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. Theaters allocate significantly fewer showings to non-integrated films. This foreclosure effect is particularly pronounced in two scenarios: when an integrated theater faces limited spatial competition, and when an integrated film is similar to competing films. To measure welfare effects, we estimate a model of consumer preferences and theater showings choice using a novel method that combines standard demand data with film ratings data. Our results show that integrated theaters internalize a substantial portion of their upstream profits, driving foreclosure behavior that distorts showings. Counterfactual simulations show that vertical integration increases consumer welfare by 2.4% in the median market, but reduces consumer welfare in 7% of markets. The welfare effects of foreclosure vary with upstream competition between films and downstream competition between theaters, and we show that targeted antitrust policy that removes of integration based on measures of market competition can substantially increase welfare.

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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 following the update and subsequent withdrawal of the 2020 Vertical Merger Guidelines and the release of the unified 2023 Merger Guidelines. Compared to the 1984 Non-Horizontal Merger Guidelines, these recent 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 foreclose 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 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, product provision decisions, and consumer welfare 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 its own 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] 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 a firm's *ability* and *incentive* to foreclose,

[1] This form of foreclosure, termed the *Edgeworth-Salinger* effect, has been documented by Luco and Marshall (2020) in the soft drinks industry.

which we 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 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.

[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.

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 meaningful differences in prices between vertically integrated and non-integrated films. On the other hand, we find significant effects on showings. The number of weekly showings for vertically integrated films is around between 3% and 4% higher than non-integrated films that do not face competition from an integrated rival. The number of showings for potentially foreclosed films - nonintegrated films that are shown alongside integrated films - is between 4% and 6% lower than non-integrated films that do not face competition from an integrated rival. 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 for a direct effect of integration on 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: vertically integrated films have 6% lower marginal revenue than non-integrated films in the same theater-week. This difference is significantly larger when there are fewer competing theaters nearby, and when non-integrated films are closer in attribute space to the integrated film, rising to 15.4% for very close competitors. These results suggest that foreclosure is significant when the foreclosed film is a close substitute to the integrated film.

We estimate a supply model in which firms choose showings and prices optimally given an internalization parameter which measures how much weight they place on upstream revenue for integrated films. We find that theaters which are integrated with a distributor internalize 43.4% of distributor revenue for vertically integrated films. The internalization parameter rationalizes differences in the marginal revenue of showings between integrated and non-integrated films.

To measure welfare effects, we use the estimated model to solve for counterfactual equilibria in which we remove vertical integration entirely. We compute a counterfactual for each market in the data and examine heterogeneity in the resulting changes across markets. On average, removing vertical integration reduces the number of showings for integrated films by 14 and increases the number of showings for potentially foreclosed films by 3. The simulated effect on the showings of foreclosed films is significantly decreasing in the number of nearby theaters and in the distance to the nearest integrated film in latent attribute space, consistent with our descriptive results. In the median market, vertical integration *increases* consumer surplus by 2.4% relative to the no-integration benchmark. Although there is significant heterogeneity in the welfare effects across markets, vertical integration reduces consumer welfare in only 7% of markets.

At first glance, these results suggest that antitrust policy which removes integration would reduce consumer welfare. However, we show that the probability that vertical integration reduces consumer welfare is maximized when there is limited competition between theaters and films are close substitutes - precisely the conditions under which the foreclosure effect is largest. This suggests that a *targeted* policy which conditions on measures of upstream and downstream competition might increase consumer welfare.

To test this hypothesis, we measure the aggregate effects on consumer surplus of four different policies. A total ban on vertical integration would reduce consumer surplus by $44 million. However, an oracle regulator who could remove integration only where it is harmful would *increase* surplus by around $13.5 million. We suggest two practical targeting regimes based on observable market characteristics. A threshold rule that eliminates vertical integration in all markets with sufficiently little downstream competition and sufficiently high upstream competition increases consumer surplus by about 7% of the gains achieved by the

oracle regulator. A more sophisticated policy that predicts welfare effects using a random forest on a set of market characteristics achieves between 23% and 46% of the oracle's welfare gains. These results suggest that, even in settings where vertical integration improves welfare in the vast majority of markets, antitrust enforcement rules based on simple measures of upstream and downstream competition can improve consumer welfare.

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 from 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, to 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.

From a methodological perspective, our approach builds on a growing literature that incorporates auxiliary data to augment standard demand estimation. Early contributions include Berry et al. (2004), who use survey-based second-choice data to generate additional moments in automobile demand estimation, and Petrin (2002), who combine demographic data with price and quantity information to recover richer substitution patterns. More recent work expands this agenda: Grieco et al. (2023) propose an efficient method for combining product- and consumer-level data. Conlon and Gortmaker (2025) develop a general framework for incorporating a wide range of micro data into discrete choice models.

Our setting provides a complementary example where demand-relevant information about products—movies—cannot be fully summarized by a limited set of observable characteristics. The ability of a demand model to capture substitution and measure competition depends

on how well observed characteristics reflect underlying substitution patterns. Motivated by similar concerns, recent studies have leveraged unstructured data and embeddings to enrich demand estimation. For instance, Han et al. (2021) use deep neural networks to embed the product space for fonts; Armona et al. (2021) recover latent product attributes from web browsing histories to estimate hotel demand; Compiani et al. (2025) apply embeddings from images and text to estimate a nested logit model with overlapping nests; Magnolfi et al. (2022) fit embeddings from consumer surveys and incorporate them into a discrete choice based demand system; Conlon et al. (2023) show that incorporating second-choice diversion ratios—defined in product space and estimated semi-parametrically—can meaningfully improve demand estimates without relying heavily on product characteristics or parametric assumptions.

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. Estimation is discussed in Section 6. Results and counterfactuals are discussed in Sections 7 and 8, and Section 9 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 toward 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 downward 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 toward the film with the higher revenue share.

Equation (2) also indicates that the downward/upward 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

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

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

$$R_A p_A \frac{\partial q_A}{\partial S_A} > R_B p_B \frac{\partial q_B}{\partial S_B} = c. \tag{4}$$

This increase in the theater's revenue share from film A from R^0 to R^1 will lead to upward 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* or *foreclosure* 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 toward 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 identification of vertical incentives in the supply model discussed in Section 7.

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. Upon obtaining distribution licenses, distributors 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 a standardized revenue-sharing scheme. According to this scheme, the State Administration of Radio, Film, and Television (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 B3 provides a summary of these 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 was 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 B1 in Appendix B.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. Appendix Figure A1 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 a film industry consulting firm. The data are sourced from the administrative box-office system.[4] We construct the following theater-film-week level variables from this dataset: box-office revenue, average admission fee, admissions, and the number of showings. We collect this information for the top 100 movies in each year for their entire release window, and augment this with data for the top 15 movies in each week. We then exclude observations for propaganda films, niche films, nonprofit theaters, and small cities.[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.

[3] Theater managers actively track film popularity to allocate screening capacity. 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.

[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.

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 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 infor-

[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.

[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.

mation, 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 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 median of 110 ratings. Films in our dataset receive an average of 1,164.71 ratings, with a median of 780 ratings.

Finally, Panel C 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:

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

[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 B2 (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 C.

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: 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
Median	11,047	3.38	0.944	1	4	5
At film level						
Number of ratings	1,544	1,164.71	1,000.007	63	780	5,958
Median	1,544	3.25	0.916	1	3	5

Panel C: 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. Panel B summarizes film rating data. Lastly, Panel C provides tabulations of the vertical integration status at three different levels: film-theater, film, and theater.

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 $\delta_{f,c(t)}, \delta_{w(f)}$, 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:

$$y_{ftw} = \beta VI_{ft} + \delta_{f,c(t)} + \delta_{fw} + \delta_{tw} + \varepsilon_{ftw} \tag{6}$$

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 (5) and (6), 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 (5) using the subsample of the observations from the first week. 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. 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 (6). The results are reported in Columns (5) and (6): vertical integration increases weekly showings by 2.9%.

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***
	(0.0008)	(0.0037)	(0.0017)	(0.0042)	(0.0005)	(0.0025)
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	2,013,782	2,013,782
R^2	0.7421	0.7708	0.7322	0.7895	0.7980	0.7566

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 film-theater level, following equation (5). Columns (5)–(6) are at the film-theater-week level, following equation (6). Standard errors, clustered at the market level, are shown in parentheses. *** p <0.005, ** p <0.01, * p <0.05.

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).

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 frequently screened. The film-theater level regression model is:

$$y_{ft} = \beta_1 VI_{ft} + \beta_2 FC_{ft} + \delta_{f,c(t)} + \delta_{w(f)} + \delta_t + \varepsilon_{ft} \tag{7}$$

and the film-theater-week level regression model is

$$y_{ftw} = \beta_1 VI_{ft} + \beta_2 FC_{ftw} + \delta_{f,c(t)} + \delta_{fw} + \delta_t + \varepsilon_{ftw}. \tag{8}$$

$FC_{ft} = 1\{VI_{ft} = 0, VI_{-f,t} > 0\}$ and $FC_{ftw} = 1\{VI_{ft} = 0, VI_{-f,t,w} > 0\}$ are indicators for *potential foreclosure*, where $VI_{-f,t,w} > 0$ if there is at least one newly released vertically integrated film shown in theater t in week w.[12] FC_{ftw} therefore equals one if film f is non-integrated and screened in theater t alongside newly released 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

[12] Newly released means that the film was released no more than two weeks ago.

integration on supply decisions for integrated films, while β_2 measures the foreclosure 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 is economically small.

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. Similar patterns are found in Column (5), which examines total showings in the initial run. In Column (3), we examine the duration of the first release. The results show that a film's release duration is 2.8% shorter if it is screened alongside a film owned by the theater. However, vertical integration does not give a film a 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 on both 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 examine how the impact of vertical integration varies with downstream spatial competition among theaters. We measure the downstream competition faced by theater t in week w using $\log(\text{Theater}_{tw})$, which represents the log number of theaters (including itself) within a 5 km radius. Table 4 presents estimates from a regression model that includes interactions between the key explanatory variables in equations (7) and (8) with $\log(\text{Theater}_{tw})$.

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)
FC_{ft}	-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 film-theater level, following equation (5). Columns (5)–(6) are at the film-theater-week level, following equation (6). Standard errors, clustered at the market level, are shown in parentheses. *** p <0.005, ** p <0.01, * p <0.05.

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, moving from 0 to 1 competitor within 5 km of a theater reduces the foreclosure effect by 13%.

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 (4)) is mitigated by substitution between films across competing theaters.

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

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)
FC_{ft}	-0.052***	-0.038***	-0.084***	-0.015***
	(0.007)	(0.003)	(0.008)	(0.004)
$VI_{ft} \times \log(\text{Theaters}_{tw})$	-0.006	-0.000	-0.005	-0.010***
	(0.004)	(0.002)	(0.004)	(0.002)
$FC_{ft} \times \log(\text{Theaters}_{tw})$	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	2,017,380
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 film-theater level. Column (4) is at the film-theater-week level. The variable $\log(\text{Theater}_{tw})$ is the log number of theaters (including itself) within a 5 km radius. Standard errors, clustered at the market level, are shown in parentheses. *** p <0.005, ** p <0.01, * p <0.05.

