

# Demand for Performance Goods: Import Quotas in the Chinese Movie Market

Chun-Yu Ho  
University at Albany, SUNY

Marc Rysman  
Boston University

Yanfei Wang <sup>\*</sup>  
Business School, Renmin University of China

July 2, 2026

## Abstract

We introduce a model of *performance goods* in which dynamic consumers purchase infrequently and consume each product only once due to *consumption durability*. We use our model to evaluate Chinese restrictions on the number of foreign movies distributed domestically, particularly an increase in the quota in 2012. Our model finds much lower importance for reduced-form age profiles than a static model. We find relatively little substitution between foreign and domestic movies, and counterfactual experiments show that consumer welfare increases by 7.7% due to the import liberalization. However, the static model finds even lower substitution and welfare gains. Revenue in China expands due to liberalization because of demand expansion, which provides insights into Chinese motivation for the quota.

**Keywords:** Demand Estimation, Choice Set, Trade Liberalization.

**JEL classifications:** L10, L82, F13

---

<sup>\*</sup>We thank many seminar audiences and especially our referees and editor for helpful comments. Yanfei Wang acknowledges financial support from the Young Scientists Fund of the ~~National Natural Science Foundation of China~~ (grant No. 72203220). Corresponding author: Yanfei Wang. Email: [wangyanfei@rmbs.ruc.edu.cn](mailto:wangyanfei@rmbs.ruc.edu.cn).

# 1 Introduction

A widely recognized feature of new cultural goods, such as movies and books, is that their sales decline as the product ages. A common approach to demand estimation in such cases is to apply a static model that contains a reduced-form age profile. However, it is puzzling from the perspective of economics why the utility from a cultural good would decline at a very rapid rate. If the static model is incorrect, we may obtain biased elasticities and faulty welfare predictions. In this paper, we provide a new approach based on *consumption durability* in which consumers obtain reduced value from a good they have already purchased, which endogenously reduces demand over time. We apply our model to movie-going in China in the context of a liberalization of a quota on foreign movies. We show that our model fits the data well, and finds substantially different results than the static approach.

We term the general class of goods we study as *performance goods*. Performance goods are distinguished by three features. First, performance goods have a frequently evolving choice set. For example, new movies are constantly being introduced and they typically displace existing movies, so that older but still somewhat recent movies are often unavailable in theaters for consumers. Second, consumers have limited time to allocate towards consuming movies. Regardless of their income level, consumers would not attend every movie in the theater. Third, and perhaps most importantly, movies exhibit consumption durability. Consumers typically receive significantly lower utility from seeing a movie a second time, so that consumers see most movies only once at most.

Consumption durability is a feature of many cultural goods, such as books, museum exhibits, and music albums.<sup>1</sup> Many of these goods exhibit stark declines in demand after introduction. Examples of previous research on performance goods that applied static models with an age profile are Einav (2007) in movies and Hendricks & Sorensen (2009) for album sales. A goal of our project is to show that this decline in sales is better explained by a model with consumption durability than a reduced-form age profile.

---

<sup>1</sup>Not all cultural goods are performance goods, such as music on streaming services, and some performance goods may not be cultural goods, such as online courses in computer programming. Note that consumption durability has long been considered in the literatures on macroeconomics and finance to understand consumption dynamics (Hayashi, 1985; Ferson & Constantinides, 1991).

In our model, consumers face an exogenously evolving choice set. Consumers have persistent heterogeneous preferences over movie characteristics. We assume that consumers can see no more than one movie per week and face reduced utility from going to the movies with high frequency (i.e., multiple weeks in a row), both of which reflect consumers’ limited time for attending cinemas. Further, we assume that consumers cannot see the same movie more than once. Thus, the choice set of a given consumer evolves endogenously as the consumer makes decisions over which movies to see. In estimation, we find the level of unobserved quality for each movie-week that rationalizes the observed market share, and we form a GMM estimator around this term. For much of the paper, we assume that consumers choose myopically which movie to see. Under this assumption, consumers do not account for how seeing a movie today affects future outcomes. We also consider a model of perfect foresight, but we show that forward-looking behavior does not fit our data well.

We apply our model to data drawn from movie-going in China. Like many developing countries, China restricts the entry of cultural goods such as movies and books. We study the welfare implications of this restriction in the foreign film market from the perspective of consumer choice. We are particularly motivated by China’s liberalization of the quota on foreign movies from 20 movies to 34 in early 2012. We ask how much consumer benefit resulted from this expansion, how much this expansion led to substitution away from other movies, and the implications for revenue for the Chinese movie industry. We focus on distinguishing between the effects on foreign and domestic movies, which is relevant for evaluating industry protection policies. For data, we use national box office revenues by week from Chinese movie theaters from January 2012 to June 2015. We collect movie characteristics, such as whether the movie is foreign or domestic, the genre of the movie, and the run-time. We augment the data with a survey from a consulting firm that reports how often people go to the movies, which we use to construct additional “micro-moments” for our estimation.

Although movies experience an extreme drop-off in sales from week to week, our results show that the drop-off can be entirely explained by consumption durability. In particular, when we estimate a traditional static random coefficients logit model with a reduced-form age profile, we find that the age profile is strongly significant and negative, reflecting the steep drop-off in sales over the life of a

movie. However, when we estimate our dynamic model with both consumption durability and the age profile, we find that consumption durability is important and that the coefficient on the age profile is insignificantly different from zero.

We also find substantial heterogeneity in preferences for foreign movies, suggesting that foreign and domestic movies are not close substitutes. However, the static model generates even lower substitution. That is because substitution interacts with consumption durability in important ways. Consider a sequence of periods with the same movies available. Without consumption durability, consumers that prefer foreign movies will watch foreign movies each period. But with consumption durability, consumers may exhaust the available foreign movies and then switch to domestic movies. That is, with consumption durability, consumers that see both foreign and domestic movies are not necessarily a sign of high substitution. We show how our model can generate complex substitution patterns that are not feasible under a static model. In addition, we find that a static model leads to lower estimates of the welfare benefit of liberalization. The higher substitution with other foreign movies in the static model means less market expansion, thus lowering welfare. Furthermore, the static model allows consumers to purchase the same product every period, thus lowering the value of choice set expansion.

Because the liberalization going from 20 to 34 movies takes place just before the start of our data, we cannot evaluate the market before the policy change. Rather, we employ our structural model to determine outcomes in the counterfactual scenario. In order to determine which of the 34 movies get dropped when switching to 20 movies, we estimate a probit model of the decision-making by the Chinese government over which movies are chosen. We use the results of this estimation to generate a distribution of possible movies in China if there was no liberalization. We show that consumer welfare increases by 7.71% due to the liberalization. The import liberalization reduces the total market share of the competing foreign movies more than domestic movies because the extra foreign movies are closer substitutes. This result raises questions about the value of infant industry policies, as substitution between the foreign and domestic products is limited. Indeed, we find that losses to domestic film production from liberalization are more than offset by gains to domestic distributors,

theaters, and government tax receipts. This result suggests that either the quota is motivated by cultural protection rather than economic protection or the Chinese government particularly values protection for domestic movie production as opposed to other parts of the supply chain.

Countries may restrict the entry of cultural goods in order to protect domestic industries and also to protect the distinctive nature of their culture from global incursion. We evaluate the implications of the quota only for economic outcomes, such as consumer welfare. Thus, for a policy-maker considering such cultural or industry protection, we provide a measure of the economic cost. Note that in our counterfactual calculations, we assume the set of movies does not change. However, some research and popular press argue that Chinese policies affect foreign movie production in terms of genre and content (see for instance Leung & Qi, 2023). We do not address that issue here, although it may be important.

## 2 Literature

Our work contributes to literatures on trade in movies and cultural goods as well as demand estimation. We are related to the growing empirical literature on trade in motion pictures, such as Marvasti & Canterbury (2005), Hanson & Xiang (2011), Holloway (2014), and McCalman (2004), which study factors that lead US movies to be imported into a country, such as trade barriers and intellectual property policies. Relative to these papers, we focus on the import choices of a single country, China, and so focus on which movie characteristics determine entry. Ferreira, Petrin & Waldfogel (2016) estimate a structural model to evaluate the role of product quality in determining gains from trade in motion pictures. Similarly, we use a structural demand model to examine the welfare effects of import liberalization, although we highlight the importance of consumption durability.

Several papers study demand for movies, such as Einav (2007), which focuses on seasonality of demand, Moul (2007), which studies word-of-mouth in generating demand, de Roos & McKenzie (2014), which estimates a price elasticity by exploiting a discounting strategy. Particularly in China, Gil, Ho, Xu & Zhou (2024) and Chen, Yi & Yu (2024) estimate price elasticities to movies using more

disaggregate data than ours. Accounting for consumption durability as we do is new in this literature, although we exploit the Chinese elasticity results to calibrate one part of our counterfactual. Hodgson & Sun (2025) studies the implications of vertical integration in the Chinese movie industry, although does so with a static demand system that does not address consumption durability. Like us, Sun (2022) finds little substitution between foreign and domestic movies in China. His paper emphasizes that liberalization made theaters more profitable, and thus more numerous, which benefited local movie producers.

