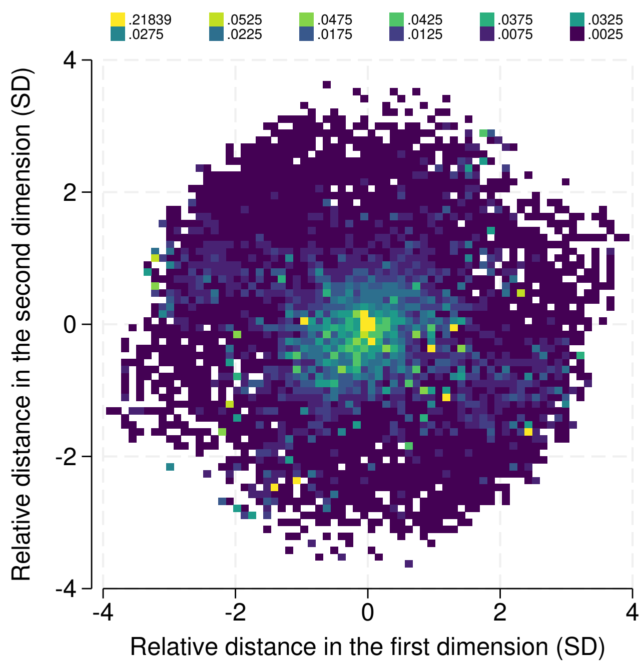
Notice that this is the *total* marginal revenue from film f, not the internalized marginal revenue used in equation (**??**), which is a function of λ_1. As discussed in Section 2, if theaters do not internalize upstream revenues, then this marginal revenue should be equalized across films. If firms do internalize upstream revenue, then the total marginal revenue of vertically integrated films should be lower than that of independent films.

The results of this exercise are displayed in Table 8. The first column regresses log marginal revenue on an indicator for vertical integration, and an indicator for films that are not integrated in theaters that are currently showing integrated films. Coefficients thus record the average difference in $\ln(MR_{mft}$ between films in these categories and films in the omitted category, which are non-integrated films when there are no integrated films available. The coefficients indicate that marginal revenue is about 14% lower for vertically integrated films and 48% higher for non-integrated films when an integrated film is available. These patterns are consistent with theaters reallocating showings away from non-integrated films when an

[19] The 10^{th}, 25^{th}, 50^{th}, 75^{th}, and 90^{th} percentiles are 13.41%, 41.15%, 78.50%, 96.75%, and 99.83%, respectively.



(a) Cross Theater



(b) Within Theater

Figure 2: Substitution Patterns

Notes: Cross-theater elasticities computed for markets with two theaters showing a single film with showings, film, and theater utility all set at their mean level. The showings elasticity is computed for different distances between the two theaters.

Table 8: Marginal Revenue Regressions

	Dependent Variable: $\ln(MR_{mft})$		
$VI_{ft} = 1$	-0.155***	-0.108***	-0.085***
	(0.011)	(0.010)	(0.024)
$VI_{-ft} = 1 \& VI_{ft} = 0$	0.044***	0.010	0.051***
	(0.008)	(0.007)	(0.018)
Movie-City Fixed Effects	No	Yes	Yes
Theater Fixed Effects	Yes	Yes	Yes
Sample	All	All	Local Monopolies
N	445,070	445,070	109,834

Notes: Standard errors in parentheses. Marginal revenues are computed for every available film for each theater in a market, including film-theater pairs where $s_{mft} = 0$. $VI_{ft} = 1$ when theater t is integrated with film f. $VI_{-ft} = 1$ when there is at least one currently available film other that f that is integrated with theater t. The fourth column restricts the sample to theaters with no competitors within 2km.

integrated film is available.

The effect of vertical integration on marginal revenue is robust to controlling for film-city and theater fixed effects. However, when both sets of fixed effects are included, $\ln(MR_{mft}$ is no longer statistically significantly lower for non-integrated films when an integrated film is available. However, significance is restored when the sample is restricted to theaters with no competitors within 2km. In this sample, marginal revenue is 9.5% higher for non-integrated films when an integrated film is available, consistent with the expected effect of downstream competition on foreclosure.

7.2. Supply Estimates

Supply parameter estimates are reported in Table 9. We first estimate bounds for the internalization parameter λ_1 - the share of integrated upstream profit a theater internalizes when pricing films - assuming λ_1 is the same across all theaters. The lower and upper bounds of the identified set for λ_1 are respectively 0.728 and 2.266. We next allow for theater chain-specific internalization parameters and report the estimates for the top four theater chains. The lower bounds range between 0.586 and 1.13, and the upper bounds range between 1.109 to 2.967.[20].