(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:

$$\sum_i \sum_{f \in \mathcal{F}_i} \left(r_{if} - b_i - b_f - \sum_{k=1}^{K} \nu_{ik}\tau_{kf} \right)^2 + \lambda \left(b_i^2 + b_f^2 + \sum_{k=1}^{K} (\tau_{kf}^2 + \nu_{ik}^2) \right), \tag{9}$$

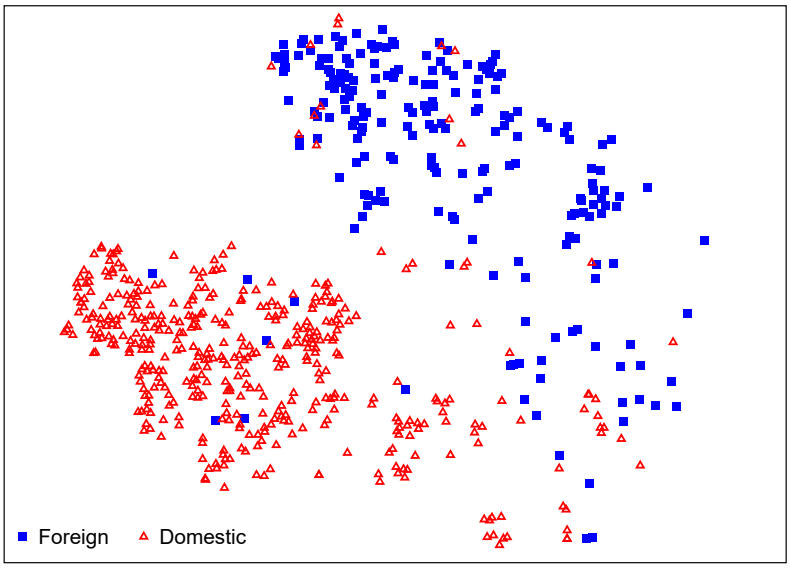
where b_i is the individual rating "bias," which accounts for systematic tendencies of some

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. Ultimately, we estimate $K = 4$ characteristics for each film. The technical details are provided in Appendix D.

Figure 1: Visualization of Film Attributes



Notes: This figure presents a scatter plot of all films in the first two dimensions of the latent attribute space. Foreign films are indicated by blue squares and domestic films are indicated by red triangles.

We will use the relative position of films in the latent attribute space as a measure of film similarity. Although the attributes themselves have no direct interpretation, intuitive patterns emerge when we compare the position of films in latent attribute space to observable characteristics. Figure 1 plots the position of all the films in the first two dimensions of the latent attribute space. Foreign films (in blue) are clearly clustered separately from domestic films. This is a result of correlation in reviews being strongly determined by whether a film is domestic - some consumers have a preference for domestic films over foreign and vice versa - and is consistent with existing demand analyses of domestic and foreign films in China (e.g., Ho et al., 2021).

Among foreign films, the latent attribute space generates similarities that are correlated with genre and content. Table 5 records the two most similar films for three focal foreign

films. We selected these films because they exhibit different patterns. Notice that the most similar film to *Marvel's the Avengers*, a science fiction film, is another science fiction film, and the first and second closest films to *Big Hero 6*, an animated film, are also animations. However, the measure of similarity is not always perfectly correlated with observed genre. For instance, the closest substitute to *The Hobbit*, a live action fantasy, is *Rise of the Guardians*, an animation. Although these films are of different genres, they both have fantasy themes and appeal to older children. A measure of similarity based only on observable genres would not be able to capture this.[13]

Table 5: Similar Films in Latent Attribute Space

Focal film	Most similar film	Second most similar film
The Hobbit: The Battle of the Five Armies (Fantasy)	Rise of the Guardians (Animation) 0.098	Star Trek Into Darkness (Science Fiction) 0.302
Marvel's The Avengers (Science Fiction)	Pacific Rim (Science Fiction) 0.029	Mission: Impossible - Ghost Protocol (Action) 0.081
Big Hero 6 (Animation)	How to Train Your Dragon 2 (Animation) 0.078	Despicable Me 2 (Animation) 0.116

Notes: This table reports the closest films in latent attribute space among foreign films for three focal films, with standardized distances reported in parentheses.

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. Intuitively, 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 according to the theoretical model in Section 2. The results of the regression are presented in Table 6.

Column (1) examines the heterogeneity in the effects of vertical integration for first-week observations. As expected, the foreclosure effect is statistically significant and economically meaningful. Importantly, the foreclosure effect diminishes when films face less competition from integrated rivals. For instance, 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 (17%) relative to the effect when the competing films are at the same location in latent attribute space, *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).[14]

[13] Appendix D contains further analysis of the correlation between latent attributes and genre.

[14] Note that across specification the coefficient on VI_{ft} is not significant. We include a control , $\text{VI}_{ft} \times \max_{f'}(1 - \text{VI}_{f't})$ for the presence of a non-integrated rival conditional on $\text{VI}_{ft} = 1$ because we set $\min_{f':\text{VI}_{f'}=0} d_{f,f'} = 0$ if there is no non-integrated rival within the same theater. After adding this control the coefficients on VI_{ft} lose statistical significance due to a loss of power.

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 away from the non-integrated film.

Table 6: 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}	0.006	0.009	0.021	-0.004
	(0.013)	(0.006)	(0.014)	(0.014)
FC_{ft}	-0.042***	-0.031***	-0.064***	-0.006
	(0.004)	(0.002)	(0.005)	(0.004)
$\text{VI}_{ft} \times \max_{f'}$ (1-$\text{VI}_{f't}$)	0.028*	-0.001	0.013	0.036*
	(0.013)	(0.006)	(0.015)	(0.014)
$\text{VI}_{ft} \times \min_{f':VI_{f't}=0} d_{f,f'}$	0.001	0.001	0.005	-0.007***
	(0.003)	(0.002)	(0.004)	(0.002)
$\text{FC}_{ft} \times \min_{f':VI_{f't}=1} d_{f,f'}$	0.007***	0.006***	0.011***	-0.001
	(0.002)	(0.001)	(0.002)	(0.002)
Week FE	Yes	Yes	Yes	
Theater FE	Yes	Yes	Yes	
Film-city FE	Yes	Yes	Yes	Yes
Theater-week FE				Yes
Film-week FE				Yes
N	650,755	650,755	650,755	2,013,782
R^2	0.771	0.732	0.790	0.757
Median($\min_{f':VI_{f't}=1} d_{f,f'} \mid VI_{ft}=0$)	0.368	0.368	0.368	1.211
p90($\min_{f':VI_{f't}=1} d_{f,f'} \mid VI_{ft}=0$)	2.454	2.454	2.454	2.705

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 film-theater level. Column (4) is at the film-theater-week level. The variable $\min_{f':VI_{f't}=0} d_{f,f'}$ is the minimum standardized distance between film f and its non-integrated rival f', and variable $\min_{f':VI_{f't}=1} d_{f,f'}$ is the minimum standardized distance between film f and its integrated rival f', both in the latent attribute space shown in Figure 1. 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 on 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 a theater's 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 district-week, indexed by m.[15] A consumer i obtains the following utility from seeing film f at theater t,

$$\begin{aligned} u_{imft} &= p_{mft}\beta_1 + VI_{ft}\beta_2 + \log(S_{mft})\beta_3 + \gamma_{imf} + \delta_{it} + \xi_{mft} + \epsilon_{imft} \\ &= \tilde{u}_{imft} + \epsilon_{imft} \end{aligned} \tag{10}$$

Consumer utility is given by an individual-specific taste for film f, γ_{imf}, an 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:

$$\gamma_{imf} = \gamma_{w(m)f} + \gamma_m + \sigma_1 \left(\sum_{k=1}^{K} \nu_{ik} \hat{\tau}_{kf} \right) + \sigma_0 b_i, \tag{11}$$

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

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

$$\delta_{it} = \delta_t - \eta \|X_t - X_i\|, \tag{12}$$

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 mean 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,

$$s_{mft} = \int \frac{\exp\left(\tilde{u}_{imft}\right)}{1 + \sum_{(f',t') \in \mathcal{F}_m} \exp(\tilde{u}_{imf't'})} dF(\boldsymbol{\nu}_i, X_i), \tag{13}$$

where the integrand is the probability of choosing film and theater pair (f, t). This expression

[15] Districts are subdivisions of cities.

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, $(\boldsymbol{\nu}_i, b_i)$. We use the distribution of these preferences estimated from the rating data in Section 4.3.2. The crucial assumption here is that the rating data comes from a representative sample of the population, and that the distribution of preferences for latent characteristics is identical across markets.[16] The latter assumption is standard in random coefficients models. The integral is also over consumer locations, X_i, collected from the geocoded population census data described in Section 3.3.3.

5.2. Supply

We model a theater's decisions as a static profit maximization problem. Specifically, we assume that theater t in market m chooses the vector of ticket prices $p_t = (p_{ft})_{f \in \mathcal{F}_m}$, and the number of showings, $S_t = (S_{ft})_{f \in \mathcal{F}_m}$, for each available film $f \in \mathcal{F}_m$ to maximize profit. Suppressing the m subscript, the problem is stated as

$$(p_t^*, S_t^*) = \arg \max_{p_t, S_t \in \mathbb{R}_{\geq 0}^{|\mathcal{F}|}} \sum_{f \in \mathcal{F}} M \lambda_{ft} (p_{ft} - mc_{ft}) s_{ft}(p_t, S_t, p_{-t}, S_{-t}) - C_t(S_t) \tag{14}$$

where M is the population in the market, $C_t(S_t)$ is the fixed cost of allocating screening capacity as S_t, and $s_{ft}(p_t, S_t, p_{-t}, S_{-t})$ is the market share of film f at theater t, as defined in equation (13). 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.[17]

An important component of this model is the revenue weight λ_{ft}, which represents the share of gross sales that a theater internalizes. This parameter depends on the revenue sharing scheme and vertical integration. It is given by

$$\begin{aligned} \lambda_{ft} = R_{ft} \times (&\lambda_0 1\{VI_{ft}^{dist} = 0, VI_{ft}^{prod} = 0\} + \lambda_1 1\{VI_{ft}^{dist} = 1, VI_{ft}^{prod} = 0\} \\ &+ \lambda_2 1\{VI_{ft}^{dist} = 0, VI_{ft}^{prod} = 1\} + \lambda_3 1\{VI_{ft}^{dist} = 1, VI_{ft}^{prod} = 1\}). \end{aligned} \tag{15}$$

Here, R_{ft} denotes the revenue share of final ticket sales for film f at theater t, which is

[16] This interaction term $\left(\sum_{k=1}^{K} \nu_{ik} \hat{\tau}_{kf}\right)$ 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.

Crucially, this approach assumes that reviews are an affine transformation of the film-specific component of utility, γ_{if}, and that the distribution of preferences among the reviewer sample is representative of the population.

[17] 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.

established according to the standard industry revenue-sharing rules described in Appendix Table B3. This term is multiplied by the internalization weight ($\lambda_0, \lambda_1, \lambda_2$, or λ_3), which captures the extent to which the downstream theater internalizes profits from its share of final sales.

λ_0 represents the share of downstream film exhibition revenue internalized by a theater chain that is not integrated with any producer or distributor. The parameters $(\lambda_1, \lambda_2, \lambda_3)$ capture the extent to which a downstream theater internalizes profits from its share of final sales for theater chains with varying degrees of vertical ownership in upstream sectors.[18] λ_0 is normalized to 1, so $(\lambda_1, \lambda_2, \lambda_3)$ can be interpreted as degrees of internalization relative to non-integrated theater–film pairs. If theaters fully internalize all upstream revenue from integrated films, then $\lambda_1 = \lambda_2 = \lambda_3 = 1$.

5.2.1. Equilibrium and First-Order Conditions

Theaters are assumed to play a pure strategy Nash equilibrium in pricing and showings. That is, their pricing and showing 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}.

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

$$\lambda_{ft} s_{ft} + \sum_{f' \in \mathcal{F}_t} (\lambda_{f't} p_{f't} - mc_{f't}) \frac{\partial s_{f't}}{\partial p_{ft}} = 0, \tag{16}$$

$$M \sum_{f' \in \mathcal{F}_t} (\lambda_{f't} p_{f't} - mc_{f't}) \frac{\partial s_{f't}}{\partial S_{ft}} = \frac{\partial C_t(S_t)}{\partial S_{ft}} \quad \text{if } S_{ft} > 0, \tag{17}$$

$$M \sum_{f' \in \mathcal{F}_t} (\lambda_{f't} p_{f't} - mc_{f't}) \left. \frac{\partial s_{f't}}{\partial S_{ft}} \right|_{S_{ft}=1} \leq \frac{\partial C_t(S_t + \iota_{ft})}{\partial S_{ft}} \quad \text{if } S_{ft} = 0. \tag{18}$$

Equation (17) states that for a film a theater chooses to show, the marginal revenue from increasing its showings must equal its marginal cost. Equation (18) is the "extensive margin" condition for a zero-showing film f, which states that the marginal revenue from adding the first showing is less than or equal to its marginal cost. ι_{ft} is a vector with a one in the position of film f and zero elsewhere, representing the addition of a single showing.