Our paper adds to the lengthy literature on the benefits of new goods in industrial organization and trade. Whereas most industrial organization papers, such as Trajtenberg (1989) and Petrin (2002), study new goods in the context of innovation, we focus on the liberalization of a quota, which links to the literature on trade barriers. A leading trade example is Krugman (1979). The welfare gain from more product variety from trade appears quantitatively large for manufacturing sectors (see Feenstra, 1994; Broda & Weinstein, 2006; Blonigen & Soderbery, 2010; Sheu, 2014). Our paper particularly studies a cultural good, which are sometimes exempted from trade agreements. The protection of national culture played a role in the Uruguay Round of the GATS, which ended in 1994, and the UNESCO Convention on the Protection and Promotion of the Diversity of Cultural Expressions (in particular Articles 6 and 8).<sup>2</sup> In addition to protecting national culture, countries sometimes restrict the entry of foreign goods to encourage the development of local producers, so-called infant industry protection. See Greenwald & Stiglitz (2006) and the literature that follows. We show that benefits to liberalization were high in the Chinese movie context due to low substitution between foreign and domestic products, which limits the potential importance of infant industry protection.

Trade barriers are of particular concern for U.S. movies as U.S. producers increasingly rely on foreign revenues and U.S. movies dominate the market share in many foreign countries.<sup>3</sup> Article IV

---

<sup>2</sup>Cultural goods and services “encompass values, identity and meanings that go beyond their strictly commercial value,” according to a submission from the Coalition for Cultural Diversity to the UNESCO Convention on the Protection and Promotion of the Diversity of Cultural Expressions. Francois & van Ypersele (2002) and Rauch & Trindade (2009) argue that restrictions on trade in cultural goods can raise welfare. Chu-Shore (2010) reports that there is a homogenization of cultural goods in response to trade liberalization. Maystre, Olivier, Thoenig & Verdier (2014) provide theory and evidence to support that trade integration leads to convergence in cultural values across countries.

<sup>3</sup>Marvasti & Canterbury (2005) report that export revenues are an increasing portion of total revenue for U.S.

of the GATT agreements in 1947 provides the conditions under which countries may impose quotas on foreign movies.<sup>4</sup>

Our paper is the first to estimate a dynamic model of movie demand or account for consumption durability in movies or other cultural goods. We build on the methodology developed by Berry, Levinsohn & Pakes (1995) to estimate a demand system for differentiated products with market-level data, and Gowrisankaran & Rysman (2012) to incorporate product durability and forward-looking consumers. Consumer dynamics arise in many contexts in addition to performance goods, such as durable goods, storable goods, and subscription goods (Gowrisankaran & Rysman, 2020). Our main specification, which focuses on myopic consumers but still with consumption durability, simplifies the problem of Gowrisankaran & Rysman (2012) substantially. While we focus on a model of myopia, we also estimate a model of perfect foresight and estimate the discount rate in the spirit of Magnac & Thesmar (2002). Other papers that estimate the discount rate are Lee (2013), Dalton, Gowrisankaran & Town (2020), and De Groote & Verboven (2019).

### 3 Institutional background

This section discusses Chinese import policies for foreign movies. Until 1994, foreign movies were purchased mainly on a flat-fee basis. Between 1978-1993, the China Film Group was the only authorized agent to import and distribute these films. In each year, the China Film Group spent about USD \$1 million to import about 30 foreign movies, and each foreign movie was purchased at about USD \$30,000. As a result, the imported movies were usually considered “outdated and low-grade but cheap.” (Rosen, 2002).

In 1994, the Film Administrative Bureau, under the Ministry of Radio, Film and Television adopted a revenue-sharing practice to import 10 foreign movies per year. The policy aimed to stimulate declining movie attendance and create opportunities for domestic studios. China was

---

movies. Export revenues were less than one-third of domestic box office revenues in 1986 but were about 90% of domestic box office revenues in 2000. Hanson & Xiang (2009) document that U.S. movies acquire more than 70% of box office revenue in 19 European countries over the period 1995-2004. According to a report by the Motion Picture Association of America, the global box office for U.S. movies released in each country around the world reached \$USD 36.4 billion in 2014, of which \$USD 26.0 billion was acquired from the international box office. Source: <http://www.mpa.org/wp-content/uploads/2015/03/MPAA-Theatrical-Market-Statistics-2014.pdf>

<sup>4</sup>Many countries impose trade barriers on foreign movies. Marvasti & Canterbury (2005) shows that non-tariff trade barriers, such as quotas, are more commonly imposed than tariffs, especially for developing countries.

approved to join the WTO in 2001. Under the agreement, China increased the quota for revenue-sharing movies to 20. In order to diversify the imported films, in 2004, the State Administration of Radio, Film and Television (SARFT) reserved about six slots for non-U.S. movies.

China has become the largest foreign market for U.S. movies as the annual box office in China has been accelerating faster than 20% annually during the past decade. Specifically, the box office of U.S. movies in China was at \$USD 4.8 billion in 2014. In February 2012, China agreed to significantly increase market access for U.S. movies in order to resolve a WTO dispute that the U.S. had filed in 2007. With immediate effect, China enlarged its quota for revenue-sharing imports of foreign films from 20 to 34 per year. The extra 14 films were specified to be in 3D or IMAX formats. In addition, revenue sharing was set at 25% of box office revenues instead of the previous rate of 13-17%. All of the 34 revenue-sharing movies and all movies imported under the fixed fee plan are imported and distributed by the China Film Group, and some are co-distributed by Huaxia, both of which are state-owned enterprises. There is no specific quota to import movies on a fixed-fee basis, and it is usually 20-30 per year. It does not appear that the prevalence of entering by fixed fee changed around the policy change in 2012, with the number of top movies entering by fixed fee remaining small.<sup>5</sup>

A third option for movies to be distributed in China is for them to be co-produced. In a co-production agreement, a foreign producer collaborates with a Chinese investor. In addition, the movie must be sufficiently oriented towards the Chinese market, which SARFT interprets to mean that the movie must feature Chinese actors, Chinese settings, and Chinese themes. Foreign producers obtain attractive revenue-sharing terms, the same as domestic producers (about 30%), and are not subject to the quota. A challenge is that producers cannot be sure of their co-production status until SARFT reviews the movie. A well-known example in China is *Ironman 3*, which was planned as a co-produced movie but was turned down by SARFT as not being sufficiently Chinese after

---

<sup>5</sup>In 2010-2012, the number of movies entering China via flat fee among the top 100 movies by North American box office that year were 4, 8, and 7. In 2014 and 2015, the numbers were 6 and 7. The outlier is 2013, when 11 of the top 100 movies entered by fixed fee. That year had some unusual circumstances. The movie *Ironman 3* was aiming for co-production status but was denied at a late date, and *Hunger Games: Catching Fire* also faced a distributional issue. It is difficult to say why the fixed-fee market is not more active given the quota on revenue sharing, although we note that we are not aware of fixed fees between distributors and producers being used anywhere in the world. Perhaps it is difficult to contract on fixed fees when products have highly uncertain outcomes.

it was produced. The movie entered China under the fixed fee plan. The movie *Looper* had a similar experience. A successfully co-produced movie was *The Great Wall*. There were only 14 co-production movies from the United States over 2001-2016 (Kokas, 2017, Appendix 1).

The way revenue from the box office is split between the various levels is determined by regulation and bargaining. The government gets 8.3% in tax revenues. Of the remaining, 25% go to the foreign producer of a revenue-sharing movie, whereas for domestic and co-produced movies, that number is 30%. The rest goes to the distributors and theaters. The share going to theaters varies very little, if at all, across foreign and domestic movies.<sup>6</sup> Thus, from the perspective of receipts in China, the difference between a foreign revenue-sharing movie and a domestic movie is that China retains about 77% ( $1 - (1 - 0.083) \times 0.25$ ) of box office revenue from foreign movies but 100% of box office revenue for domestic movies. Thus, if liberalization decreases domestic admissions by less than 77% of the increase in foreign admissions, China gains overall from liberalization even ignoring any benefits to consumers. We return to this calculation in our counterfactual results in Section 9.

While we can calculate how much revenue accrues to the levels of taxes, production, distribution, and theatrical showings, determining the exact gains and losses from liberalization (and the political economy of determining the quota) is complex because producers own some theaters, and furthermore, the government owns the main distributors and may have ownership stakes at other levels. We do not account for these ownership patterns, but from the perspective of infant industry protection, even if direct losses to domestic producers from competition through liberalization are offset by gains from ownership stakes at other levels of the supply chain (such as cinemas), those gains will not incentivize investment in domestic production. To the extent that industry protection is aimed at domestic production as opposed to domestic producers in all of their lines of business, our approach is sufficient.