The bounds of the marginal cost of adding one additional showing are 40.796 and 118.271 (in US Dollars). Allowing for chain-specific marginal costs, the lower bounds for the top four theater chains range between 41.50 to 68.03, and the upper bounds range between 64.39 to 110.34. Our estimates are in line with the industry estimates of the marginal costs of

[20]Our bounds cover the point estimate in Chen et al. (2022)

showings, 17.41–66.12 US dollars.[21]

Table 9: Supply Parameter Estimates

	λ_1	c
All Theaters	[0.728, 2.266]	[40.796, 118.271]
Chain 1	[0.627, 1.109]	[68.034, 110.349]
Chain 2	[0.826, 1.359]	[41.507.390, 64.397]
Chain 3	[1.130, 2.967]	[41.693, 101.429]
Chain 4	[0.586, 1.127]	[43.434, 82.771]

Notes: The first row records estimated bounds under the assuption that $\lambda_{it} = \lambda_1$ and $c_t = c$ for all theaters. The lower four rows are estimates for the four largets theater chains when λ_{it} and c_t are allowed to vary by chain.

The estimated lower bounds on λ_1 are all greater than $\lambda_0 = 0.57$. Theaters are estimated to internalize a greater share of revenue from integrated films than non-integrated films, consistent with the marginal revenue regressions in Table 8. The estimated bounds are quite wide, coveting 1 in most cases. This means that we cannot reject that theaters "over-internalize" upstream revenue for integrated films. The bounds also vary substantially across chains. Our vertical integration indicator includes various ownership models in which the theater may be a franchise or wholly owned by the chain, and in which the chain is wholly or partly owned by one or more upstream firms. It is therefore not surprising that the level of internalization varies across chains. Whether this variation is correlated with variation in ownership structure remains to be investigated.

7.3. Heterogeneous Welfare Effects of Vertical Integration

In this subsection, we use a simple simulation based on our estimates in Tables 6 and 9 to illustrate the importance of theaters' *ability* and *incentive* in shaping consumer welfare in the vertical market for films.

Suppose there are two films of the same vertical quality, each distributed by a firm that owns a theater. The films are horizontally differentiated, and the extent of product differentiation is measured by their Euclidean distance in the latent attribute space. The more substitutable the two films are, the greater the incentive each theater has to foreclose rival films by allocating fewer screenings. The theaters are spatially differentiated, and the extent of spatial differentiation is measured by their geographical distance. The greater this distance

[21]Source: https://www.toutiao.com/question/6672326767002255630/?wid=1670971990919, retrieved on December 13, 2022.

is, the greater the retail market power (i.e., ability to foreclose rival films) each theater enjoys.

We plot the difference in consumer welfare with the one under a ban on vertical integration in Figure 3. First, the region where vertical integration is welfare-decreasing is larger when theaters are located farther apart (i.e., they have greater ability to foreclose rival films). Second, in the extreme case when films are perfect substitutes, theaters have the strongest incentive to foreclose rival films. However, vertical integration is welfare-enhancing as the welfare loss from losing access to a perfectly substitutable film is limited. In this case, the efficiency effect dominates in vertical integration, consistent with conventional wisdom. Lastly, when there is significant differentiation between films, the incentive to foreclose is weak, and the screening decisions are not significantly distorted by vertical ownership. The effect of vertical integration on consumer welfare is positive.