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

[18] λ_1, λ_2, and λ_3 correspond, respectively, to theaters integrated with only a distributor (λ_1), only a producer (λ_2), and both a distributor and a producer (λ_3).

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 (10). 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 model allows for heterogeneity in upstream and downstream competition, and therefore in the theater's *ability* and *incentive* to distort showings toward 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 a market are 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 above in Section 2. In particular, if $\lambda_1 > 0$ theaters have an incentive to allocate more showings to integrated films.

Finally, 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. 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.[19]

6. Estimation and Identification

This section outlines our empirical specification for estimating the structural parameters of the model and discusses the assumptions required to identify the key parameters. Prior to estimating the structural parameters, we obtained the four-dimensional latent product attributes, $\{\tau_{kf}\}_{k=1}^{4}$, and the empirical distribution of consumer latent tastes for these attributes, $\{\nu ik\}_{k=1}^{4}$, as described in Section 4.3.2. The estimation sample is from the data used in the descriptive analysis in Section 4. To mitigate computational burden, we focus on

[19] 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.

districts located within metropolitan statistical areas (MSAs) with populations exceeding two million, as identified in Chen et al. (2024).

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 general method of moments (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 (10). Consequently, $\xi_{mft}(\theta_D)$ captures the *transitory* unobservable demand shock at the film-theater-week level.

6.1.1. Demand Moments

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

$$E(\xi_{mft}(\theta_D) \times VI_{ft}) = 0. \tag{19}$$

The remaining parameters are identified using two sets of instrumental variables: the opening of new theaters and variation in film release schedules. The key identifying assumption is that these instruments are uncorrelated with the transitory unobserved demand shock ξ_{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 interactions 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 strategies in Nevo, 2001; Houde, 2012).[20]

The second set of instrumental variables, Z_2^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.[21] The

[20] 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, leading 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.

[21] Specifically, the set of instruments $Z_{2,fmt}^D$ associated with film f in theater t, market m includes the following variables: (1) the number of new releases (within the previous two weeks) shown in theater t week w; (2) the difference between an indicator for film f being foreign and the share of foreign rival films in theater t; (3) the weighted average of pairwise differences in latent attributes, $\sum_{f' \in \mathcal{F}_{mt}} (b_f - b_{f'}) \times \left[\sum_k (\tau_{kf} - \tau_{kf'})^2\right]$, where $\mathcal{F}_{mt}$ denotes the set of films shown in theater t, market m; (4) an analogous term interacting with indicators for recently released rival films, $\sum_{f' \in \mathcal{F}_{mt}} (b_f - b_{f'}) \times 1\{weeks_{mf'} \leq 2\} \times \left[\sum_k (\tau_{kf} - \tau_{kf'})^2 \in D\right]$, for

exogeneity assumption of the release schedule is supported by institutional practices: films are released nationwide across 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_2^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).

The identification of structural parameters relies on the assumption that the extensive margin decision is independent of ξ_{fmt}:

$$E\begin{bmatrix}\xi_{fmt}(\theta_D) \times Z^D_{1,fmt} \\ \xi_{fmt}(\theta_D) \times Z^D_{2,fmt}\end{bmatrix} = 0. \tag{20}$$

6.1.2. Identification

We assume that price and showings are endogenous, potentially correlated with unobservable demand shocks, and use variation in Z_1^D and Z_2^D 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, lower-quality films.

The coefficients on individual taste for films (σ_0, σ_1) are identified using changes in the distribution of latent types among available films. The instrumental variables Z_1^D 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_0 is large, films that are closer to competing films in latent attributes $\{\tau_{kf}\}_{k=1}^4$ should face more competition. Thus, σ_0 is identified by the correlation between changes in these instruments and market shares. σ_1 is identified by the extent to which substitution to newly released films comes from other films rather than from the outside option.

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 include instruments in Z_1^D that measure the number of competing theaters within 2km and 5km for each theater-week.

6.2. Supply

The supply parameters are $\theta_S = (\lambda_1, \lambda_2, \lambda_3)$. 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 (15), to be the same across theater-film pairs.

$D = (0, 1/2]$ and $(1/2, 1]$, where $weeks_{mf'}$ denotes the number of weeks since the release of film f' as of week w; and (5) FC_{ft}, $\text{VI}_{ft} \times \min_{f':VI_{f'}=0} d_{f,f'}$, and $\text{FC}_{ft} \times \min_{f':VI_{f'}=1} d_{f,f'}$, as defined in Section 4.

We normalize $\lambda_0 = 1$ and parameterize fixed costs as $\log(c_{fmt}) = c_{mt} + \tilde{c}_{fmt}$, where c_{mt} captures theater-week–level fixed costs, and $\tilde{c}_{fmt}$ represents idiosyncratic shocks reflecting the discrepancy between the marginal revenue of showings for film f and the average marginal revenue across films shown in theater t.

To identify θ_S, we use supply instruments Z^S to construct the following supply-side moment conditions

$$E\left(\tilde{c}_{fmt} \times Z^S | (f,t) : S_{fmt} > 0\right) = 0, \tag{21}$$

$$E\left(\max\{\tilde{c}_{fmt} \times Z^S, 0\} | (f,t) : S_{fmt} = 0\right) = 0. \tag{22}$$

The supply instruments include a saturated set of vertical ownership indicators between theater t and film f: whether t is not integrated with f, integrated with f's distributor, or integrated with f's but not its distributor. Identification of the equality moments in (21) follows from theaters' profit-maximization behavior: within a given time period, the marginal revenues of all films shown in a theater should be equalized up to idiosyncratic shocks $\tilde{c}_{fmt}$; otherwise, theaters would reallocate showings to increase profits. Hence, if films of a particular ownership type systematically exhibit higher or lower *gross* marginal revenues, this difference reflects differences in internalization (λ_{ft}) rather than in cost shocks ($\tilde{c}_{fmt}$). In other words, *net* marginal revenues are equalized, and $\tilde{c}_{fmt}$ is assumed orthogonal to vertical ownership.

Equation (22) is derived from the inequality optimality conditions implied by theaters' profit maximization: films that are not shown should, in expectation, have marginal revenues below the cost of adding one more showing.[22] If a film exhibits high *gross* marginal revenues yet is not screened, this must reflect lower internalization rather than higher costs.

7. Results

7.1. Demand Estimates

Table 7 reports parameter estimates for the demand model. We estimate two specifications: one allowing for consumer heterogeneity in the baseline preference parameter b_i through an estimated standard deviation σ_1, and another imposing $\sigma_1 = 0$. Across both specifications, the parameters entering mean utility have the expected signs and imply reasonable price elasticities: utility decreases with price ($\beta_1 < 0$) and increases with showings ($\beta_3 > 0$).[23]

The estimate of parameter β_2 suggests that there is no significant *direct* effect of vertical integration on utility. There is therefore limited evidence of additional utility gain from vertical integration that could be the result of promotional effort by the integrated theater or other synergies arising from integrated distribution and exhibition.

[22] Formally, the condition is $E\left(\tilde{c}_{fmt} \mid (f,t) : S_{fmt} = 0\right) \leq 0$. Following the literature, we interact $\tilde{c}_{fmt}$ with a set of indicator variables to preserve the direction of the inequality and apply the max operator to incorporate this restriction into the supply-side GMM estimator (Pakes et al., 2015; Crawford and Yurukoglu, 2012).

[23] The average own-price elasticity is 3.42 in specification (1) and 1.99 in specification (2).

Table 7: Demand Estimates

Parameter	Utility component	(1)	(2)
Non-linear parameters			
η	Distance	-1.081	-0.687
		(0.373)	(0.453)
σ_1	Taste for film f	12.701	13.770
		(2.405)	(2.390)
σ_0	Overall film tastes		2.221
			(2.760)
Linear parameters: endogenous product characteristics			
β_1	Price	-0.696	-0.402
		(0.191)	(0.180)
β_3	Log showings	0.942	1.279
		(0.155)	(0.132)
Linear parameters: exogenous product characteristics			
β_2	VI_{ft}	0.015	0.008
		(0.013)	(0.013)
δ_t	Theater FE	Yes	Yes
$\gamma_{w(m),f}$	Movie-week FE	Yes	Yes
$\gamma_{month(m),d(m)}$	District-month FE	Yes	Yes

Notes: This table shows the estimated structural parameters in individual demand for a film-theater in equation (10). Standard errors, clustered at the market level, are shown in parentheses.

The coefficient on individual tastes for film latent attributes, σ_1, which control the importance of idiosyncratic film tastes are positive and significant. This means that the estimated latent characteristics of films contribute to the cross-film substitution patterns observed in the data. The parameter σ_1 is not well identified and the coefficient on log showings is implausibly high in specification (2), so we use specification (1) in what follows.

7.1.1. Substitution Patterns

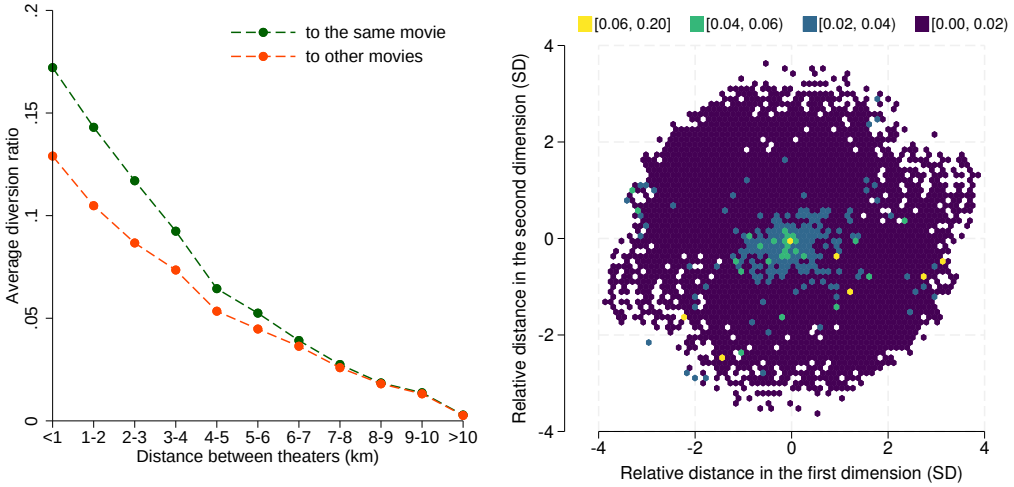
The parameter η controls the substitution between theaters at different distances. Figure 2(a) illustrates how cross-theater substitution varies with distance at the estimated parameters. We compute cross-theater diversion ratios for all film-theater pairs in our dataset. The green line plots the average diversion ratio between the same film shown in two different theaters at varying distances between theaters. The diversion ratio falls from about 0.17 for theaters within 1 km of each other to less than 0.05 beyond 6 km.

The parameter σ_1 controls the extent to which films that are closer in latent attribute space are more substitutable. The difference between the green and orange lines in Figure 2(a) shows that diversion ratios between the same film at different theaters - pairs of products with the same location in latent attribute space - are significantly higher than the average diversion ratio between pairs of films with different latent attributes. Figure 2(b) shows the diversion ratios between all pairs of films in the first two dimensions of the latent characteristic space. For very close substitutes, such as those listed in Table 5, the diversion ratio is above

0.06, and can be as high as 0.2. For films with a distance in latent attribute space of more than one standard deviation, the diversion ratio is close to zero.