All films, whether they are foreign, domestic, or co-produced, face censorship by SARFT. Review usually takes 30 days. Article 25 of the Regulation on the Administration of Movies, effective in February 2002, prohibits ten aspects of content that are not allowed in any films. The list

---

<sup>6</sup>See *China-International Film Co-Production Handbook* produced by the Motion Picture Association and the China Film Co-Production Corporation.

includes, among other things, “endangers the unity of the nation, sovereignty, or territorial integrity,” “propagating evil cult or superstition,” and “propagating obscenity, gambling, violence, or instigates crimes.”

Similar to other markets, price variation in the Chinese movie market is limited. While prices vary by time of day, day of the week, and theater within a cinema, they do not tend to vary by movie, and which movie appears in which theater is a choice made by the cinema.<sup>7</sup> Conditional on theater and time, prices do not vary by whether a movie is foreign or domestic. Similar to Einav (2007) and others in this literature, we do not attempt to estimate a price coefficient. Rather, we capture the mean level of movie utility with a movie fixed effect and present counterfactual results as percentage changes from the observed outcome. We compute a dollar value as a “back-of-the-envelope” calculation rather than as part of our formal estimation.

Figure 1 depicts that the share of domestic movies at the box office remained at about 55% over a long period, which may relate to the import restrictions by China on foreign movies.<sup>8</sup> The 55% share is higher than those in European countries documented in Hanson & Xiang (2009). Interestingly, the domestic share does not appear to change much as a result of the liberalization in 2012. As discussed in the next section, we do not rely on pre-2012 data in the rest of the paper as we view it as less reliable. However, this result foreshadows our finding that there is significant differentiation between foreign and domestic movies.

## 4 Data

The empirical analysis is based on a novel dataset from a media consulting firm that works with SARFT of China. The data contain information on box office revenue, the number of tickets sold, and the number of showing screens of each movie each week. Beginning in January 2012, SARFT implemented a system in which cinemas participated in an electronic ticketing program, which greatly enhanced the accuracy with which SARFT could measure these variables. The number of tickets sold is also referred to as *admissions*. Our data is drawn from SARFT’s program. Our

---

<sup>7</sup>Orbach & Einav (2007) discuss this issue in the U.S., which exhibits constant prices not only across movies but also across time of day and week.

<sup>8</sup>The data for this figure were collected by the authors from several online sources, particularly reports by Entgroup.

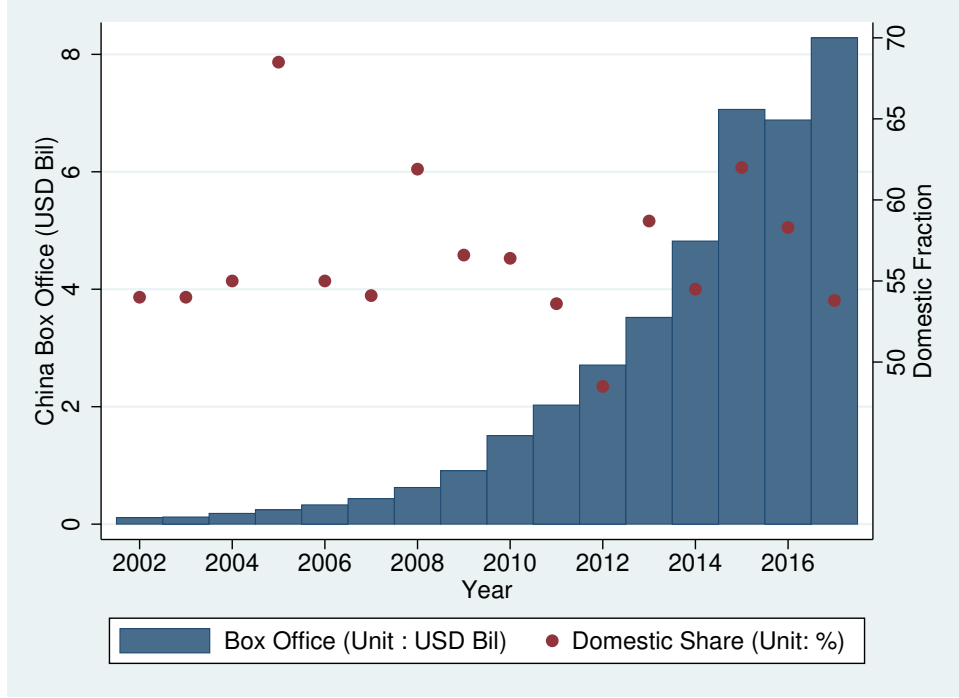


Figure 1: Chinese box office revenue and domestic Share.

empirical analysis includes the movies with admission share for the week larger than 0.1% in at least one week from January 2012 to June 2015. There are 939 movies shown in 183 weeks. We supplement this dataset with hand-collected information on movies, such as genre, run-time, the release date, whether a movie is in 3D or IMAX format, and the nationality of the producing firms.

#### 4.1 Descriptive statistics

Table 1 presents a description of the characteristics that we use in our paper. The table presents simple means of the variables, as well as means weighted by ticket sales. The table also breaks out the variables by foreign and domestic movies. We see that foreign movies are more likely to be 3D, IMAX, and action movies, especially when weighted by ticket sales. For instance, 12% of domestic movies are produced in 3D, whereas 44% of foreign movies are produced in 3D, which represents 71% of foreign ticket sales. Similarly, 29% of foreign movies are in IMAX relative to 3% of domestic movies, and foreign IMAX movies represent 70% of foreign ticket sales. Foreign movies are more likely to be action movies and less likely to be comedies or dramas, and this is even more extreme

Table 1: Movie characteristics

| Variables            | Unweighted |                 |                | Admission-Weighted |                 |                |
|----------------------|------------|-----------------|----------------|--------------------|-----------------|----------------|
|                      | (1)<br>All | (2)<br>Domestic | (3)<br>Foreign | (4)<br>All         | (5)<br>Domestic | (6)<br>Foreign |
| Age (Week)           | 7.06       | 7.57            | 5.66           | 7.71               | 9.73            | 5.33           |
| RunTime (Minute)     | 101.9      | 98.45           | 111.5          | 117.2              | 110.7           | 125.0          |
| Indicator variables: |            |                 |                |                    |                 |                |
| IMAX                 | 0.10       | 0.03            | 0.29           | 0.42               | 0.18            | 0.70           |
| 3D                   | 0.20       | 0.12            | 0.44           | 0.49               | 0.30            | 0.71           |
| Foreign              | 0.27       | 0               | 1              | 0.46               | 0               | 1              |
| Action               | 0.28       | 0.19            | 0.53           | 0.49               | 0.31            | 0.70           |
| Comedy               | 0.31       | 0.35            | 0.21           | 0.26               | 0.35            | 0.16           |
| Drama                | 0.33       | 0.35            | 0.28           | 0.34               | 0.47            | 0.19           |

Number of observations: 939, Foreign movies: 250, Domestic: 689.

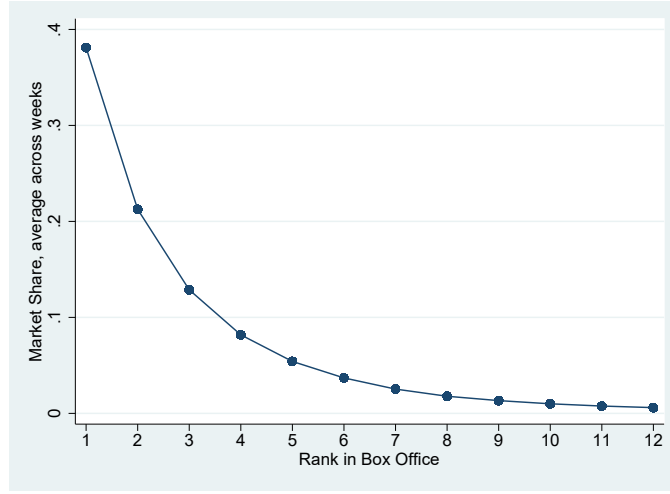


Figure 2: Average share of ticket sales by weekly sales rank

when we weight by admissions.<sup>9</sup>

As is common for cultural goods such as books and music, market shares for movies are highly skewed. For each week in our sample, we calculate the share of admissions going to each rank of movie, i.e., the top-ranked movie, the second-ranked movie, and so on. We average this over the 183 weeks in our data and graph the results in Figure 2. The top-ranked movie at 38% is more than 70% higher than the second-ranked movie at 22%. The top six movies cover 89.6% of the revenue, and the seventh-ranked movie collects less than 4% of tickets, with percentages declining thereafter.

<sup>9</sup>Lee (2006) examines the U.S. movies shown in Hong Kong and finds that the movies with a higher U.S. box office and action movies achieve a higher box office in Hong Kong. Kwak & Zhang (2011) report that, among the foreign movies shown in China, action and comedy movies enjoy a higher box office than drama movies.