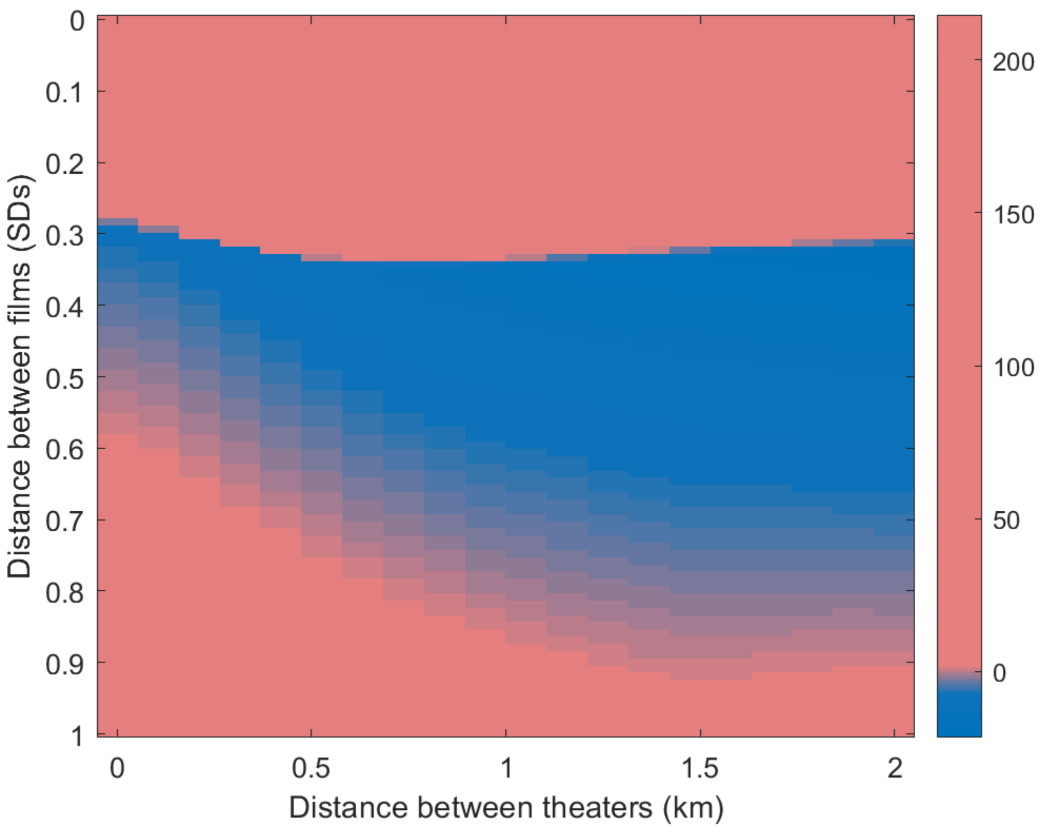


Figure 3: Ability, Incentive, and Consumer Welfare under Vertical Integration

8. Conclusion

This paper attempts to shed light on the heterogeneous effects of vertical integration by documenting how vertical foreclosure varies with market structure in the Chinese film industry. Consistent with theory, we show that theatres allocate more showings to vertically integrated films than non-integrated films, and that this effect is largest when the theater faces little local competition. To account for the possible direct effect of vertical integration on demand, we develop and estimate a structural model of film demand. We use data on theater location and film attributes recovered by applying a matrix factorization algorithm to review data to capture flexible cross-theater and cross-film substitution patterns. The estimated model allows us to test for vertical foreclosure using computed marginal revenues.

Estimates supply-side "internalization" parameters are consistent with 100% internalization of upstream revenue from integrated films. In future revisions we will use the estimated demand and supply model to perform a counterfactual analysis in which we remove vertical integration and recompute equilibrium showings. The results of this exercise will allow us to investigate how the net welfare effects of vertical integration vary across markets with different levels of upstream and downstream competition.

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Appendix A. Details on Institutional Background

A.1. Vertical Integration

Table A1 tabulates the revenue and vertical integration status of top distributors and theater chains. For integrated distributors and theater chains, we also report the starting year of vertical integration. Most integration started before or during the 2002–2008 reform period. Note that typically a film has multiple distributors, we calculate a distributor's revenue as the sum of the gross revenue of its films without adjusting for the number of cooperating distributors.

Table A1: Top Theater Chains and Distribution Companies (2011–2015)

Rank	Distributors		Theater chains	
	VI with Chain (year)	Revenue	VI with Distributor (year)	Revenue
1	Yes (1984)	21338.99	No	754.84
2	Yes (2003)	11569.51	Yes (2001)	722.64
3	No	8410.31	Yes (2004)	640.77
4	No	6261.88	Yes (2005)	552.35
5	No	5881.13	Yes (2004)	524.98
6	Yes (2005)	5062.03	No	397.96
7	Yes (1996)	3427.03	Yes (2006)	312.32
8	No	2967.72	Yes (2001)	246.25
9	Yes (2013)	2644.7	Yes (2010)	241.24
10	No	1932.96	Yes (2005)	238.38

Notes: The integration status and the starting year of the status are reported. A distribution company's revenue column shows the gross revenue of its films over the sample period. The subtotal revenue from integrated chains is reported in parentheses. Similarly, a theater chain's revenue and the subtotal from integrated films are reported.

A.2. Film Distribution

Table A2 summarizes the producer-distributor pairs of films in our sample period 2011–2015. Integrated producers (distributors) refer to those integrated with at least 1 theater chain. For non-integrated and integrated producers, we calculate the count and total box office (in millions of Chinese Yuan) of their films distributed by their own distributors, rival integrated distributors, and non-integrated distributors. Own and rival integrated distributors refer to distributors that are integrated with the producer and rival producers, respectively.

First, no non-integrated producers have a film distribution division but produced 501 films out of the 637 films. Most of these films were distributed by integrated distributors. Second, only 136 films were produced by producers with integrated theater chains, the majority of which were distributed by their own distributors. Taken together, it is less common and economically less important for producers to integrate with theater chains compared to distributors.