The estimated substitution patterns generate meaningful variation in the degree of competition faced by theaters and in substitution between films. About 54.6% of the theater-week pairs in the estimation sample have no competitors within 1 km, and 40% have no competitors within 2 km. This suggests that the extent of downstream competition depends sensitively on the spatial configuration of theaters, and that taking a geographically large district as a single market without considering spatial substitution would generate misleading results. Likewise, cross-film substitution varies substantially across film pairs. A model that treats cross-film substitution as symmetric (even within genre) would similarly yield misleading implications about the incentive to foreclose competing films.

Figure 2: Substitution Patterns



(a) Cross Theater

(b) Within Theater

Notes: Panel (a) plots the average diversion ratios by distance between theaters. For each market in the data, we compute the diversion ratio between every theater-film pair, and then average over all pairs and all markets. The green line restricts to same-film pairs and the orange line restricts to different-film pairs. Panel (b) is a scatter plot of film pairs in the first two latent attribute dimensions. The color corresponded to the within-theater diversion ratio between those films.

7.2. Supply Estimates

Supply parameter estimates are reported in Table 8. In the first column of Panel A, we present estimates of the internalization parameters from equation (15). Theaters vertically integrated with a film distributor internalize 92.1% of the combined distribution and exhibition revenue. Theaters integrated with a film producer internalize 63.5% of the combined production and exhibition revenue. Theaters integrated with both a producer and a distributor internalize 56.9% of the combined upstream and downstream revenue.

In the second column, we report the implied internalization of upstream profits, assuming that a theater's profit weight on its own downstream (exhibition) profit is normalized to 100%.

Theaters integrated with distributors place a 43.8% weight on their upstream distribution profits,[24] while theaters integrated with producers only internalize between 4.8% and 8.5% of upstream production profits.

These results suggest that the distortion in theaters' showings decisions is driven by vertical integration between theaters and distributors, rather than producers. This might be rationalized by the fact that distributors have direct contact with theater chains and can possibly influence showings allocations through negotiations with chain managers, while producers are separated by one "layer" in the supply chain.

In Panel B, we report summary statistics of the estimated marginal costs of one additional admission and fixed cost of a marginal showing. Average marginal cost of admission is 0.936 and average fixed cost of a showing is 17.122, both in 2012 USD.

Table 8: Supply Parameter Estimates

Panel A: Internalization parameters		
	Internalization parameters	Implied upstream internalization
λ_1	0.921	0.438
λ_2	0.635	0.085
λ_3	0.569	0.048
Panel B: Marginal and fixed costs		
	Marginal cost of admissions	Fixed cost of showings
p25	0.578	10.827
p50	0.933	18.215
p75	1.353	28.796
Mean	0.936	22.308

Notes: Panel A reports the estimates of (1) the internalization parameter and (2) the implied internalization of upstream profits when internalization of downstream theater profit is normalized to 100%. Standard errors, clustered at the market level, are shown in parentheses. Panel B reports summary statistics of marginal and fixed costs.

7.2.1. Marginal Revenue

To illustrate identification of the distributor internalization parameter, we compute the gross revenue (less the marginal cost of admissions) from the marginal showing for each film-theater-week by setting $\lambda_{ft} = 1$ in equation (17), which equates this marginal revenue to the marginal cost of an additional showing.[25] This is the *gross* marginal revenue from film f, not the internalized marginal revenue used in equation (17), which is a function of λ_{ft}. 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

[24] When a theater is integrated with a distributor, the share of final sales it internalizes is $92.1\% \times (52\% + 8.5\%) = 55.72\%$. The difference between this and the exhibition-only profit share is $55.72\% - 52\% = 3.72\%$, which corresponds to 43.8% of the 8.5% share received by the distributor.

[25] We call this marginal revenue for consistency, but note that this is really a measure of marginal variable *profit* because it includes the marginal cost of admissions (but not of showings).

Table 9: Marginal Revenue Regressions

	Gross marginal revenue (log)			Net marginal revenue (log)
	(1)	(2)	(3)	(4)
VI_{ft}	-0.061***	-0.074***	-0.155***	0.003
	(0.0031)	(0.0056)	(0.0035)	(0.0031)
VI_{ft}^{prod}	-0.041***	-0.051***	-0.091***	0.009
	(0.0069)	(0.0139)	(0.0079)	(0.0069)
$\text{VI}_{ft} \times \log(\text{Theaters}_{tw})$		0.007*		
		(0.0029)		
$\text{VI}_{ft}^{prod} \times \log(\text{Theaters}_{tw})$		0.005		
		(0.0068)		
$\text{VI}_{ft} \times \min_{f':VI_{f'}=0} d_{f,f'}$			0.175***	
			(0.0037)	
$\text{VI}_{ft}^{prod} \times \min_{f':VI_{f'}^{prod}=0} d_{f,f'}$			0.110***	
			(0.0102)	
N	1,427,310	1,427,310	1,427,310	1,427,310
R^2	0.5495	0.5495	0.5512	0.5495

Notes: This table reports marginal revenue regression results. All regressions include theater-week fixed effects. VI_{ft} is an indicator for vertical integration with a distributor. VI_{ft}^{prod} is an indicator for vertical integration with a producer but not a distributor. The variable $\log(\text{Theater}_{tw})$ is the log number of theaters (including itself) within a 5 km radius. The variable $\min_{f':VI_{f'}=0} d_{f,f'}$ is the minimum standardized distance between film f and its non-integrated rival f' in the latent attribute space shown in Figure 1. Standard errors, clustered at the market level, are shown in parentheses. *** p <0.005, ** p <0.01, * p <0.05.

revenue of vertically integrated films should be lower than that of independent films.

We then regress $\log(MR_{mft})$ on indicators for vertical integration with a distributor and for integration with a producer but not a distributor, controlling for theater-week fixed effects. The inclusion of theater-week fixed effects capture all variation at the theater-week level, it is not possible to include the interaction between VI_{ft} and an indicator for film f facing a non-VI rival, as in Table 6.[26] The coefficients on VI indicators measure the wedge in gross marginal revenue between VI films and non-integrated films. The first-order condition in equation (17) suggests that a higher wedge indicates a greater degree of upstream revenue internalization.

The results of this exercise are displayed in Table 9. The first column regresses gross log marginal revenue on an indicator of vertical integration. The coefficient indicates that marginal revenue is about 6% lower for vertically integrated films. This is consistent with theaters internalizing upstream revenue, and is the source of identification for the parameters λ_{ft}. Note that the fourth column repeats this exercise using *internalized* marginal revenue at the estimated internalization parameter. As expected, the coefficient on vertical integration is not statistically significant.

The second and third columns include interactions of vertical integration with upstream

[26] This interaction term becomes perfectly collinear with VI_{ft} once theater-week fixed effects are included, as it can be expressed as VI_{ft} minus a theater-week–level indicator for showing only VI films.

and downstream market structure. The second column indicates that the difference in marginal revenue between integrated and non-integrated films is larger when there are fewer competing theaters within 5 km. The third column indicates that the difference in marginal revenues is larger the closer in latent attribute space is the nearest non-integrated film. When the closest non-integrated film is at the same location in latent attribute as the integrated film, then the difference in marginal revenue is 15.5%. This finding is consistent with foreclosure of "similar" non-integrated films.

8. Heterogeneous Effects of Vertical Integration

In this section, we quantify the effects of removing vertical integration by simulating counterfactual equilibria and reporting changes in showings, prices, and consumer welfare. As discussed in Section 2 and suggested by the descriptive results in Section 4, the effects of vertical integration vary by upstream and downstream market structure. We compute a no-integration counterfactual equilibrium for each market (district-week) by setting VI_{ft} to 0 for all film-theater pairs and solving for equilibrium prices and showings by iterating best responses. Parameters and structural errors are held fixed at the estimated values. The counterfactual equilibria allow us to compare the effects of vertical integration across markets with different levels of upstream and downstream competition. Details of counterfactual computation are provided in Appendix E.

8.1. Effects on Prices and Showings

Table 10: Price and Showings Effect of VI

	$\Delta\text{Showings}_{ftw}$		ΔPrice_{ftw}	
	Mean	SD	Mean	SD
Full sample	0.810	10.507	-0.036	0.080
$\text{VI}_{ft} = 1$	14.834	12.578	-0.168	0.102
$\text{FC}_{ft} = 1$	-3.419	8.565	-0.001	0.034
No-VI Level	25.500	25.877	5.341	1.427
N	1,160,892			
N markets	36,149			

Notes: Table reports the mean and standard deviation across film-theater-market observations of the difference in log price and showings between the data and a no-VI counterfactual which removes integration from all VI films. For the showings/price columns we drop observations where the change in showings/price was above the 99th percentile or below the 1st percentile.

For each theater-film-market, we compute the difference between the observed and counterfactual level of prices and showings. This measures the effect of *restoring* the observed vertical integration in the market.[27] Table 10 records the mean and standard deviation of

[27] Note that these counterfactuals remove vertical integration for all firms in the market. The equilibrium

the effect of vertical integration on equilibrium prices and showings for all film-theater-market observations in the data. Restoring vertical integration increases the average number of showings per theater-film-week by 0.8, which is around 3% of the average number of showings in the no-VI equilibrium. This suggests that, on average, consumers are likely to be better off under the observed level of integration than under no-integration. This average effect is driven by the large increase in showings for integrated films, which have an average of 14.8 more showings under integration than in the no-integration counterfactual, a 58% increase relative to the average level of showings in the no-integration case. This reflects the *efficiency effect* of vertical integration - the integrated theater internalizes more of the upstream revenue and therefore faces a marginal revenue above marginal cost at the no-integration level of showings. However, this increase in the supply of showings for integrated films is offset by a reallocation of showings away from non-integrated films due to *foreclosure* incentives. Showings for films that could be foreclosed (non-integrated films that face an integrated rival in the same theater) fall by around 3.4, or 13% of the no-integration average, when vertical integration is restored. The effects on prices are much smaller, consistent with the results in Section 4.

Table 11: Heterogeneity in Effects of VI on Showings and Prices

	$\Delta \log(\text{Price}_{ftw})$			$\Delta \log(\text{Showings}_{ftw})$		
	(1)	(2)	(3)	(4)	(5)	(6)
VI_{ft}	-0.030***	-0.032***	-0.030***	2.425***	2.740***	2.454***
	(0.000)	(0.000)	(0.000)	(0.007)	(0.013)	(0.011)
FC_{ft}	0.002***	0.002***	0.003***	-0.083***	-0.096***	-0.117***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.003)	(0.002)
$\text{VI}_{ft} \times \log(\text{Theaters}_{tw})$		0.001***			-0.173***	
		(0.000)			(0.007)	
$\text{FC}_{ft} \times \log(\text{Theaters}_{tw})$		0.000***			0.006***	
		(0.000)			(0.002)	
$\text{VI}_{ft} \times \min_{f':VI_{f'}=0} d_{f,f'}$			0.001***			-0.170***
			(0.000)			(0.008)
$\text{FC}_{ft} \times \min_{f':VI_{f'}=1} d_{f,f'}$			-0.000***			0.042***
			(0.000)			(0.002)
Observations	1,137,675	1,137,675	1,137,675	1,137,674	1,137,674	1,137,674

Notes: All specifications include a constant. Specifications (2) and (5) also include a control for $\log(\text{Theaters}_{tw})$. Specifications (3) and (6) also include a control for $\min_{f':VI_{f'} \neq VI_f} d_{f,f'}$. We also include a control for the presence of a non-integrated rival conditional on $VI_{ft} = 1$ because we set $\min_{f':VI_{f'}=0} d_{f,f'} = 0$ if there is no non-integrated rival within the same theater. For the log showings/log price columns we drop observations where the change in log showings/log price was above the 99th percentile or below the 1st percentile. Standard errors clustered at the market level are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Although these average effects are substantial, the second column of Table 10 indicates

outcomes therefore not only reflect changes in the incentives of integrated theaters, but also the responses of all other theaters. We also run counterfactuals in which we turn off integration for one theater-film at a time. Results for these simulations look similar, and are recorded in Appendix Table A2.

that there is substantial cross-theater and cross-market variation in the magnitude of showings changes. To investigate the extent to which this heterogeneity in the equilibrium effects of integration is driven by upstream and downstream horizontal competition, we estimate regressions of $\Delta \log(\text{Showings}_{ftw})$ and $\Delta \log(\text{Price}_{ftw})$ on indicators for integration and foreclosure, and their interactions with upstream and downstream market structure, similar to the specifications reported in Tables 4 and 6. Note that $\Delta \log(\text{Showings}_{ftw})$ is the difference in log showings between the data and the no-integration counterfactual for a particular film-theater-week.[28] Thus, the outcome variable should be interpreted as the change in prices and showings from *restoring* vertical integration.