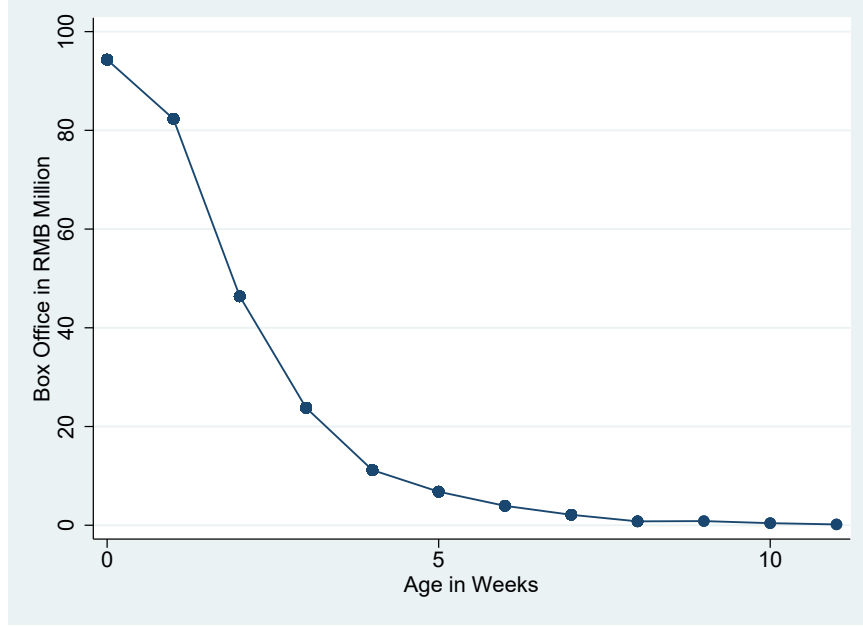


Figure 3: Age profile of movie revenue

A common feature of box office revenue data is the steep drop-off in revenue that takes place from week to week. That is the case in our data as well. In order to see this, we perform a regression of the log of admissions by movie and week on movie, year, month-of-year, and age fixed effects. For this regression, we use only the top six movies by box office revenue in each week, which enables us to drop movies that are re-released long after their original release. Age is defined as the number of weeks since the release of the movie, so there is a separate fixed effect for each age, up to eleven weeks (given our focus on the top six, there are only two movies in the data that make it to eleven weeks). Based on this regression, we predict sales for the average movie by week. For this prediction, we set the date to April 2012, make the prediction for every movie, and take the mean.<sup>10</sup> The result appears in Figure 3. Predicted sales start around 95 million in the first week and drop to less than 50 million by week 3, and are under 10 million by week 5, with continued declines afterward.<sup>11</sup>

<sup>10</sup>In order to account for the non-linear transformation in using a log regression to predict the level of sales, we use Duan's smearing estimate. We use `levpredict` in Stata. See also Duan (1983).

<sup>11</sup>Note that with product fixed effects, age and calendar date are not non-parametrically identified, so the fact that we restrict calendar date to enter by year and month-of-year is potentially important. We do not further explore the issue here, but it might be possible to exploit plausibly exogenous variation in release delays of foreign movies in China, similar to the way Mehta, Rysman & Simcoe (2010) use patent office delay in the context of patent citation age profiles.

## 4.2 Time-varying variables

Einav (2007) reports that there is seasonality in movie demand. Thus, we use a dummy variable for whether the current week has a holiday ( $Holiday_t$ ) to capture the demand fluctuations of movies within a month. The holidays included are New Year’s Day, Chinese New Year, Qingming Festival, May Day, Dragon Boat Festival, Mid-Autumn Day, and National Day. On average, 20% of observations belong to movies showing on a holiday.

We further include a linear time trend in the month as well as year fixed effects to capture the dramatic increase in the Chinese movie market documented in Figure 1. The time trend captures issues such as growing income in China as well as growth in the number of theaters. We include a separate set of month-of-the-year dummies for foreign and domestic movies. Having two separate sets of month-of-the-year dummies is meant to capture anecdotal evidence that SARFT’s treatment of foreign movies varies by season.

## 4.3 Market size and choices

In this subsection, we motivate several important modeling assumptions. An important restriction that we make for computational reasons is that consumers can select among six *named* movies in each week, in addition to a generic foreign and a generic domestic outside option. We assume consumers can select among the six movies with the highest market share in each week.

There appears to be little gain to adding more named movies to the choice set. We calculate the box office share of the top six movies each week, the remaining foreign and the remaining domestic movies, and take the average over weeks. The results appear in Table 2. This table has 1,464 observations, which consist of the six top movies in each week and the two generic options (one foreign and one domestic) for 183 weeks.<sup>12</sup> We find that the top six movies have an average of 89.6% of the market. Thus, similar to what we saw in Figure 2, considering only the top six still captures most of the market. The generic foreign option gets about 3% and the generic domestic option gets about 7%. If we increase the top six movies to be the top ten, we capture 96.2%, an increase of less than 7 percentage points. Thus, there is little gain to expanding this number, and

---

<sup>12</sup>For 16 weeks, we observe zero ticket sales for the foreign generic option, and we assume there was 1 ticket sold.

Table 2: Market shares

| Variables                                  | (1)<br>Mean | (2)<br>SD | (3)<br>Min | (4)<br>Max |
|--------------------------------------------|-------------|-----------|------------|------------|
| Box Office Share (%)                       |             |           |            |            |
| Average movie                              | 12.5        | 12.7      | 0.1        | 88.5       |
| Top six movies                             | 89.6        | 6.1       | 68.3       | 98.8       |
| Other domestic movies                      | 7.0         | 4.7       | 0.3        | 29.9       |
| Other foreign movies                       | 2.9         | 2.8       | 0.1        | 14.7       |
| Market Share (% , out of potential market) |             |           |            |            |
| Average over top six                       | 0.5         | 0.6       | 0.0        | 8.5        |

Note: 1,464 observations, 8 movies in each week, 183 weeks.

the computational cost would be high.

There are two or three foreign movies in the top 6 in more than half the weeks, and no foreign movies available in only 7 of the 183 weeks in our data. Note that throughout the paper, we treat co-produced movies as domestic and we combine fixed fee and revenue sharing movies as foreign movies. Among movies that make it into the top six, fixed fee movies account for about 5.4% of total box office revenue relative to 41.6% for foreign movies overall so breaking them out leads to very small sample sizes. The characteristics presented in Table 1 are similar when using only the 427 movies that appear in the top six. For completeness, we recalculate Table 1 for these movies and present the results in Table A1 in Appendix A (all appendices are online).

A potentially restrictive assumption in our model is that agents are myopic. While we consider a dynamic model for robustness, we believe the myopic model is reasonable. An important way in which agents might act dynamically is that they know when movies exit the theaters and make sure to see movies before that happens. However, in our data, for movies that are ever in the top six, the average percentage of their time that is spent in the top six is only 55.2% . That is, at the end of their time in the top six, movies do not disappear. Instead, they enter one of our generic options. Thus, consumers do not have to perceive movies in a dynamic way in order to be sure to see a given movie. In contrast, a movie’s time in the top six accounts for most of its revenue: For movies ever in the top six, 85.7% of revenue is realized while in the top six. Weighted by ticket sales to emphasize top sellers, the average percentage of time spent in the top six is still only 69%, whereas the percentage of revenue realized while in the top six is 95.4%. Overall, we find these descriptive

statistics consistent with our assumptions that consumers are not forward-looking, and that they choose among six top movies and two generic options (and the outside option).

In order to define market shares, we must define the potential market. We define China as a whole as the geographic market, which is analogous to Einav (2007) in the United States. Because movie theatres are often located in urban areas, we employ the population in an urban area instead of the total population to measure the market size. We use the annual figure of total urban population in the year 2011, i.e., 354.256 million people, to measure the market size. In the mathematical model below, this size is denoted  $M$ . The population data is obtained from the China Statistical Yearbook. To compute market shares, we divide admissions (recall that admissions is quantity, not revenue) of movie  $j$  in week  $t$  by the market size. Let  $q_{jt}$  be the admissions of movie  $j$  in week  $t$ . Then,  $s_{jt}^{\text{data}} = q_{jt}/M$  is the market share of movie  $j$ . The outside good is defined as not watching a movie in a theater. The average market share of a movie is 0.5%, whereas the outside option averages 96%.