Table A2: Revenue and the Counts of Producer-Distributor Pairs by Integration Type

	Own distributors	Rival integrated distributors	Non-integrated distributors	Total
Non-integrated producers	0	1916.15	3183.66	5099.81
	(0)	(288)	(205)	(493)
Integrated producers	1184.11	184.86	380.7	1749.67
	(88)	(20)	(27)	(135)
Total	1184.11	2101	3564.36	6849.48
	(88)	(308)	(232)	(628)

Note: The table summarizes the revenue (in millions of Chinese Yuan) and the counts of the vertical integration status of the producers and distributors of 637 films in the box-office data. Integrated producers (distributors) refer to those integrated with at least 1 theater chain. Own and rival integrated distributors refer to distributors that are integrated with the producer and rival producers, respectively.

A.3. Revenue Sharing

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

Table A3: Film Supply Chain in China

Players	Role	Revenue share of total box office
Government		8.5%
Tax authorities	Taxation	3.3%
SARFT	Release date coordination	5%
Upstream firms		43%*(1-8.5%)
Producers	Production	
Domestic		34.5%*(1-8.5%)
Foreign		13%*(1-8.5%) (before 2012)
		25%*(1-8.5%) (after 2012)
Distributors	Contracting & marketing	
Domestic films		8.5%*(1-8.5%)
Imported films	State duopoly	30%*(1-8.5%) (before 2012)
		18%*(1-8.5%) (after 2012)
Downstream firms		57%*(1-8.5%)
Theater chains	Screenings	5%*(1-8.5%)
Theaters	Pricing	52%*(1-8.5%)

Data sources: https://piaofang.maoyan.com/rankings/year, Hou and Wu (2014) and Gao et al. (2018).

Appendix B. Additional Empirical Results

B.1. Variance Decomposition of Price and Showings

In this subsection, we follow Abowd et al. (1999) to decompose a film's average weekly price and per-screen showings in a theater to film-week level variation and exhibitor level variation. Specifically, we regress a film's average price on film-week fixed effects and theater-week or chain-week fixed effects. We regress film-theater-week level showings on film-week fixed effects and theater-week or chain-week fixed effects. The variance of the dependent variables (price or showings) is then decomposed to the sum of the variance of each fixed effect and the covariance between fixed effects.

Table B1 reports the decomposition results. For price variation decomposition, film-week fixed effects control for the declining popularity over time. Theater-week fixed effects account for 64% of the price variation while chain-week fixed effects only account for 11%. This suggests that there is significant price variation across theaters under the same chain, possibly driven by differences in retail competition.

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

Table B1: Variance Decomposition

	Price				log (showings)			
Total variance	2.02				563.2			
	Level	%	Level	%	Level	%	Level	%
Theater-week	1.31	64.86			102.18	18.14		
Chain-week			.25	12.5			30.49	5.41
Movie-week	.18	9.14	.19	9.36	295.82	52.53	293.01	52.03

Notes: All rows use observations at the theater-film-week level. Price is in dollars. A film's showings per screen is the weekly screening of the film divided by the number of screens in the theater.

B.2. Regression Results

Table B2: Vertical Integration with Producers and Distributors

	First-week sample		Film-theater totals sample		Full sample	
	log(price)	log(showings)	log(duration)	log(showings)	log(price)	log(showings)
	(1)	(2)	(3)	(4)	(5)	(6)
VI_{ft}	-0.003*	0.024***	0.014***	0.032***	-0.002***	0.023***
	(0.001)	(0.006)	(0.003)	(0.007)	(0.001)	(0.004)
Week FE	Yes	Yes	Yes	Yes		
Theater FE	Yes	Yes	Yes	Yes		
Film-city FE	Yes	Yes	Yes	Yes	Yes	Yes
Film-week FE					Yes	Yes
Theater-week FE					Yes	Yes
N	650,755	650,755	650,755	650,755	2,013,804	2,013,804
R^2	0.742	0.771	0.732	0.789	0.798	0.757

Notes: Standard errors are clustered at the market level and are reported in parentheses. *** $p<0.005$, ** $p<0.01$, * $p<0.05$.

Appendix C. Details of the Rating Model

C.1. Interpreting the Latent Attributes

The correlation between latent and observable characteristics is plotted in Figure C1.