Table 11 summarizes the results of these counterfactual regressions. Columns (1) and (4) show that vertical integration reduces the prices and increases the showings of integrated films, and increases the prices and reduces the showings of non-integrated films that face an integrated rival in the same theater, restating the results in Table 10. These findings are consistent with a foreclosure effect that distorts the pricing and showings of non-integrated films in order to drive consumers toward integrated films.

The remaining columns show heterogeneity in the price and showings effects by upstream and downstream market structure. Because the price effects are small, we focus our discussion on showings. Column (5) interacts the VI and foreclosure dummies with $\log(\text{Theaters}_{tw})$, the log number of competing theaters within 5 km of theater t. The foreclosure effect on non-integrated films is decreasing in this measure of local downstream competition. In particular, a one standard deviation increase in the number of nearby theaters reduces the foreclosure effect by about 5%. As local downstream competition increases, the *ability* of theaters to foreclose is reduced, and therefore the average distortion to the showings of non-integrated films is reduced. Column (6) includes interactions with $\min_{f':VI_{f'} \neq VI_f} d_{f,f'}$, the distance in latent attribute space between film f and the closest film in the same theater-week with the *opposite* integration status. The estimated coefficients indicate that the foreclosure effect is highest when the foreclosed film is similar in latent attribute space to an integrated film. A one standard deviation increase in the distance between films reduces the foreclosure effect by about 33%. When films are close substitutes, theaters have a greater *incentive* to foreclose.

Notice that the interactions with VI_{ft} also have the opposite sign of the coefficient on VI_{ft}, indicating that the positive effect of integration on the showings of integrated films is larger when the firm's ability and incentive to foreclose are larger. There are at least two reasons for this. First, showings for different films are substitutes in profit maximization: reducing the showings of a foreclosed film increases demand for integrated films, pushing up marginal revenue from integrated films and increasing the optimal number of showings. Second, the *efficiency effect* is decreasing in downstream competition, which is measured here by $\log(\text{Theaters}_{tw})$.[29]

[28] The baseline equilibrium is directly observed in the data because we hold structural errors fixed at the levels that rationalize the observed prices and showings.

[29] To see this, note that the increase in the marginal revenue of a showing from integration is $(R_1 - R_0)p_j \frac{\partial q_j}{\partial S_j}$,

To illustrate how these effects vary across markets, we construct market-level analogs of our measures of upstream and downstream competition, $\log(\text{Theaters}_{tw})$ and $\min_{f':VI_{f'} \neq VI_f} d_{f,f'}$:

$$\begin{aligned} \text{Film Distance}_m &= \hat{E}_m \left[\min_{f':VI_{f'}=0} d_{f,f'} | VI_{ft} = 1 \right], \\ \text{log Nearby Theaters}_m &= \hat{E}_m \left[\log(\text{Theaters}_{tw}) \right], \end{aligned} \tag{23}$$

where $\hat{E}_m$ is the empirical mean in market m. These measures capture the average similarity of integrated films to non-integrated films and the average local theater competition in market (district-week) m. The distribution of these measures over markets is illustrated in Appendix Figure A2.

In Figure 3, we illustrate how the average change in showings at the market level varies with these measures. We construct market-level measures of the change in showings:

$$\begin{aligned} \text{Foreclosure}_m =& \hat{E}_m \left[\Delta \log(\text{Showings}_{ftm}) \middle| FC_{ft} = 1 \right] \\ & - \hat{E}_m \left[\Delta \log(\text{Showings}_{ftm}) \middle| FC_{ft} = 0, VI_{ft} = 0 \right] \\ \text{Efficiency}_m =& \hat{E}_m \left[\Delta \log(\text{Showings}_{ftm}) \middle| VI_{ft} = 1 \right] \\ & - \hat{E}_m \left[\Delta \log(\text{Showings}_{ftm}) \middle| FC_{ft} = 0, VI_{ft} = 0 \right]. \end{aligned} \tag{24}$$

Our measure of foreclosure is the average change in log showings for potentially foreclosed films, and our measure of efficiency is the average change in log showings for integrated films. Both measures are defined relative to the average change in log showings for films that are neither integrated or foreclosed (non-integrated films that do not face an integrated rival).[30]

Figure 3(a) illustrates a local linear regression of Foreclosure_m on the market characteristics defined in equation (23). As expected, the foreclosure effect reduces the showings of non-integrated films that face an integrated rival. The distortion of showings away from foreclosed films is largest when the integrated and non-integrated films are close substitutes and when there is little local competition between theaters. That is, when the *ability* and *incentive* to foreclose are highest.

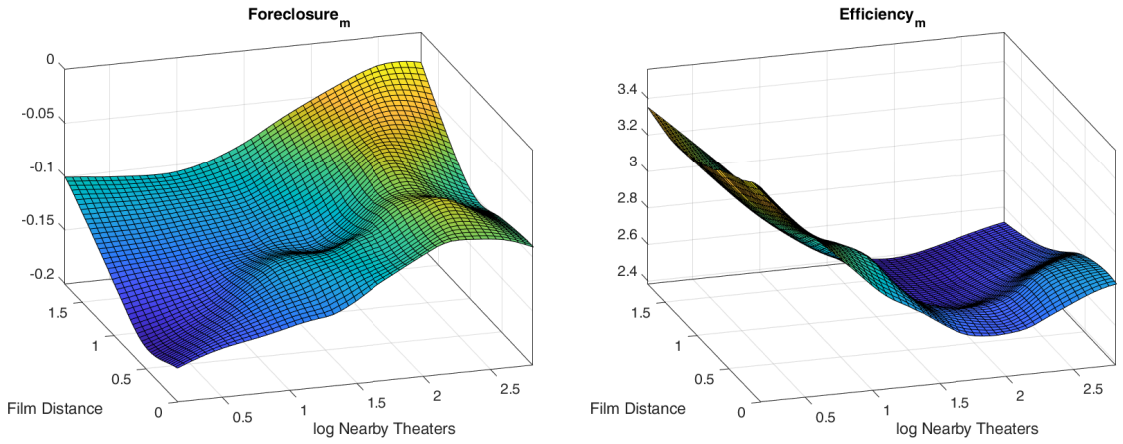
Figure 3(b) illustrates an analogous regression of Efficiency_m on market characteristics. The increase in showings for integrated films, which offsets the loss from foreclosure, is strongly decreasing in the average number of nearby theaters. At the market level, competition between theaters limits the gains from vertical integration by driving down firms' marginal revenues and, consequently, the change in marginal revenue from integration.[31]

where $R_1 - R_0$ is the increase in the revenue share. This expression is increasing in $\frac{\partial q_j}{\partial S_j}$, which tends to increases with market share under logit demand, and therefore decreases with competition.

[30] This controls for market-level heterogeneity that might be correlated with our measures of upstream and downstream competition.

[31] See footnote 29. In Figures 3 and 4 we drop observations where $\text{log Nearby Theaters}_m = 0$, because the increase in showings and reduction in prices for integrated films is discontinuously large for markets with no

Figure 3: Heterogeneous Showings Effects of VI



(a) Foreclosure Effect

(b) Efficiency Effect

Notes: Local linear regression of the market-average change in log showings from integration on market characteristics defined in equation (23). Dependent variables are defined in equation (24). Observations above the 99th percentile and below the 1st percentile of the dependent variable are dropped.

8.2. Effects on Consumer Surplus

Table 12 records the distribution of changes in market (district-week) level consumer surplus due to vertical integration. In the median market, consumer surplus is \$628 or around 2% higher under observed vertical integration compared to the counterfactual of no integration. This suggests that the efficiency benefits of VI outweigh the foreclosure distortion on average. However, the heterogeneity in price and showings effects across markets generates heterogeneity in the change in consumer surplus. Indeed, for 7.3% of markets, vertical integration *lowers* consumer surplus.

Table 12: Consumer Surplus Effect of VI

	Mean	Median	SD	25th pctl	75th pctl
ΔCS	560.334	628.199	14631.696	137.627	2101.460
$\Delta \log(CS)$	0.079	0.023	0.374	0.006	0.074
% ΔCS	0.382	0.024	5.646	0.006	0.076
$\Delta CS > 0$	0.927	1	0.260	1	1

Notes: ΔCS is the difference between market level total consumer surplus at the prices and showings in the data and total consumer surplus at the no-integration counterfactual levels of prices and showings. An observation is a market (district-week) and the sample includes all markets with at least one integrates theater-film pair.

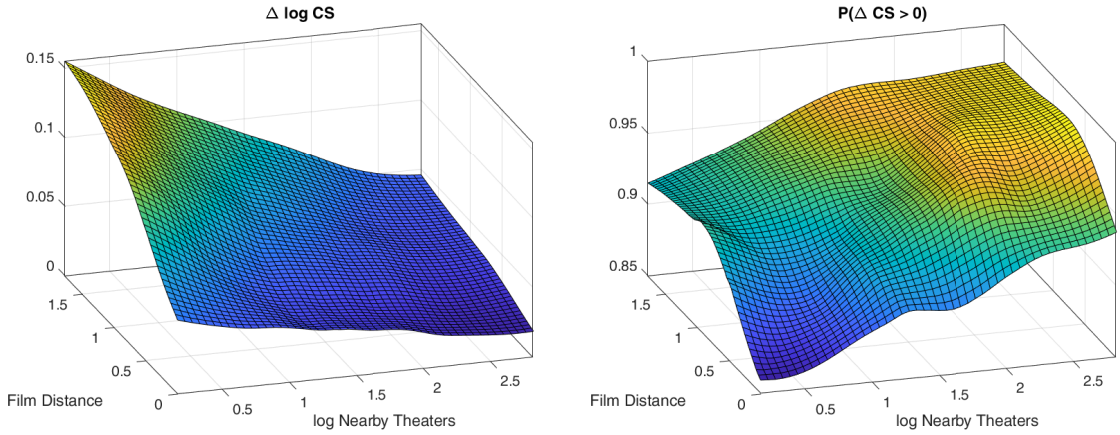
In this section we ask to what extent markets where vertical integration is harmful to consumers can be identified using observed market characteristics, in particular, the measures of upstream and downstream competition defined in equation (23). Figure 4 presents local

local theater competition, which makes the local regression figures somewhat misleading. Appendix Figures A3 and A4 show equivalent results including these observations.

linear regressions of $\Delta \log(CS)$ and $\Delta CS > 0$ on these market characteristics. Figure 4(a) shows that the average increase in log consumer surplus due to vertical integration is lower when integrated and non-integrated films are close substitutes - that is, when Film Distance$_m$ is low. This is consistent with the results in Figure 3(a), which show that foreclosure of non-integrated films is highest when films are close substitutes and theaters' incentives to foreclose are strongest. The distortion due to foreclosure therefore appears to have a significant impact on consumer surplus.