#### 4.4 Data for micro-moments

We collect the annual frequency of movie watching from *China Moviegoer Survey Report 2012-2013*, a survey conducted by a Chinese consulting firm called Entgroup. The survey was conducted online in February and March of 2013. The 6,027 respondents are consumers who watched at least one movie in the theater in the previous year. Entgroup’s sampling method ensures the geographical distribution of survey respondents is consistent with the empirical geographic distribution of moviegoers in 2012. The survey shows that 23.2% of the respondents watched 1-3 movies, 19.2% watched 4-6 movies, and 57.6% watched more than 6 movies in the previous year.<sup>13</sup>

## 5 Model

This section presents our model for consumer demand for movies. It is meant to capture what we consider to be the three features of performance goods: rapid exogenous evolution in choice

---

<sup>13</sup>We can use the survey data to get perspective on the total movie-going. In our admissions data, admissions from February 2012 to January 2013 is 463.82 million. As an approximation, suppose 23.2% see two movies, 19.2% see five movies, and 57.5% see 9 movies. That would imply 70.2 million households see a movie in that year, about 19.2% of our potential market size of 354 million. The annual growth rate in admissions is 34.4%, and naturally, we want to allow for consumers to see a movie in one year and not another. For both reasons, we need a potential market size substantially higher than 70.2 million. Thus, our choice of the potential market size is not particularly large by the standards of the discrete choice demand estimation literature.

sets, limited time to consume performances, and consumption durability. The limited time that consumers may allocate to performances is captured by assuming consumers can see at most one movie per week. Obviously, this is not strictly true, but we believe that it is a good representation of consumer decision-making. Consumption durability is captured by assuming that consumers see a given movie no more than once. We discuss relaxations of this assumption below. In addition, we allow consumers to experience disutility from seeing a movie soon (within a few weeks) after seeing another movie, which we interpret as another facet of limited time, but could also be seen as a form of consumption durability.

In addition, we assume for now that consumers make their current choice myopically. This assumption might be problematic in some performance markets, but we believe it is reasonable in our setting. We relax this assumption below.

## 5.1 An overview

We present a simplified version of how the model works in Figure 4. The figure represents four time periods (weeks). The top row reports the time period and the set of exogenously available movies. For this example, we assume only two movies are available rather than six. In the first three periods, movies  $A$  and  $B$  are available. In the fourth period, movie  $A$  drops out, and movie  $C$  arrives. A consumer starts in period 1 having not seen any movies, and so starts with the choice set  $\{A, B\}$ . The three arrows from  $\{A, B\}$  represent the three choices the consumer may make: the consumer can choose to see  $A$ ,  $B$ , or choose not to see a movie.

The exogenously available movies stay the same in period 2, so consumers will face one of three choice sets in period 2, depending on what they choose in period 1. Consumers that saw  $A$  are in the set  $\{B\}$  in period 2, consumers that saw  $B$  are in the set  $\{A\}$ , and consumers that did not see a movie are again in  $\{A, B\}$ . Consumers can reach one of four states in period 3, because consumers that saw movies in both periods are now in state  $\{\phi\}$ , the empty set. These consumers cannot see a movie in period 3. In period 4,  $A$  drops out and  $C$  enters, so there are only two possible choice sets that consumers may reach in period 4: choice set  $\{C\}$  for consumers that have already seen movie  $B$  in periods 1, 2, or 3, and choice set  $\{B, C\}$  for consumers that have not yet seen  $B$ .

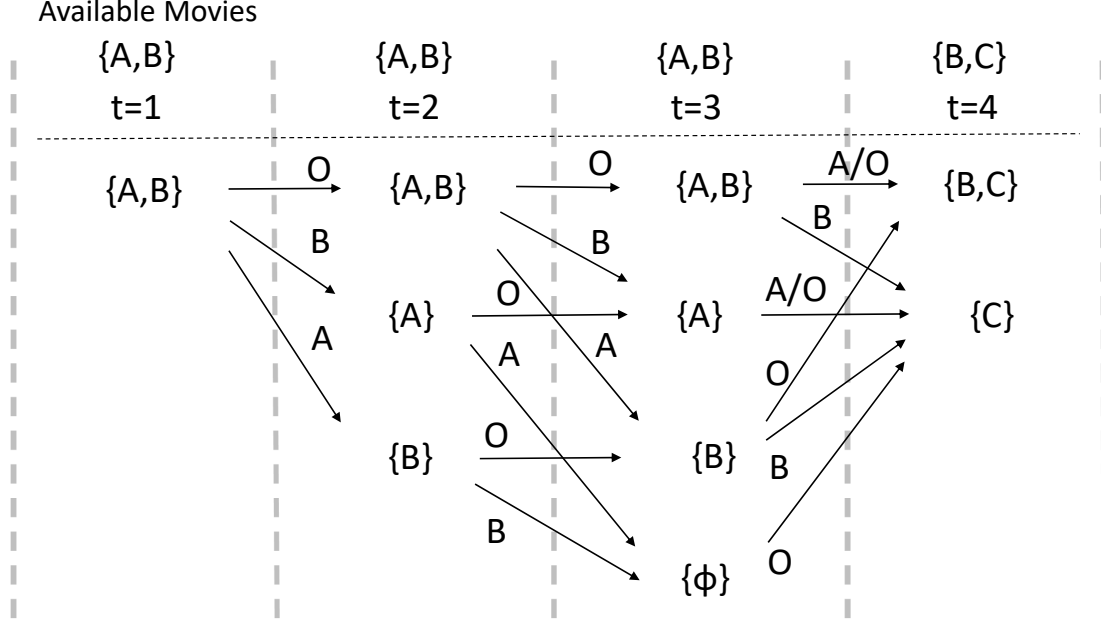


Figure 4: Simplified representation of the demand model

Figure 4 illustrates several points about our model. The set of potential choice sets evolves over time as movies exogenously enter and exit the market. If we think of the consumer's choice set as the consumer's state in a dynamic model, the number of states can grow from one period to the next, especially if there is no change in the available movies. However, turnover in the available movies typically leads to reductions in the number of potential states, and thus simplifies our computational problem. Also, there are typically multiple paths by which a consumer may reach any given choice set. For instance, there are four arrows pointing to set  $\{C\}$  in period 4, and there are multiple ways to reach each of the states that can lead to  $\{C\}$ .

In estimation, we assume a population of consumers starts in the first choice set in period 1 and then follows choice probabilities across each option (each arrow in Figure 4). Thus, we compute the share of the population that lands in each state in each period. Note that there is no simulation in this process. We compute the shares of consumers in each state exactly following the choice probabilities. In practice, we compute this for six movies per period rather than two, for three non-dynamic options (the two generic movies plus the outside option) rather than one, and for 183 time periods rather than four, so the problem is numerically challenging. In addition, we allow for persistent consumer

heterogeneity in the form of permanent random coefficients, and our computation must be done separately for each consumer type. As described below, and as is standard, we use simulation to handle consumer heterogeneity.

## 5.2 The consumer problem

Now we present the model more formally. A continuum of consumers of size  $M$  indexed by  $i$  face discrete, finite time indexed by  $t = 1, \dots, T$ , where one period represents one week in the data. The set of all movies ever available can be indexed by  $j$  from 1 to  $J$ . These are the named movies that a consumer can see only once. In our case,  $J = 427$ . A subset of six of these movies is available in any given period. Denote the set of movies available in  $t$  as  $\mathbf{C}_t$ . We assume that  $\mathbf{C}_t$  follows an exogenous process. The set of six movies in  $\mathbf{C}_t$  can be combined into different choice sets. Denote the set of choice sets that can be reached by consumers as  $\mathcal{C}_t$ . The set  $\mathcal{C}_t$  has  $G_t$  elements, so  $G_t$  may be as high as  $2^6$ . We denote the elements of  $\mathcal{C}_t$  as  $C_{gt}$ ,  $g = 1, \dots, G_t$ . In Figure 4,  $\mathbf{C}_t$  is the top row of a column,  $\mathcal{C}_t$  is a column,  $C_{gt}$  is each element of the column, and  $G_t$  is the number of elements in the column.

We augment each choice set  $C_{gt}$  with three additional choices: the option not to purchase ( $j = 0$ ), a generic foreign movie ( $j = J + 1$ ), and a generic domestic movie ( $j = J + 2$ ). These last options differ from the elements in  $\mathbf{C}_t$  in that they are always available and consumers may choose them repeatedly over time.

Denote the choice that consumer  $i$  makes in period  $t$  as  $d_{it} \in \{0, \dots, J + 2\}$ . Denote the history of choices by  $i$  up to period  $t$  as  $H_{it}$ , so  $H_{it} = \{d_{it-1}, d_{it-2}, \dots, d_{i1}\}$ . Let the function  $C(H_{it}, \mathbf{C}_t)$  return consumer  $i$ 's choice set in  $t$ :

$$C(H_{it}, \mathbf{C}_t) = \{j : j \in \mathbf{C}_t, j \notin H_{it}\} \cup \{0, J + 1, J + 2\}.$$

The first part of the right-hand side says that consumers may choose among movies available in the current period (that is, in  $\mathbf{C}_t$ ) but that they have not seen previously (that is, not in  $H_{it}$ ). The second part adds the outside options to the choice set. It must be that  $C(H_{it}, \mathbf{C}_t)$  equals an element  $C_{gt}$  of  $\mathcal{C}_t$ .

Because consumers may not want to go to the movies week after week, we allow consumer utility to depend on how recently the consumer has seen any movie. Let  $w(H_{it})$  be the number of weeks since consumer  $i$  has seen a movie:  $w(H_{it}) = \min\{\tau : \tau \in \mathbb{Z}_+, d_{i,t-\tau} > 0\}$ , with  $w(H_{it}) = \infty$  if  $i$  has never seen a movie (i.e.  $d_{i\tau} = 0 \forall \tau = 1, \dots, t-1$ ). Here,  $\mathbb{Z}_+$  are the strictly positive integers. Note that  $w(\cdot)$  does not distinguish whether the last movie seen was named or generic, and so treats them symmetrically.