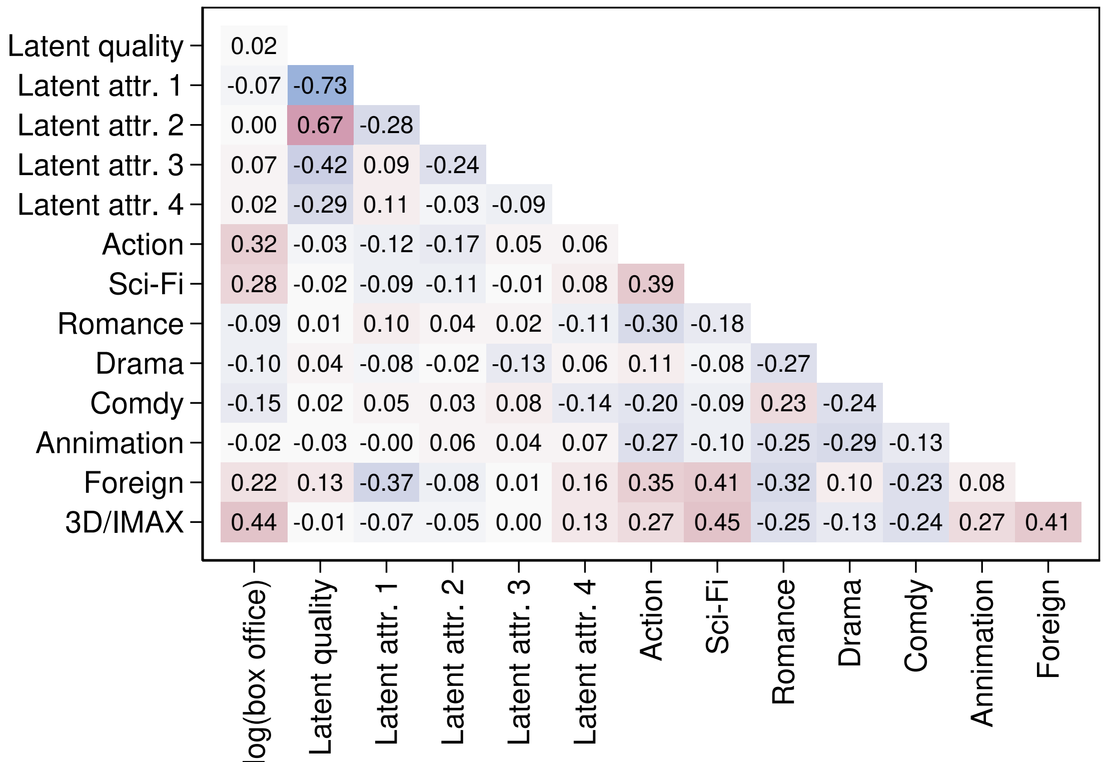

Figure C1: Correlation between Latent and Observable Characteristics

C.2. Hyperparameter Tuning: Bi-Cross Validation

To avoid over-fitting, we use the "bi-cross-validation" method proposed in Owen and Perry (2009) to pin down the dimension of latent characteristics (K) and the regularization parameter which penalizes the norm of the preference and characteristic vectors (λ). Similar to k-fold cross validation, it first divides the sample into k sub-samples. Each of the k sub-samples is used as the testing sample with the rest $k-1$ together as the training one. The average of the resulting k MSEs is used as a measure of model fit.

Unlike other machine learning tasks, data for matrix factorization is sparse: users rate a small fraction of films and films are rated by a small fraction of users. If folds are specified at random, we may not be able to calculate MSE for the testing sample (for example, films in k