Figure 3(a) also shows that foreclosure is decreasing in local competition between theaters. However, this reduction in foreclosure does not appear to be passed through into higher log consumer surplus on average. Indeed, in Figure 4(a) the change in log consumer surplus due to integration is *falling* in the level of local competition. This is consistent with the reduction in foreclosure being offset by a reduction in the overall increase in showings of integrated films due to the efficiency effect, as illustrated by Figure 3(b). Figure 4(b) shows that although these forces offset each other on average, the share of markets in which integration *reduces* consumer surplus is maximized when local competition is low.[32] Indeed, a comparison of Figures 4(b) and 3(a) shows that the market characteristics that maximize the probability of vertical integration harming consumers are very close to those that maximize the distortion due to foreclosure.

Figure 4: Heterogeneous Consumer Surplus Effects of VI



(a) Change in Consumer Surplus

(b) Probability of CS Decrease

Notes: Local linear regression of the market-level difference in log consumer surplus between the baseline and no-integration counterfactual on market characteristics defined in equation (23). Observations above the 99th percentile and below the 1st percentile of the dependent variable are dropped.

[32] Appendix Figure A5 explains this apparent contradiction by showing that the average *absolute* change in consumer surplus (as opposed to log consumer surplus) is *negative* when Film Distance$_m$ and log Nearby Theaters$_m$ are low - that is, when the foreclosure effect is large. The difference between this figure and Figure 4(b) is due to the log-transform.

8.3. Targeted Enforcement

These results suggest that measures of upstream and downstream competition, which correspond to the downstream firm's incentive and ability to foreclose, are predictive of the effect of integration on consumer surplus. In this section, we ask whether consumers can be made better off through targeted antitrust policies that use these measures to predict consumer harm.

We consider four counterfactual policies. We start with two benchmarks. The **Net** policy removes integration from all markets. Based on the results discussed above, this policy lowers consumer surplus. The **Oracle** policy removes integration only in markets where it reduces consumer surplus. This provides an upper bound on consumer surplus gain from selectively banning harmful vertical integration.

We then consider two targeted policies. Let X_m be a set of observed market characteristics. Targeted policies take the form $f(X_m) \in \{0, 1\}$, where integration is removed if $f(X_m) = 1$. First, based on the observation from Figure 4(b) that the probability of consumer harm from vertical integration is highest when Film Distance$_m$ and log Nearby Theaters$_m$ are low, we consider the optimal **Threshold** policy,

$$f^{TH}(X_m) = \begin{cases} 1 & \text{if Film Distance}_m < \delta_1 \text{ and log Nearby Theaters}_m < \delta_2, \\ 0 & \text{otherwise.} \end{cases} \tag{25}$$

where we search over the possible thresholds (δ_1, δ_2) to maximize the gain in consumer surplus from removing integration.

Finally, we consider a more sophisticated targeting policy based on observable market characteristics that uses a **Random Forest** to predict changes in consumer surplus,

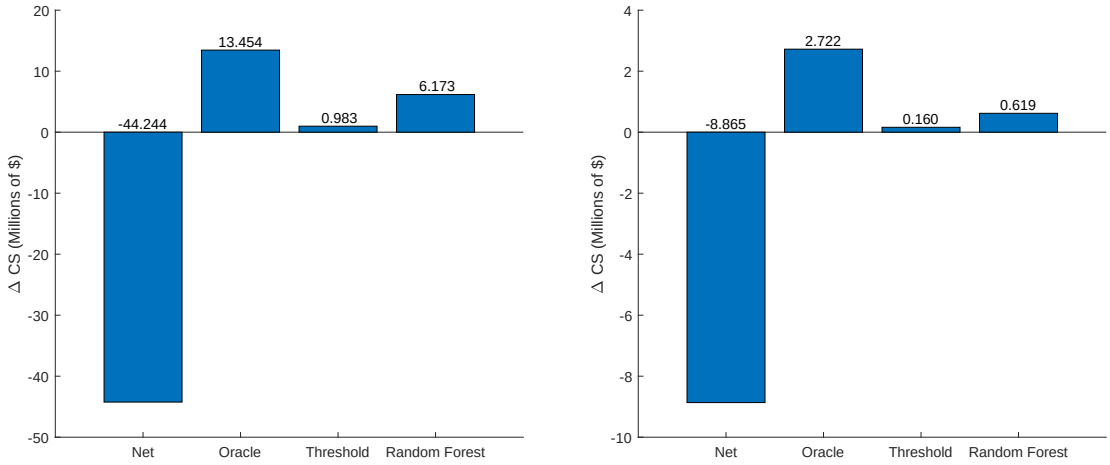
$$f^{RF}(X_m) = \begin{cases} 1 & \text{if } E_{RF}\left[\Delta CS_m | X_m\right] < 0, \\ 0 & \text{otherwise.} \end{cases} \tag{26}$$

Here, E_{RF} is the prediction from a random forest regression of ΔCS_m on an extended set of market characteristics. In addition to Film Distance$_m$ and log Nearby Theaters$_m$, we include counts of theater-film pairs by integration and foreclosure status, the average distance to the nearest vertically integrated film for foreclosed films, and market population.[33]

Figure 5 reports the results of this exercise. Figure 5(a) reports results for all markets. On net, removing vertical integration from all markets would lower consumer surplus by around $44 million. However, an oracle regulator that could remove vertical integration only in markets where it harms consumer welfare could increase consumer surplus by about $13 million.

[33] We use Matlab's `TreeBagger` with 1,000 regression trees estimated on data sampled with replacement with a minimum leaf size of 100. Throughout, we drop markets with ΔCS above the 99th or below the 1st percentile.

Figure 5: Welfare Effects of Eliminating VI



(a) All Markets

(b) 20% Holdout Samples

Notes: The figure records the total effect on consumer surplus from removing vertical integration under each counterfactual policy. In panel a, the threshold and random forest policies are estimated using all markets, and all policies are evaluated on these markets. Panel b records analogous results in which the models are estimated on an 80% training sample and then evaluated on a 20% holdout sample. The figure displays the average effect over 20 iterations of this exercise. In both panels, markets with ΔCS above the 99th or below the 1st percentile are dropped from the sample.

This is the maximum possible increase in consumer surplus from selective enforcement. The optimal threshold policy sets $(\delta_1, \delta_2) = (1.57, 0.26)$, which roughly corresponds to the region in Figure 3(a) with the highest foreclosure of non-integrated films. Removing vertical integration from all markets in this region raises consumer surplus by 7.3% of the maximum possible surplus increase. Although the effect is small, it is notable that, in a setting where an untargeted policy would *reduce* welfare in 93% of markets, a net *improvement* in consumer surplus can be achieved with a simple threshold rule based on measures of upstream and downstream competition. The more sophisticated random forest policy increases consumer surplus by 46% of the maximum attainable improvement.

To test the out of sample performance of these targeting rules, we re-estimate the thresholds and random forest parameters on a random 80% training sample of markets, and evaluate the resulting rules' performance on the 20% holdout sample. Figure 5(a) reports mean results across 20 random sample splits. The performance of the random forest policy is reduced, but it still achieves 23% of the maximum possible holdout sample surplus gain.

9. Conclusion

This paper studies 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 theaters allocate more showings to vertically integrated films, and distort showings away from non-integrated films. Foreclosure of non-integrated films is largest when

a theater faces little local competition and integrated and when non-integrated films are close substitutes. That is, when its *ability* and *incentive* to foreclose are maximized. To account for the possible direct effect of vertical integration on demand and compute full counterfactuals, we develop and estimate a structural model of film demand and theaters' choice of showings and prices. We use data on theater locations and film attributes recovered by applying a matrix factorization algorithm to review data to capture flexible cross-theater and cross-film substitution patterns.

Our estimates suggest that theaters internalize around 46.9% of upstream profits accruing to distributors for vertically integrated films. In counterfactual simulations, we remove integration and solve for equilibrium prices and showings. We find that vertical integration increases consumer surplus on average, but reduces consumer surplus for around 7% of markets. Heterogeneity analysis shows that markets where consumer surplus is reduced by integration tend to have less local competition between theaters and more substitutable films.

These results suggest that antitrust enforcement that removes integration in targeted markets could increase consumer surplus. Our final exercise evaluates four different enforcement regimes. A full ban on integration lowers consumer surplus by $44 million, whereas an optimally targeted policy would increase surplus by $13 million. Feasible targeting schemes based on measures of upstream and downstream competition achieve positive gains in consumer surplus of up to 46% of the maximum possible improvement.

Our results point towards the importance of measuring upstream and downstream competition in predicting the effects of vertical integration on consumer surplus. In particular, we highlight the potential for targeted enforcement to improve consumer welfare even when vertical integration increases welfare in the vast majority of markets.

References

John M Abowd, Francis Kramarz, and David N Margolis. High wage workers and high wage firms. *Econometrica*, 67(2):251–333, 1999.

Claudia Allende. Competition under social interactions and the design of education policies. *Job Market Paper*, 2019.

Luis Armona, Gregory Lewis, and Georgios Zervas. Learning product characteristics and consumer preferences from search data. *Available at SSRN 3858377*, 2021.

Susan Athey and Guido W Imbens. Machine learning methods that economists should know about. *Annual Review of Economics*, 11:685–725, 2019.

Patrick L Bajari, Zhihao Cen, Victor Chernozhukov, Manoj Manukonda, Jin Wang, Ramon Huerta, Junbo Li, Ling Leng, George Monokroussos, Suhas Vijaykunar, et al. Hedonic prices and quality adjusted price indices powered by ai. *Working Paper*, 2021.

Marissa Beck and Fiona Scott Scott Morton. Evaluating the evidence on vertical mergers. *Review of Industrial Organization*, pages 1–30, 2021.

Steven Berry, James Levinsohn, and Ariel Pakes. Automobile prices in market equilibrium. *Econometrica: Journal of the Econometric Society*, pages 841–890, 1995.

Steven Berry, James Levinsohn, and Ariel Pakes. Differentiated products demand systems from a combination of micro and macro data: The new car market. *Journal of political Economy*, 112(1):68–105, 2004.

Thomas Brinkhoff. City population. *www.city-population.de (accessed 7 May 2022)*, 2022.

Luming Chen, Xuejie Yi, and Chuan Yu. The welfare effects of vertical integration in china's movie industry. *Available at SSRN*, 2022.

Ting Chen, Yizhen Gu, and Ben Zou. China's commuting-based metropolitan areas. *Journal of Urban Economics*, 144:103715, 2024. ISSN 0094-1190. doi: https://doi.org/10.1016/j.jue.2024.103715. URL https://www.sciencedirect.com/science/article/pii/S0094119024000858.

Tasneem Chipty. Vertical integration, market foreclosure, and consumer welfare in the cable television industry. *American Economic Review*, 91(3):428–453, 2001.

Federico Ciliberto. Does organizational form affect investment decisions? *The journal of industrial economics*, 54(1):63–93, 2006.

Giovanni Compiani, Ilya Morozov, and Stephan Seiler. Demand estimation with text and image data. *arXiv preprint arXiv:2503.20711*, 2025.

Chris Conlon, Julie Mortimer, and Paul Sarkis. Estimating preferences and substitution patterns from second choice data alone. *Preliminary and incomplete*, 2023.

Christopher Conlon and Jeff Gortmaker. Incorporating micro data into differentiated products demand estimation with pyblp. *Journal of Econometrics*, page 105926, 2025.

Christopher T Conlon and Julie Holland Mortimer. Efficiency and foreclosure effects of vertical rebates: Empirical evidence. *Journal of Political Economy*, forthcoming.

Gregory S Crawford and Ali Yurukoglu. The welfare effects of bundling in multichannel television markets. *American Economic Review*, 102(2):643–85, 2012.

Gregory S Crawford, Robin S Lee, Michael D Whinston, and Ali Yurukoglu. The welfare effects of vertical integration in multichannel television markets. *Econometrica*, 86(3):891–954, 2018.

Jose Ignacio Cuesta, Carlos Norton, and Benjamin Vatter. Vertical integration between hospitals and insurers. *Working Paper*, 2019.