Let the utility to consumer  $i$  from choosing movie  $j$  in period  $t$  with history  $H_{it}$  be denoted by  $u_{ijt}(H_{it})$ . Consumer  $i$  solves:

$$\max_{j \in C(H_{it}, \mathbf{C}_t)} u_{ijt}(H_{it}).$$

We assume that utility takes on the functional form:

$$u_{ijt}(H_{it}) = x_{jt}\beta + \xi_{jt} + \mu_{ijt} + \rho \mathbb{1}\{w(H_{it}) < 5\} + \varepsilon_{ijt}.$$

The variables  $x_{jt}$  are  $K$  characteristics, observable to both the agent and the researcher. The characteristics reflect both movie characteristics, such as whether a movie is foreign, and calendar characteristics, such as the month of the year and whether it is a holiday weekend. The scalar  $\xi_{jt}$  is observed by the agent but not the researcher. It represents unobserved quality and plays the role of the econometric error term. The parameter  $\rho$  measures the *recency effect* of having seen a movie, so we expect to find  $\rho < 0$ . This allows consumers who have seen a movie in the last four weeks to be less likely to see a movie in the current week. We also experimented with different numbers of weeks, and allowing the recency effect to decline over the four weeks. The term  $\varepsilon_{ijt}$  is distributed according to the Extreme Value distribution and generates the familiar logit probability of choice.

The term  $\mu_{ijt}$  represents the consumer's match to the product based on observable characteristics. Following Berry (1994) and Berry et al. (1995), we specify it as:

$$\mu_{ijt} = \sum_{l=1}^L x_{jlt} \sigma_l \nu_{il}$$

where  $\nu_{il} \sim \mathcal{N}(0, 1)$ . Thus,  $\nu_{il}$  captures consumer heterogeneity over preferences for observable characteristics such as whether a movie is foreign and whether it is enhanced with features such as

IMAX filming. These preferences are assumed to be constant over time for each consumer. The parameters  $\beta$ ,  $\rho$ , and  $\sigma_l$ ,  $l = 1, \dots, L$  are to be estimated. We refer to estimation parameters together as  $\theta = \{\beta, \rho, \{\sigma_l\}_{l=1, \dots, L}\}$ . Furthermore, for convenience, we denote the mean utility of product  $j$  in period  $t$  as  $\delta_{jt} = x_{jt}\beta + \xi_{jt}$ . We assume  $\delta_{0t} = 0$  and  $x_{0t} = 0$  for all  $t$ .

### 5.3 Market shares

Given these assumptions, history affects consumer choices through two channels, the recency effect and the determination of the choice set. Conditional on knowing the choice set and the last period a consumer purchased, there is no further value to knowing history, so we define choice probabilities on these variables. The conditional probability  $P_{ijt}(C(H_{it}, \mathbf{C}_t), w(H_{it}))$ , the probability of  $i$  choosing  $j$  in  $t$  conditional on having choice set  $C(H_{it}, \mathbf{C}_t)$  and have last purchased  $w(H_{it})$  periods ago, is:

$$P_{ijt}(C(H_{it}, \mathbf{C}_t), w(H_{it})) = \frac{\exp(\delta_{jt} + \mu_{ijt} + \rho \mathbf{1}\{w(H_{it}) < 5\})}{\sum_{k \in C(H_{it}, \mathbf{C}_t)} \exp(\delta_{kt} + \mu_{ikt} + \rho \mathbf{1}\{w(H_{it}) < 5\})} \quad \begin{array}{l} j \in C(H_{it}, \mathbf{C}_t) \\ \text{otherwise} \end{array} \quad (1)$$

In Figure 4,  $P_{ijt}(C(H_{it}, \mathbf{C}_t), w(H_{it}))$  is the probability of being on each arrow leading from a given choice set.

As is clear from Figure 4, there may be multiple choices that lead from one choice set to another. Let  $B_{gg't}$  be the set of products  $j$  such that choosing one leads from choice set  $g$  in period  $t$  to choice set  $g'$  in period  $t+1$ . The set  $B_{gg't}$  accounts for the deletion of  $j$  from  $C_{gt}$ , and any products that enter or exit  $\mathbf{C}_t$ :

$$B_{gg't} = \left\{ j : C_{g't+1} = \underbrace{(C_{gt} \setminus \{j\})}_{\text{current}} \cup \underbrace{(\mathbf{C}_{t+1} \setminus \mathbf{C}_t)}_{\text{entering}} \setminus \underbrace{(\mathbf{C}_t \setminus \mathbf{C}_{t+1})}_{\text{exiting}} \right\}. \quad (2)$$

To track consumers over time, we must track the recency of their consumption in addition to their choice sets. Let the variable  $w \in \{1, 2, 3, 4, 5\}$  represent the number of periods since last seeing a movie, where  $w = 5$  indicates not having seen a movie in the last four periods. Let  $s_{igwt}$  be the share of consumers of type  $i$  (that is, with draw  $\nu_i$ ) with choice set  $g$  in period  $t$  who saw a movie  $w$  periods ago. Thus,  $\sum_{g=1}^{G_t} \sum_{w=1}^5 s_{igwt} = 1$ . We refer to  $s_{igwt}$  as the unconditional probability or

unconditional share. To compute  $s_{igwt}$ , we assume that there is only one possible choice set in the first period:  $\mathcal{C}_1 = \{\mathbf{C}_1\}$  and that no consumer has seen a movie in four periods. Thus,  $s_{i151} = 1$  for all  $i$  and  $s_{igw1} = 0$  for all  $g$  and  $w \neq 5$ . Unconditional shares evolve as follows:

$$\begin{aligned}
s_{ig'1t+1} &= \sum_{g=1}^{G_t} \sum_{w=1}^5 \sum_{j \in B_{gg't}, j \neq 0} P_{ijt}(C_{gt}, w) s_{igwt} \\
s_{ig'wt+1} &= \sum_{g=1}^{G_t} \mathbb{1}\{0 \in B_{gg't}\} P_{i0t}(C_{gt}, w-1) s_{igw-1t} \quad w \in \{2, 3, 4\} \\
s_{ig'5t+1} &= \sum_{g=1}^{G_t} \mathbb{1}\{0 \in B_{gg't}\} (P_{i0t}(C_{gt}, 4) s_{ig4t} + P_{i0t}(C_{gt}, 5) s_{ig5t}) \\
&\quad \forall g' = 1, \dots, G_{t+1}, t = 2, \dots, T-1.
\end{aligned} \tag{3}$$

The first equation in (3) defines the share of consumers transitioning to choice set  $g'$  and  $w = 1$  in  $t + 1$ , so these are consumers that purchase in  $t$ . The second equation defines the share going to  $g'$  and  $w$  from 2 to 4. Naturally, this requires that the consumer does not purchase in choice  $t$  and so chooses  $j = 0$ . The last equation defines the share for  $g'$  and  $w = 5$ . This is similar to the second equation but includes consumers with two values of  $w$  in  $t$ :  $w = 4$  and  $w = 5$ . That is, both consumers that purchased four weeks ago and purchased more than four weeks ago end up with no recency effect ( $w = 5$ ) in period  $t + 1$  if they do not purchase in  $t$ . The “ $\forall$ ” line at the bottom of (3) applies to all three lines.

In the data, we observe the unconditional share of consumers choosing each product  $j$  in each period  $t$ . Our model defines that as:

$$\hat{s}_{jt} = \int \sum_{g=1}^{G_t} \sum_{w=1}^5 P_{ijt}(C_{gt}, w) s_{igwt} f(\boldsymbol{\nu}_i) d\boldsymbol{\nu}_i \tag{4}$$

where  $f(\boldsymbol{\nu}_i)$  is the distribution of consumer types  $\boldsymbol{\nu}_i$ , and  $\boldsymbol{\nu}_i$  is the  $L \times 1$  vector of elements  $\nu_{il}$ .

## 5.4 Forward-looking behavior

In some performance goods settings, our assumption of myopic behavior may not be reasonable.<sup>14</sup> In this subsection, we provide a model that allows for forward-looking behavior. We assume consumers have perfect foresight over all future values of  $\delta_{jt}$  but not over  $\varepsilon_{ijt}$ . That is, consumers know all the movies that will arrive and leave, and the mean utilities that the movies will provide. Perfect foresight is a strong assumption, but we believe that to the extent that forward-looking behavior might be important, it is because consumers know that particular movies are arriving or leaving.