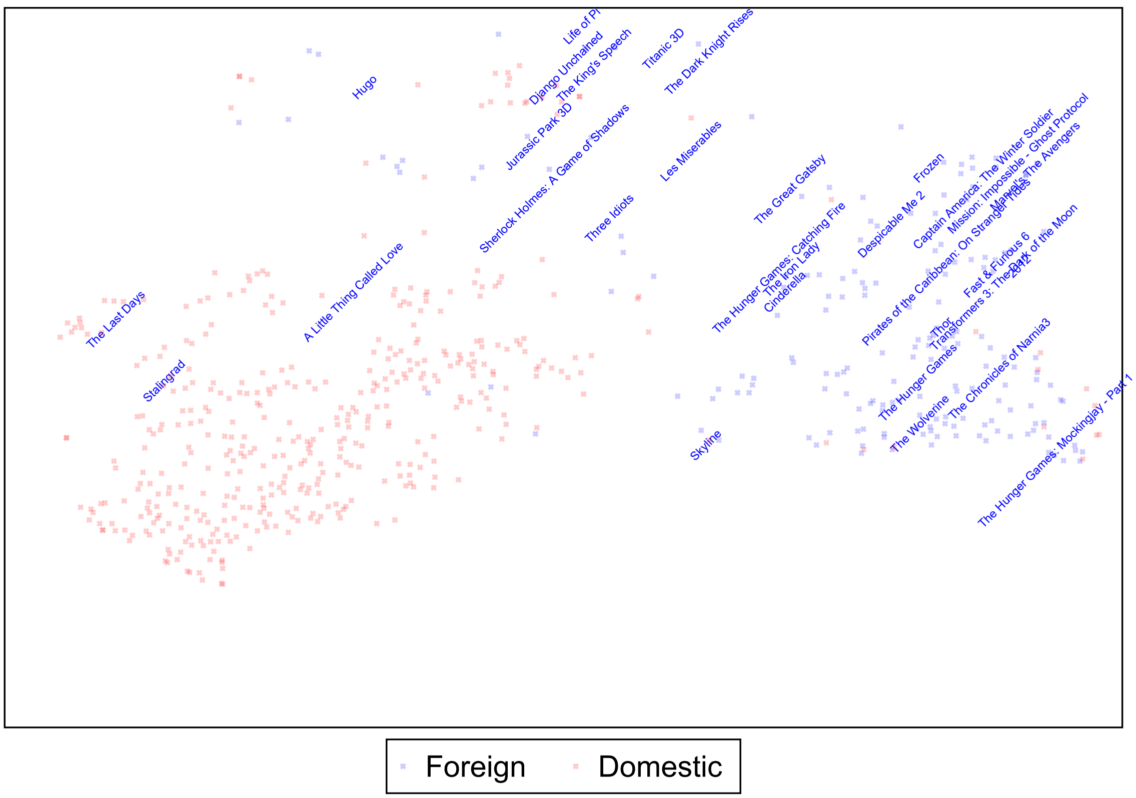

Figure C2: Visualization of Film Attributes sub-samples do not overlap). Bi-cross-validation uses a special sample division rule to avoid this problem: divide users to K_1 folds $(I_1, I_2, ..., I_{K_1})$ and films to K_2 folds $(F_1, F_2, ..., F_{K_2})$ which gives $K_1 \times K_2$ sub-samples: $\{(i, f) : i \in I_{k_1}, f \in F_{k_2}\}$. We set $K_1 = 2, K_2 = 2, k = 4$ when implementing this method.

Appendix D. Details of Demand Estimation

Table D1: First-Stage Regressions

VARIABLES	(1) Price	(2) log(showings)	(3) log inside share
VI_{ft}	-0.052***	0.042***	0.043***
	(0.007)	(0.008)	(0.009)
Weeks since release	-0.052***	-0.205***	-0.449***
	(0.002)	(0.005)	(0.005)
$1\{\text{VI}_{ft} = 0, \text{VI}_{-f,t} > 0\}$	-0.033***	-0.031***	-0.037***
	(0.007)	(0.007)	(0.010)
$\text{Theaters}_{tw}^{0-5}$	-0.023***	-0.008***	-0.028***
	(0.001)	(0.001)	(0.001)
$\text{VI}_{ft} \times \text{Theaters}_{tw}^{0-5}$	0.004***	-0.002***	-0.002***
	(0.001)	(0.000)	(0.001)
$1\{\text{VI}_{ft} = 0, \text{VI}_{-f,t} > 0\} \times \text{Theaters}_{tw}^{0-5}$	0.004***	-0.001***	-0.002***
	(0.001)	(0.000)	(0.001)
$\text{VI}_{ft} \times \min_{f':VI_{f'}=0} d_{f,f'}$	0.008**	-0.017**	-0.021***
	(0.004)	(0.007)	(0.008)
$1\{\text{VI}_{ft} = 0, \text{VI}_{-f,t} > 0\} \times \min_{f':VI_{f'}=1} d_{f,f'}$	-0.002	0.017***	0.014***
	(0.002)	(0.003)	(0.004)
Number of release (N_{tw})	-0.009***	-0.039***	0.005*
	(0.002)	(0.002)	(0.003)
$N_{tw} \times \max_w N_{tw}$	0.000**	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
Differentiation IV (new release)	-0.030***	0.171***	0.258***
	(0.003)	(0.009)	(0.010)
Observations	1,142,225	1,142,225	1,142,225
R-squared	0.680	0.517	0.714
Theater FE	Yes	Yes	Yes
Film-MSA FE	Yes	Yes	Yes
F	113.1	868.7	1676

Notes: All observations are at the film-theater-week level. All specifications control for film-MSA and theater fixed effects. Variable $\min_{f':VI_{f'}=0} d_{f,f'}$ is the minimum distance between film f and its non-integrated rival f', and Variable $\min_{f':VI_{f'}=1} d_{f,f'}$ is the minimum distance between film f and its integrated rival f', both in the latent attribute space shown in Figure C2. Variable $\text{Theaters}_{tw}^{0-5}$ is the count of rival theaters within 5 km, $\max_w N_{tw}$ is the maximum weekly showings of theater t over the sample period, Differentiation IV (new release) for film f in theater t week w is defined as $1\{weeks_{ftw} \leq 1\} - \frac{1}{N_{tw}-1} \sum_{f' \in \mathcal{F}_{tw}, f' \neq f} 1\{weeks_{f'tw} \leq 1\}$. Standard errors are clustered at the market level and are reported in parentheses. *** p <0.005, ** p <0.01, * p <0.05.