Amit Gandhi and Jean-François Houde. Measuring substitution patterns in differentiated products industries. *Working paper*, 2019.

Fuan Gao, Peiyi Song, Ruo Si, and Qing Qing. *Principles of Movie Production and Management*. Beijing Book Co. Inc., 2018.

Ricard Gil. Revenue sharing distortions and vertical integration in the movie industry. *The Journal of Law, Economics, & Organization*, 25(2):579–610, 2009.

Ricard Gil. Does vertical integration decrease prices? evidence from the paramount antitrust case of 1948. *American Economic Journal: Economic Policy*, 7(2):162–191, 2015.

Ricard Gil, Chun-Yu Ho, Li Xu, and Yaying Zhou. Vertical integration and market foreclosure in media markets: Evidence from the chinese motion picture industry. *The Journal of Law and Economics*, 67(1):143–193, 2024.

Paul LE Grieco, Charles Murry, Joris Pinkse, and Stephan Sagl. Conformant and efficient estimation of discrete choice demand models. *Unpublished manuscript*, 2023.

Sanford J Grossman and Oliver D Hart. The costs and benefits of ownership: A theory of vertical and lateral integration. *Journal of political economy*, 94(4):691–719, 1986.

Sukjin Han, Eric H Schulman, Kristen Grauman, and Santhosh Ramakrishnan. Shapes as product differentiation: Neural network embedding in the analysis of markets for fonts. *arXiv preprint arXiv:2107.02739*, 2021.

Oliver Hart, Jean Tirole, Dennis W Carlton, and Oliver E Williamson. Vertical integration and market foreclosure. *Brookings papers on economic activity. Microeconomics*, 1990:205–286, 1990.

Justine Hastings, Ali Hortaçsu, and Chad Syverson. Sales force and competition in financial product markets: the case of mexico's social security privatization. *Econometrica*, 85(6): 1723–1761, 2017.

Chun-Yu Ho, Marc Rysman, and Yanfei Wang. Demand for performance goods: Import quotas in the chinese movie market. *Working Paper*, 2021.

Ali Hortaçsu and Chad Syverson. Cementing relationships: Vertical integration, foreclosure, productivity, and prices. *Journal of political economy*, 115(2):250–301, 2007.

Guangming Hou and Minfang Wu. *Reports on China Film Industry Development 2012–2013*. China Film Press, 2014.

Jean-François Houde. Spatial differentiation and vertical mergers in retail markets for gasoline. *American Economic Review*, 102(5):2147–82, 2012.

Thomas Koch, Brett Wendling, and Nathan Wilson. How vertical integration affects the quantity and cost of care for medicare beneficiaries. *Journal of Health Economics*, 52: 19–32, 2017.

Yehuda Koren, Robert Bell, and Chris Volinsky. Matrix factorization techniques for recommender systems. *Computer*, 42(8):30–37, 2009.

Rafael La Porta, Florencio Lopez-de Silanes, and Andrei Shleifer. Corporate ownership around the world. *The journal of finance*, 54(2):471–517, 1999.

Francine Lafontaine and M Slade. Presumptions in vertical mergers: The role of evidence. *Review of Industrial Organization*, 2021.

Robin S. Lee. Vertical integration and exclusivity in platform and two-sided markets. *American Economic Review*, 103(7):2960–3000, December 2013.

Fernando Luco and Guillermo Marshall. The competitive impact of vertical integration by multiproduct firms. *American Economic Review*, 110(7):2041–64, 2020.

Fernando Luco and Guillermo Marshall. Diagnosing anticompetitive effects of vertical integration by multiproduct firms. *Review of Industrial Organization*, pages 1–12, 2021.

Lorenzo Magnolfi, Jonathon McClure, and Alan T. Sorensen. Triplet embeddings for demand estimation. *Available at SSRN 4113399*, 2022.

Andriy Mnih and Russ R Salakhutdinov. Probabilistic matrix factorization. *Advances in neural information processing systems*, 20, 2007.

Serge Moresi and Steven C Salop. vguppi: Scoring unilateral pricing incentives in vertical mergers. *Antitrust LJ*, 79:185, 2013.

Serge Moresi and Steven C Salop. When vertical is horizontal: How vertical mergers lead to increases in "effective concentration". *Review of Industrial Organization*, 59(2):177–204, 2021.

Aviv Nevo. Measuring market power in the ready-to-eat cereal industry. *Econometrica*, 69 (2):307–342, 2001.

Janusz A Ordover, Garth Saloner, and Steven C Salop. Equilibrium vertical foreclosure. *The American Economic Review*, pages 127–142, 1990.

Art B Owen and Patrick O Perry. Bi-cross-validation of the svd and the nonnegative matrix factorization. *The annals of applied statistics*, 3(2):564–594, 2009.

A. Pakes, J. Porter, Kate Ho, and Joy Ishii. Moment inequalities and their application. *Econometrica*, 83(1):315–334, 2015.

Amil Petrin. Quantifying the benefits of new products: The case of the minivan. *Journal of political Economy*, 110(4):705–729, 2002.

Patrick Rey and Jean Tirole. A primer on foreclosure. *Handbook of industrial organization*, 3:2145–2220, 2007.

Thomas W Ross and Ralph A Winter. A canadian perspective on vertical merger policy and guidelines. *Review of Industrial Organization*, pages 1–25, 2021.

Michael A Salinger. Vertical mergers and market foreclosure. *The Quarterly Journal of Economics*, 103(2):345–356, 1988.

Michael A Salinger. The new vertical merger guidelines: Muddying the waters. *Review of Industrial Organization*, pages 1–17, 2021.

Steven C Salop and David T Scheffman. Raising rivals' costs. *The American Economic Review*, 73(2):267–271, 1983.

Carl Shapiro. Vertical mergers and input foreclosure: Lessons from the at&t/time warner case. *Review of Industrial Organization*, 2021.

Joseph J Spengler. Vertical integration and antitrust policy. *Journal of political economy*, 58 (4):347–352, 1950.

Ayako Suzuki. Market foreclosure and vertical merger: A case study of the vertical merger between turner broadcasting and time warner. *international Journal of industrial organization*, 27(4):532–543, 2009.

Kenneth E Train. *Discrete choice methods with simulation*. Cambridge university press, 2009.

Chenyu Yang. Vertical structure and innovation: A study of the soc and smartphone industries. *The RAND Journal of Economics*, 51(3):739–785, 2020.

Appendix A. Additional Tables and Figures

Table A1: Additional Summary Statistics

Panel A: 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 B: 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 C: 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

Notes: Panel A reports theater-level variables. Panel B reports film-level variables for 628 films, including the shares that are imported (under revenue-sharing contracts), in enhanced formats (3D/I-MAX), and in action, adventure, romance, science fiction, and comedy genres. Panel C reports rating statistics: (i) 1,798,305 user-film star ratings, (ii) 11,047 users (number of ratings and the 25th, 50th, and 75th percentiles of ratings per user), and (iii) 1,544 films (number of ratings and the 25th, 50th, and 75th percentiles of ratings per film).

Table A2: Counterfactual Effects of VI: One theater-Film at a Time

	$VI_{ft} = 1$		$VI_{ft} = 0$	
	(1) Price Change	(2) Showings Change	(3) Price Change	(4) Showings Change
$\log(\text{Theaters}_{tw})$	-0.005*	-0.016	-0.007**	-0.019
	(0.002)	(0.018)	(0.002)	(0.011)
Have non-VI rivals	-0.004	-0.010		
	(0.003)	(0.032)		
$\min_{f':VI_{f'}=0} d_{f,f'}$	0.001	-0.066***	-0.001*	0.037***
	(0.001)	(0.007)	(0.000)	(0.003)
Constant	-0.018***	2.875***	0.020***	-0.122***
	(0.005)	(0.045)	(0.004)	(0.021)
Observations	198,050	198,037	195,670	195,667

Notes: Standard errors in parentheses. FEs: theater, movie-week, movie-city. SEs clustered at the market level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

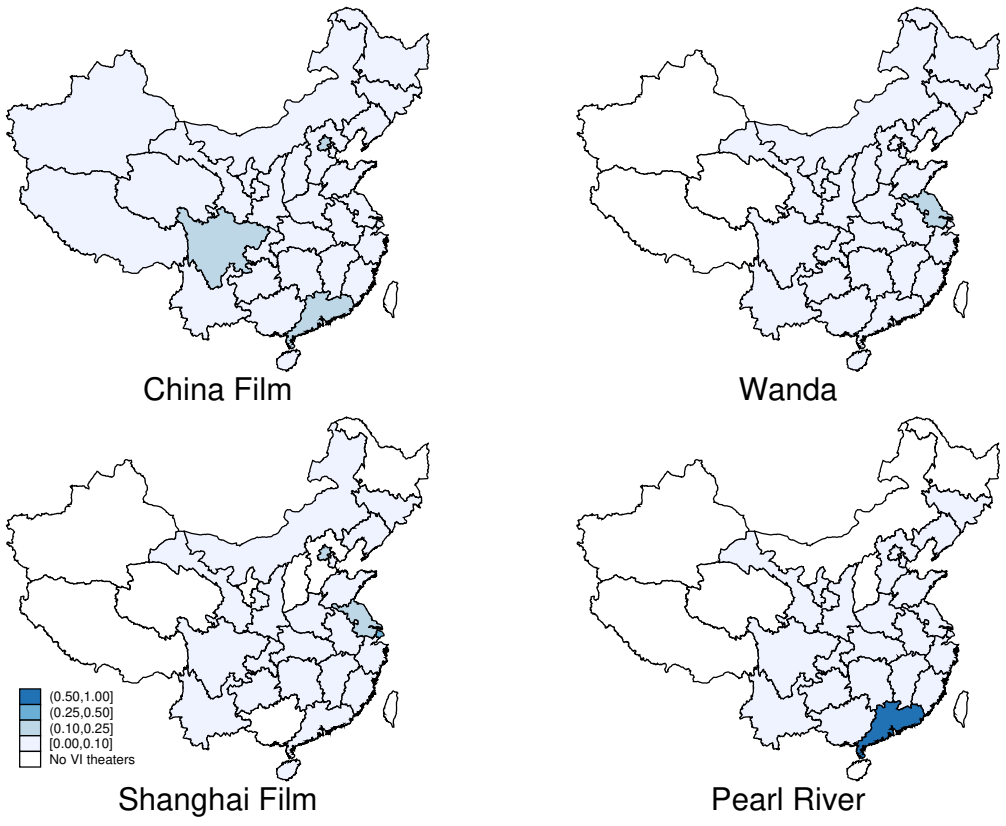
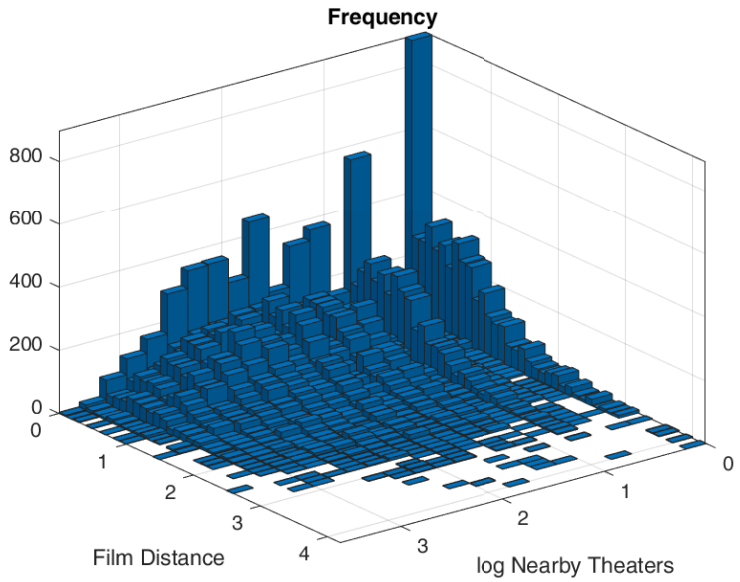