The inclusive value represents the value that a consumer expects when they face a given choice set. Under our logit assumptions, the inclusive value has a convenient closed-form. Define the inclusive value in period  $t$  with history  $H_{it}$  to be:

$$V_{it}(H_{it}) = \ln \left( \sum_{j \in C(H_{it}, \mathcal{C}_t)} \exp(\delta_{jt} + \mu_{ijt} + \rho \mathbb{1}\{w(H_{it}) < 5\} + \lambda V_{it+1}(H_{it+1})) \right)$$

where the consumer's history in  $t + 1$  is the choice  $j$  in  $t$  added to  $H_{it}$ , that is,  $H_{it+1} = \{j, H_{it}\}$ .<sup>15</sup> The variable  $\lambda$  is the discount rate. For this calculation, we assume that  $V_{iT+1}(H_{iT+1}) = 0$  for all  $i$  and  $H_{iT+1}$ . Thus, for a consumer in the final period  $T$ , the choice problem is the same whether we use myopic or forward-looking behavior.

We can define the utility to  $i$  from movie  $j$  as:

$$u_{ijt}(H_{it}) = \delta_{jt} + \mu_{ijt} + \rho \mathbb{1}\{w(H_{it}) < 5\} + \lambda V_{it+1}(H_{it+1}) + \varepsilon_{ijt}$$

We use this utility specification to adjust Equation 1 accordingly. The rest of the model, such as the determination of  $s_{igt}$ , remains the same. We estimate this model by backward induction. For a given guess of the parameters, we calculate the utility and probability of each choice in the last period. We then calculate the utility and probabilities of each choice in period  $T - 1$ , accounting for the continuation value associated with each choice. We proceed backward through each period

<sup>14</sup>For example, we understand from private conversations with staff at the Museum of Fine Arts in Boston that when the museum announces that a temporary exhibit will be closing, attendance at that exhibit increases. That is evidence of dynamic behavior in exhibit attendance.

<sup>15</sup>The inclusive value also includes that addition of Euler's constant. We exclude it from this equation as it does not affect decisions since it is constant.

sequentially. Implicitly, we assume that consumers are myopic in the final period, which is not ideal, but the implications of this are minimized as we move farther backward, and with a relatively high  $T = 183$ , we believe this issue has a minimal effect on our estimates.

We wish to estimate the discount rate. To identify the discount rate, we rely on variation in the continuation value that is not reflected in the current values, as in Magnac & Thesmar (2002). This kind of variation is natural in perfect foresight models. In our setting, movies that arrive or leave in future periods affect the future payoff but not otherwise the current payoffs.

In considering the discount rate, it is important to recognize that the discount rate we estimate is unlikely to correspond to the time value of money. The discount rate in our model reflects how consumers adjust movie-going this week to changes in movie availability in future weeks. Our prior belief is that consumers heavily discount this continuation value, and indeed, that is our finding below.

We focus on the perfect foresight model not only because we believe that it well-captures the issues that concern us, but also because it is computationally straightforward to estimate. The perfect foresight model requires no further assumptions, no discretization or approximation of the state space, and does not require a fixed-point algorithm.

## 5.5 Multiple purchase

We briefly describe how we would extend the model to relax the assumption that consumers see a movie only once. We do not estimate this model, but the extension is useful in order to understand the model. It would be relatively easy to allow consumers to see a movie multiple times with decreased utility. Intuitively, thinking of Figure 4, consider a consumer in period 2 who has already seen movie  $A$ . The consumer is in set  $\{B\}$ , where  $A$  is not allowed. But the important feature of set  $\{B\}$  is not that  $A$  is not allowed, but rather that the consumer has already seen  $A$ . It would be straightforward to allow a consumer with choice set  $\{B\}$  to choose between both  $A$  and  $B$ , but assign  $A$  some reduction in utility, presumably a parameter to be estimated. We could assume that choosing to see a movie multiple times does not further reduce the utility of the movie after the first viewing. As a result, this extension does not affect the overall dynamic process in our model,

and thus would be no more difficult to estimate but for the extra parameter. This approach would be appealing if we had data on how often consumers saw individual movies, and the data showed that multiple viewings were important.

This approach would assign the same utility reduction to each viewing of a movie after the first one. That is, the consumer would get the same utility from seeing a movie the second, third, and fourth time. In some settings, it might be more natural to assume that consumers experienced further declines in utility the more times the consumer saw a performance. That would be a more significant extension to our model in terms of computational difficulty, but we believe our model provides a good template for how to approach this problem.

## 6 Reduced-form results

There are several implications of our model of consumption durability relative to a static model of demand. One is that a movie introduced at the same time as a strong rival is likely to have relatively higher sales later in its life cycle. In the opening week, consumers choose between the two movies and many will choose the strong rival. But in later weeks, the rival is no longer part of those consumers' choice sets, and those consumers are more likely to choose other movies. In contrast, a static model with an age profile predicts that a movie introduced at the same time as a strong rival will have lower sales throughout its lifetime.

Consumption durability also has complex implications for substitution patterns. Consumers that strongly prefer foreign movies may still go to domestic movies if they have exhausted all of the foreign movies available, whereas a static model allows those consumers to go to foreign movies every period. Another implication is that large expansions of the choice set may be more beneficial under consumption durability because consumers cannot repeatedly consume the top products. However, recognizing that consumers have limited time to consume performance goods may moderate the benefits of choice expansion. There are more implications one may consider, but they are outside the focus of our study, such as the implications for release date strategies.

In this section, we provide reduced-form analysis to show that our data exhibit the effects that

our model highlights. We focus on the first hypothesis, that consumption durability implies relatively high sales later in the life cycle for movies released alongside popular movies. In Appendix B, we also provide a reduced-form estimate of the extent of substitution between foreign and domestic movies, but delay analysis of the more complex timing of substitution, as well as welfare effects, for the structural estimation.

In order to explore the first hypothesis, we define a set of top movies, for instance, the top twenty movies over our sample by Chinese box office admissions. We define a dummy variable that equals one for movie  $j$  if movie  $j$ 's first week coincides with week one or two of a top movie. We then interact the dummy variable with indicators for movie  $j$  being in week two or later. We interpret this interaction as an indicator for consumption durability affecting movie  $j$ . Formally:

$$\text{ConsumptionDurability}_{jt} = \mathbb{1}\{j \text{ is introduced alongside a top movie}\} \mathbb{1}\{\text{age}_{jt} > 1\}$$

We estimate linear models of the log of box office sales as a function of our indicator for consumption durability along with movie fixed effects, age fixed effects, and calendar control variables. We use the same calendar controls we use in our structural estimation: year fixed effects, a month time trend, month-of-the-year fixed effects, and a dummy for being a holiday weekend. We estimate via OLS. To best mimic our structural estimation, our sample consists of the top six movies each week by Chinese box office. We consider several definitions of top movies, such as the top 20 and top 30 over the sample, or the top six or ten each year.

Results appear in Table 3. The coefficient ranges from 0.235 to 0.351. In three of the four cases, the parameter is significant at a 95% level of significance, with the t-statistic for the fourth case equal to 1.958. The coefficients imply a percentage change increase in sales ranging from 27% to 42% across specifications, although admittedly on a relatively small base. Interestingly, the coefficient increases as we more tightly restrict the set of top movies, suggesting that the effect grows as the popularity of the rival movie grows. However, the standard error on consumption durability also grows, and differences across specifications are not statistically significant. Overall, we take these

Table 3: Consumption durability

|                                       |                  |                  |
|---------------------------------------|------------------|------------------|
| Number of top movies across all years | 20               | 30               |
| Consumption durability indicator      | 0.351<br>(0.134) | 0.295<br>(0.125) |
| R-squared                             | 0.868            | 0.867            |
| <hr/>                                 |                  |                  |
| Number of top movies across each year | 6                | 10               |
| Total Number of Top movies            | 21               | 35               |
| Consumption durability indicator      | 0.301<br>(0.142) | 0.235<br>(0.120) |
| R-squared                             | 0.867            | 0.867            |

Notes: 1,071 observations in each regression. Standard errors in parenthesis. Dependent variable is log sales in a week for a movie. Consumption durability is a dummy for being in week 2 or later and being introduced at the same time as a top movie. All specifications include movie fixed effects, age (in weeks) fixed effects, holiday weekend fixed effects, month-of-the-year fixed effects, year fixed effects, and a month time trend.

results as evidence in favor of consumption durability.

A potential concern for this regression is that we take the set of rival movies as uncorrelated with the age profile, so for instance, distributors do not introduce movies that distributors expect to have flatter age profiles at the same time as popular movies. We test for this possibility directly in our structural estimation below. We do not find evidence for heterogeneous age profiles.

A second finding in the results of our structural model below is the relatively low substitution between foreign and domestic movies. We provide descriptive evidence in support of this in Appendix B. A natural next question is how consumption durability and foreign-domestic substitution interact. For this more complicated question, we turn to the results of the structural model.

## 7 Structural estimation

This section discusses the estimation of the model. We first discuss the approach to the aggregate sales data and then discuss micro-moments.