Appendix E. Details of the Moment Inequalities

E.1. Inverting Fixed Costs of Showings

Stacking first-order conditions of pricing to get the matrix form of first order conditions

$$\lambda \odot s + (\Omega \odot \Delta_p)(\lambda \odot p - mc) = 0,$$

which allows for inverting variable profit at optimal pricing of each film

$$M(\lambda \odot p - mc) = -M(\Omega \odot \Delta_p)^{-1}(\lambda \odot s).$$

We can then express marginal variable profit for it into equations (13) and (14)

$$c = -M(\Omega \odot \Delta_s)(\Omega \odot \Delta_p)^{-1}(\lambda \odot s) \qquad \text{if } S_{ft} > 0, \tag{15}$$

$$c \geq -M(\Omega \odot \Delta_s)(\Omega \odot \Delta_p)^{-1}(\lambda \odot s) \qquad \text{if } S_{ft} = 0. \tag{16}$$

where λ, p, and s are column vectors, with the i^{th} elements representing the VI-dependent revenue share, price, and market share of the i^{th} product, respectively. Ω is the ownership matrix, where $\Omega_{ij} = 1$ if the i^{th} and j^{th} products are two films shown in the same theater. The symbol $\odot$ denotes the element-by-element product operator, and Δ is the matrix of price derivatives from the demand system, with $\Delta_{ij} = \partial s_j / \partial p_i$.

E.2. Construction of the Estimator of Fixed Costs

1. For non-zero-showing films, invert mean utilities, fixed effects, demand shocks ξ_{ft}.
2. Predict mean utilities of zero-showing films in its counterfactual market:

$$\delta_{ft} = (VI, \hat{p}_{ft}, log(1))\hat{\beta} + \delta_t + \delta_{fw} + \hat{\rho}\xi_{ft,w-1}, s_{ft} = 0.$$

3. Create a counterfactual market dataset for each zero-showing film $f : s_{ft} = 0$

$$\{f\} \cup \{f' : s_{f't} > 0, f' \in \mathcal{F}_{d(f)}\}.$$

   Predict reduced-form prices $\hat{p}_{ft}$ and set $s_{ft} = 1$ for f.
4. Use Equations (15) and (16) to compute showing elasticities and form the lower cost bound.

In section 6, we introduce moment inequalities used to set identify the supply parameters. However, sometimes the feasibility constraint bind such that $s_{mft} = 0$ or $\sum_{f \in F} s_{mft} = C_t$. In these cases, the inequality does not necessarily hold since the deviations of adding and subtracting one showing are not feasible. Simply dropping the constrained observations from the data will introduce a selection bias on ν_{mft} (See PPHI). To deal with this, we adopt a reweighting scheme for the moments similar to PPHI. Our scheme extends PPHI in two dimensions. First, the number of showings is bounded from above *and* below. Second, changes in revenue depend on an unknown parameter λ that we seek to identify, in addition to a linearly separable marginal cost c. Both of these features require adaptations of PPHI's scheme.

Upper Bounds

Consider the case for $VI_{tf} = 0$. Similar argument applied for $VI_{tf} = 1$. Define the set of observations not bounded from below:

$$L_0 = \{(t, m, f) : s_{mft} > 0 \,\&\, VI_{tf} = 0\}$$

Let $q_{L_0} = \frac{n_{L0}}{n_0}$, be the share of observations that are unconstrained .

$$U_{R0} = \{(t, m, f) : VI_{tf} = 1 \& R_f^+(s_{tm}, s_{-tm}, \lambda = 0) \geq R_f^+(s_{tm}, s_{-tm}, \lambda = 0)_{(n_1 q_{L_0} | VI_{tf}=1)}\}$$

Where the subscript $(n_1(1 - q_{L_0}) | VI_{tf} = 1)$ is order statistic notation among the set of (t, m, f) for which $VI_{tf} = 1$). Similarly define U_{R1} using $((n_1 + 1)q_{L_1} | VI_{tf} = 1)$.

$$U_{\nu 0} = \{(t, m, f) : VI_{tf} = 1 \& \nu \leq \nu_{(n_1(1 - q_{L_0}) | VI_{tf}=1)}\}$$

$$L_{\nu 0} = \{(t, m, f) : VI_{tf} = 0 \& \nu \leq \nu_{(n_0 q_{L_0} | VI_{tf}=0)}\}$$

Form the moments for $VI = 0$:

$$\frac{1}{n_0} \sum_{L_0} \left(R_f^-(s_{tm}, s_{-tm}, \lambda) - c \right) + \frac{1}{n_1} \sum_{U_{R0}} \left(R_f^+(s_{tm}, s_{-tm}, \lambda = 0) + c \right)$$