Figure A1: Locations of Integrated Theaters

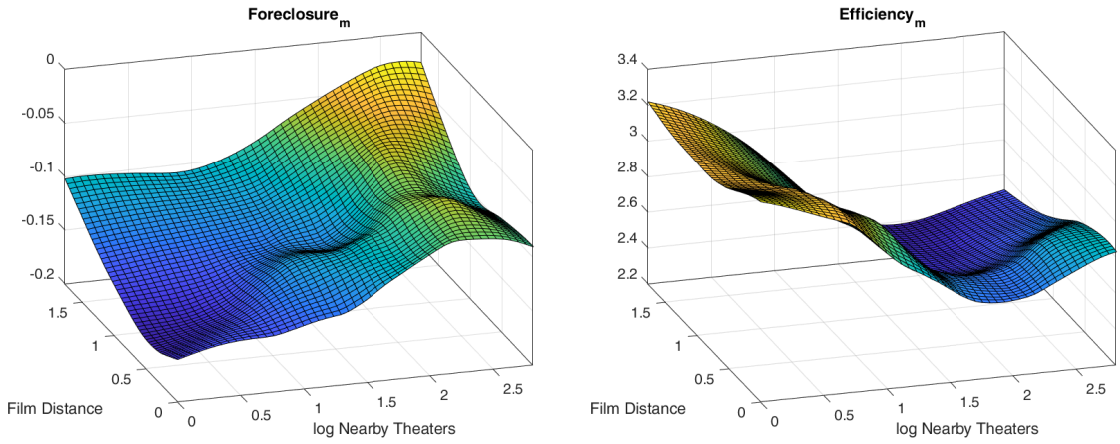
Note: This figure plots, for four upstream distributors, the geographic distribution of their downstream integrated theaters revenue during the 2011-2015 sample period.

Figure A2: Distribution of Market Characteristics



Notes: Joint distribution across markets of measures defined in equation (23). Sample includes all markets except those in which there are no vertically integrated films.

Figure A3: Heterogeneous Showings Effects of VI: Including 0 Theaters

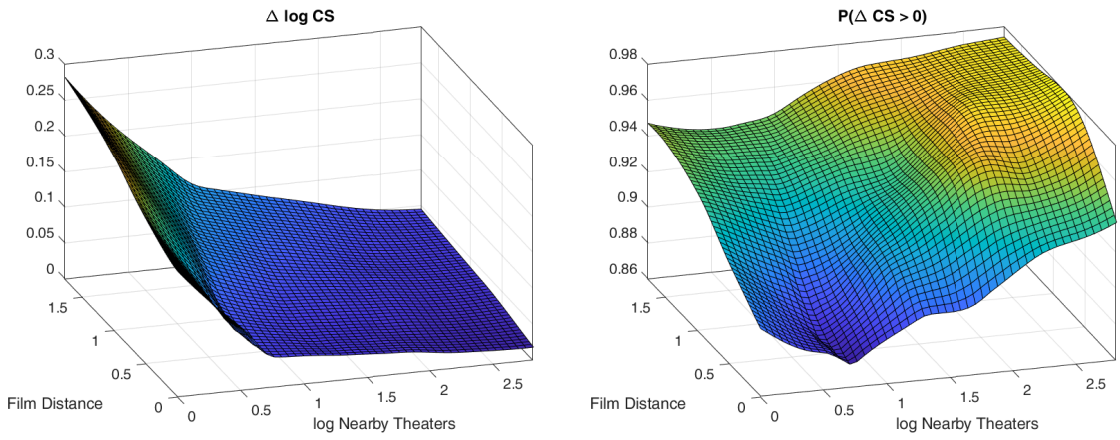


(a) Foreclosure Effect

(b) Efficiency Effect

Notes: Local linear regression of market average change in log showings from integration on market characteristics defined in equation (23). Dependent variables are defined in equation (24). We drop observations from above the 99th percentile and below the 1st percentile of the dependent variable.

Figure A4: Heterogeneous Consumer Surplus Effects of VI: Including 0 Showings

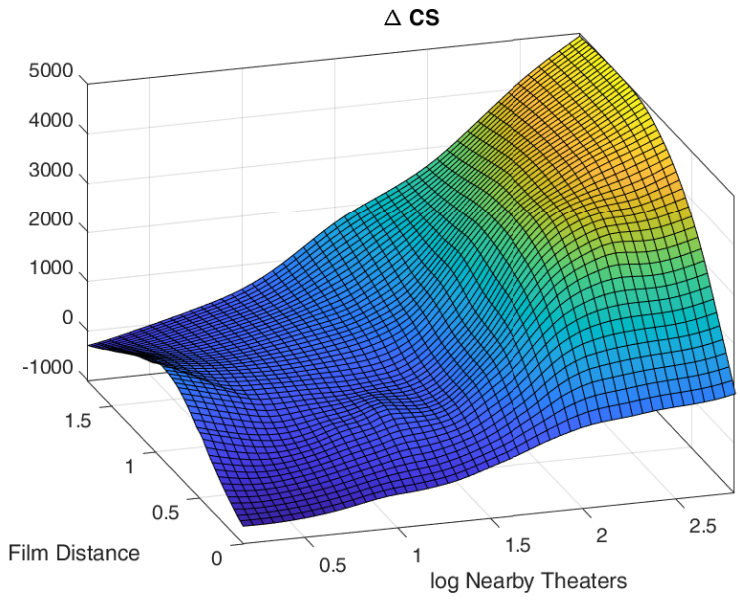


(a) Change in Consumer Surplus

(b) Probability of CS Decrease

Notes: Local linear regression of market-level difference in log consumer surplus between the baseline and no-integration counterfactual on market characteristics defined in equation (23). We drop observations from above the 99th percentile and below the 1st percentile of the dependent variable.

Figure A5: Heterogeneous Consumer Surplus Effects of VI: Levels



Notes: Local linear regression of market-level difference in log consumer surplus between the baseline and no-integration counterfactual on market characteristics defined in equation (23). We drop observations from above the 99th percentile and below the 1st percentile of the dependent variable.

Appendix B. Details on Institutional Background

B.1. Vertical Integration

Table B1 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 B1: 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.

B.2. Film Distribution

Table B2 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 B2: 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.

B.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 B3: 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 C. Additional Empirical Results

C.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 C1 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 C1: 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.

C.2. Regression Results

Table C2 presents the impact of vertical integration on supply decisions using an alternative definition of vertical integration. Here, VI_{ft} is defined as vertical integration between a theater chain and both a producer and a distributor. We re-estimate the main specification from Table 2 using this definition. The results remain robust under this alternative specification. Vertical integration has a positive and significant effect on showings, while its effect on price is minimal. These findings are consistent with those from the main specification.

Table C2: 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	2,013,782	2,013,782
R^2	0.742	0.771	0.732	0.789	0.798	0.757

Notes: This table presents the impact of vertical integration on supply decisions using an alternative definition of vertical integration: vertical integration between a theater chain and both a producer and a distributor. Standard errors are clustered at the market level and are reported in parentheses. *** p <0.005, ** p <0.01, * p <0.05.

Appendix D. Details of the Rating Model

D.1. Interpreting the Latent Attributes

The correlation between latent and observable characteristics is plotted in Figure D1.

D.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 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.

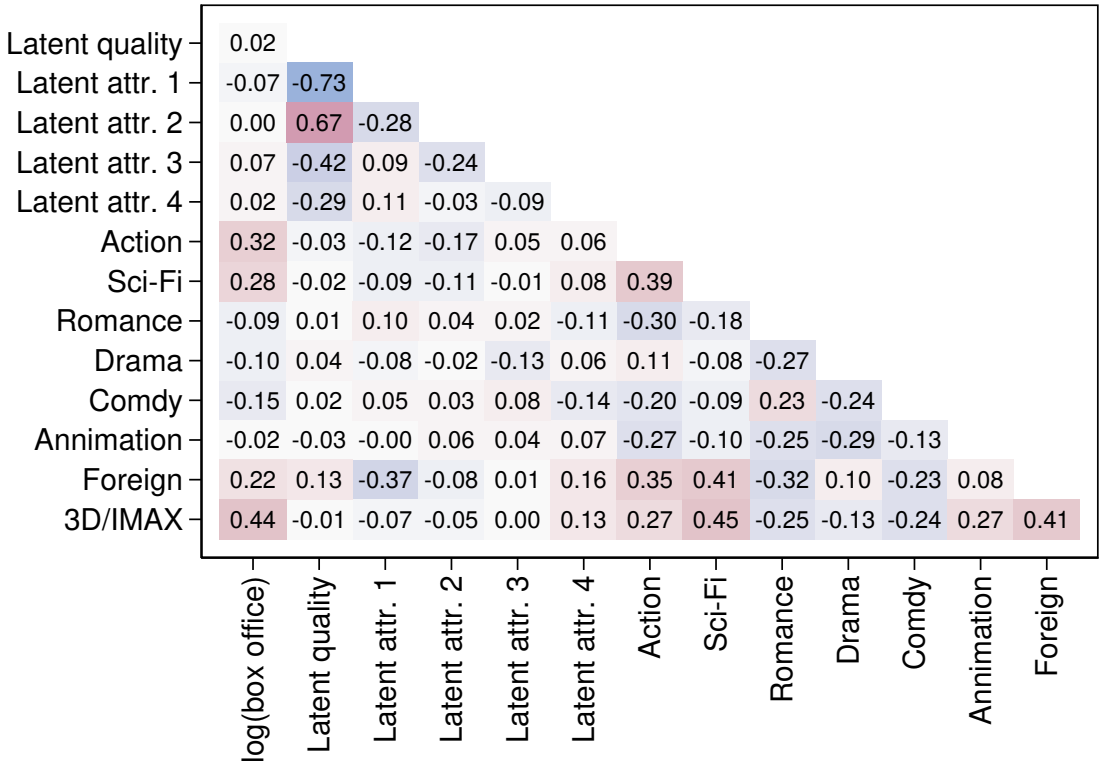


Figure D1: Correlation between Latent and Observable Characteristics

Appendix E. Details on Counterfactual Results

E.1. Counterfactual Algorithm

The goal of the algorithm described in this section is to find (p^*, S^*), the vectors of equilibrium prices p_{ft} and showings S_{ft}, that jointly satisfy the following first-order conditions:

$$\lambda \odot S^* + (\Omega \odot \Delta_p^*)(\lambda \odot p^* - mc) = 0, \tag{27}$$

$$c + \nu = M(\Omega \odot \Delta_S^*)(\lambda \odot p^* - mc), \tag{28}$$

where Ω is the ownership matrix (i.e., $\Omega_{ij} = 1$ if and only if the i-th and j-th arguments in the market share vector are from the same theater), $\odot$ denotes element-wise multiplication, and Δ_p and Δ_S are the Jacobians of the demand system with respect to prices and showings, respectively (i.e., $\Delta_{p,ij} = \partial s_i / \partial p_j$, $\Delta_{S,ij} = \partial s_i / \partial S_j$). The term $c + \nu$ denotes factual marginal cost and net marginal revenue, and λ is the revenue-share vector defined in equation (15).

To solve for the counterfactual equilibrium with two endogenous variables, we implement an iterative procedure similar to Allende (2019):

Step 1. Given showings s, compute prices that satisfy (27):

$$p^* \leftarrow \frac{mc - (\Omega \odot \Delta_p^*)^{-1}(\lambda \odot S^*)}{\lambda}.$$

Step 2. Given prices p, update showings implied by (28):

$$s \leftarrow \frac{(\Omega \odot \Delta_{\log s})(\lambda \odot p - mc)}{c + \nu}.$$

Step 3. Iterate between Steps 1 and 2 until convergence.

In constructing the counterfactual results, we begin with films that have non-zero observed showings. Consistent with the data cleaning procedure, counterfactual prices are truncated at a minimum of 0.5 USD (in 2012 dollars).