This is a known function of c and λ. Note that:

$$\geq \frac{1}{n_0} \sum_{L_0} \Big(R_f^-(s_{tm}, s_{-tm}, \lambda) - c \Big) + \frac{1}{n_1} \sum_{U_{\nu 0}} \Big(R_f^+(s_{tm}, s_{-tm}, \lambda = 0) + c \Big)$$
$$\geq \frac{1}{n_0} \sum_{L_0} \Big(R_f^-(s_{tm}, s_{-tm}, \lambda) - c \Big) + \frac{1}{n_1} \sum_{U_{\nu 0}} \Big(R_f^+(s_{tm}, s_{-tm}, \lambda) + c \Big)$$
$$\geq \frac{1}{n_0} \sum_{L_0} \nu_{mft} + \frac{1}{n_1} \sum_{U_{\nu 0}} -\nu_{mft}$$

The first line is by definition of U_{R0}. The second line holds because films are substitutes. The third line holds by profit maximization. Now note that we can write

$$\frac{1}{n_0} \sum_{L_0} \nu_{mft} + \frac{1}{n_1} \sum_{U_{\nu 0}} -\nu_{mft}$$
$$\geq \frac{1}{n_0} \sum_{L_{\nu 0}} \nu_{mft} + \frac{1}{n_1} \sum_{U_{\nu 0}} -\nu_{mft}$$
$$\xrightarrow{p} qE(\nu_{mft} | \nu < F^{-1}(q)) - (1-q)E(\nu_{mft} | \nu < F^{-1}(1-q))$$
$$= qE(\nu_{mft} | \nu < F^{-1}(q)) + (1-q)E(\nu_{mft} | \nu > F^{-1}(q))$$
$$= E(\nu_{mft}) = 0$$

Lower Bounds

Consider the case for $VI_{tf} = 0$. Similar argument applied for $VI_{tf} = 1$. Define the set of observations not bounded from above:

$$U_0 = \{(t, m, f) : s_{mft} < C_t - \sum_{j \in F \setminus f} s_{tmj} \,\&\, VI_{tf} = 0\}$$

Let $q_{U_0} = \frac{n_{U_0}}{n_0}$, be the share of observations that are unconstrained .

$$U_{R0} = \{(t, m, f) : VI_{tf} = 1 \& R_f^+(s_{tm}, s_{-tm}, \lambda = 0) \geq R_f^+(s_{tm}, s_{-tm}, \lambda = 0)_{(n_1 q_{U_0} | VI_{tf} = 1)}\}$$

$$U_{\nu 0} = \{(t, m, f) : VI_{tf} = 1 \& \nu \geq \nu_{(n_1 q_{U_0} || VI_{tf} = 1)}\}$$

$$L_{\nu 0} = \{(t, m, f) : VI_{tf} = 0 \& \nu \leq \nu_{(n_0 q_{U_0} | VI_{tf} = 0)}\}$$

Form the moments for $VI = 0$:

$$\begin{aligned}
&\frac{1}{n_0}\sum_{U_0}\Big(R_f^+(s_{tm}, s_{-tm}, \lambda) + c\Big) + \frac{1}{n_1}\sum_{L_{R0}}\Big(R_f^+(s_{tm}, s_{-tm}, \lambda = 0) + c\Big) \\
\geq &\frac{1}{n_0}\sum_{U_0}\Big(R_f^+(s_{tm}, s_{-tm}, \lambda) + c\Big) + \frac{1}{n_1}\sum_{U_{\nu 0}}\Big(R_f^+(s_{tm}, s_{-tm}, \lambda = 0) + c\Big) \\
\geq &\frac{1}{n_0}\sum_{U_0}\Big(R_f^+(s_{tm}, s_{-tm}, \lambda) + c\Big) + \frac{1}{n_1}\sum_{U_{\nu 0}}\Big(R_f^+(s_{tm}, s_{-tm}, \lambda) + c\Big) \\
\geq &\frac{1}{n_0}\sum_{U_0} -\nu_{mft} + \frac{1}{n_1}\sum_{U_{\nu 0}} -\nu_{mft} \\
\geq &\frac{1}{n_0}\sum_{L_{\nu 0}} -\nu_{mft} + \frac{1}{n_1}\sum_{U_{\nu 0}} -\nu_{mft}
\end{aligned}$$

$$\begin{aligned}
&\xrightarrow{p} -qE(\nu_{mft}|\nu < F^{-1}(q)) - (1-q)E(\nu_{mft}|\nu > F^{-1}(q)) \\
&= -E(\nu_{mft}) = 0
\end{aligned}$$