## 7.1 Aggregate data moments

We cannot compute Equation 4 analytically. For this step, we use simulation. We draw  $S$  values of  $\nu_{il}^s$ ,  $l = 1, \dots, L$  and  $s = 1, \dots, S$ .<sup>16</sup> For a given set of parameters  $\theta$  and a guess of mean utilities  $\delta_{jt}$ , we compute  $P_{ijt}(C_{gt}, w)$  and then  $s_{igwt}$  for each  $C_{gt}$ ,  $w$ , and movie  $j$  in the model, as described above in Equations 1 and 3. We do so separately for each draw of  $\nu^s$ . We then replace Equation 4 with the discrete equivalent. In order to emphasize the dependence of the predicted market share on parameters and mean utilities, we write  $\hat{s}_{jt}(\theta, \boldsymbol{\delta})$ , where  $\boldsymbol{\delta}$  is the vector of elements  $\delta_{jt}$ .

As in Berry et al. (1995), we recover  $\boldsymbol{\delta}$  for any set of parameters  $\theta$  via the fixed point equation:

$$\delta'_{jt} = \delta_{jt} + \ln(s_{jt}^{\text{data}}) - \ln(\hat{s}_{jt}(\theta, \boldsymbol{\delta})).$$

As above,  $s_{jt}^{\text{data}}$  are the market shares observed in the data. For any guess of parameters  $\theta$ , we solve this equation by successive approximation. That is, we plug in a guess of  $\boldsymbol{\delta}$ , compute  $\boldsymbol{\delta}'$  and iterate until convergence. Note that the theorem in Berry (1994) that the fixed point equation is a contraction mapping does not necessarily apply to dynamic models. As in Gowrisankaran & Rysman (2012), our method is appropriate only under the assumption that the solution is unique. We have not experienced any problems with multiple solutions in practice.<sup>17</sup>

Based on the solution to the fixed point equation, we compute the econometric error term as:

$$\xi_{jt} = \delta_{jt} - x_{jt}\beta$$

and we assume a set of instrumental variables  $Z_{jt}$  is exogenous such that  $E[m_1(\theta)] = E[\xi_{jt}|Z_{jt}] = 0$ .

We estimate via two-step GMM. As is typical in dynamic models, there is an initial conditions problem of determining the distribution of consumer choice sets at the start of the data. We assume that in the first period of the data, no consumers have seen a movie. In order to minimize the impact

<sup>16</sup>Denoting  $s$  for both samples and market shares is somewhat confusing, but it is clear in context. In practice, we try two sampling schemes. In the first, we draw  $\nu_{ik}^s$  from a Halton sequence, setting  $S = 300$ . A Halton sequence produces an even spread of draws across percentiles of the normal distribution. In the second, we use importance sampling to overweight draws of  $\nu_{ik}^s$  that are likely to attend movies, again using 300 draws. Details are available upon request. Results are similar, as we show below.

<sup>17</sup>The Berry (1994) proof of the invertibility of utility and market shares relies on the gross substitutability of products. See also Berry, Gandhi & Haile (2013). Gross substitutability does not necessarily hold in dynamic models. For instance, raising utility for one product in one period in our model raises sales of that product, which implies those consumers do not have the product in their choice set in the next period and are thus *more* likely to purchase another product, which violates substitutability.

of this assumption on our results, we drop the first four weeks of data in forming our moments. Four weeks should be sufficient because there is frequent turnover in which movies are available, so the “burn-in” period before consumers are reasonably distributed across choice sets is relatively short. As a result of dropping these observations, the tables of results in Section 8 list 1,432 observations rather than 1,464.<sup>18</sup>

In practice, we include a full set of movie fixed effects so we do not estimate  $\beta$  for any variables that do not vary over time. Our base specification places random coefficients on three variables: the constant term, an indicator for whether a movie is foreign, and an indicator for whether a movie was filmed in either IMAX or 3D, which we call *enhanced*. These are the most important variables for our research question. We experiment with other specifications as well, particularly adding a random coefficient on *action*. The generic domestic and foreign outside options each have their own fixed effect for quality and are subject to the time-varying explanatory variables (time trend, holiday, and month-of-year effects). The foreign generic movie (choice  $J + 1$ ) is also affected by the random coefficient on *foreign*.

We assume that all explanatory variables are exogenous. Recall that price is not an explanatory variable. However, the presence of consumer heterogeneity terms ( $\sigma_l$ ) means we still need additional moments to achieve identification. Our first set of additional moments follows Berry et al. (1995). Because we take product introductions as exogenous, we use sums over the characteristics of other movies in the top six in the same week as exogenous variables to construct additional moments. For this calculation, we use the following variables: dummies for whether the movie is enhanced (3D or IMAX), foreign, action, comedy, or drama, and the number of weeks since the movie’s Chinese release, the number of weeks since the movie’s international release (set to 0 for Chinese movies), and the movie’s runtime. Additionally, Gandhi & Houde (2020) recommend instruments that emphasize how differentiated a product is from others on the market. We construct these for the characteristics based on dummy variables. We do so by interacting the Berry et al. (1995) instruments with the

---

<sup>18</sup>A potential problem for our method is if movies appear in the top six in non-adjacent weeks because, as written, we would lose track of which consumers have seen the movie. That happens only once in our dataset. One movie leaves the top six in week 75 and returns in week 76. We keep this movie in  $C_t$  for  $t = 75$ , and drop the sixth most popular movie from  $C_{75}$ .

dummy variable in question. Thus, the sum over the *enhanced* dummy is interacted with whether the movie in question is enhanced, and so this exogenous variable is high only for enhanced movies. We multiply the interaction variable by the econometric error term to construct additional moments.

## 7.2 Incorporating the micro-moments

To improve the estimation, we incorporate two micro-moment conditions based on the survey data. Specifically, we use the information that, conditional on watching at least one movie, the probability of watching 1-3 movies is 23.2%, the probability of watching 4-6 movies is 19.2%, with the rest watching 7 or more.

In order to compute the predictions of these variables from our model, we augment the state space for consumers to track not only which movies they have seen and how recently they have seen a movie but also how many times they have been to the movies. That is, we denote the state of a consumer as  $\{C_{gt}, w(H_{it}), n(H_{it})\}$  where  $n(H_{it})$  is the number of movies that  $i$  has seen in the previous year, up to seven. We define  $n(H_{it}) = \min\{\sum_{\tau=0}^{51} \mathbb{1}\{d_{it-\tau} > 0\}, 7\}$ . We track the population that has seen different numbers of movies, similar to how we track the weeks since the last movie in Equation 3. Intuitively, we duplicate Figure 4 seven times, and as the population of consumers moves across the figure, the ones that see movies also move from figure to figure. We track this only for the 12-month period leading up to the observation of our moment (January 2013), not for the entire 183-week period of the data.

To be clear, this new state variable does not affect consumer decision-making. The consumer still cares only about the choice set and the time since seeing a movie. Rather, tracking the number of movies seen allows us to form predictions that may be compared to the survey data. In particular, at  $t = 57$ , we compute  $P_{in}$ , the probability that consumer  $i$  saw  $n$  movies in the previous year, for  $n = 0, 1, \dots, 6, 7$ . Conditional on watching at least one movie, the probability of watching 1-3 movies is then  $P_{i1-3} = \sum_{n=1}^3 P_{in} / \sum_{n=1}^7 P_{in}$  and the probability of seeing 4-6 movies is  $P_{i4-6} = \sum_{n=4}^6 P_{in} / \sum_{n=1}^7 P_{in}$ . Recall that  $P_{i7}$  refers to the probability  $i$  saw 7 or more movies. We take the average of  $P_{i1-3}$  and  $P_{i4-6}$ , i.e.  $P_{1-3} = \frac{1}{S} \sum_{i=1}^S P_{i1-3}$  and  $P_{4-6} = \frac{1}{S} \sum_{i=1}^S P_{i4-6}$ . We postulate the micro-moment

conditions as follows:

$$E[m_2(\theta)] = E \left[ \begin{array}{c} P_{1-3}^{\text{data}} - P_{1-3}(\theta) \\ P_{4-6}^{\text{data}} - P_{4-6}(\theta) \end{array} \right] = 0 , \quad (5)$$

The variables on the left are the probabilities observed in the survey data. Thus, the stacked moment conditions are:

$$E[m(\theta)] = E \left[ \begin{array}{c} m_1(\theta) \\ m_2(\theta) \end{array} \right] = 0 . \quad (6)$$

Here,  $m_1(\theta)$  are the aggregate-data moments as discussed in Section 7.1. The GMM estimator given our stacked moment conditions is defined as  $\min_{\theta} E[m(\theta)]' \Omega E[m(\theta)]$ . We follow the two-step procedure for GMM estimation proposed in Hansen (1982) and initialize it with an identity matrix as the weighting matrix  $\Omega$ . We draw a new sample of draws  $\nu_k^s$  for the micro-moment calculation. Thus, the weighting matrix is block-diagonal as in Petrin (2002). In the second stage of the GMM optimization routine, we compute the weighting matrix following Conlon & Gortmaker (2025), particularly Case C of their Appendix E.

### 7.3 Identification

We finish this section with a brief heuristic discussion of how variation in data guides the results we find. Our model includes the same parameters as Berry et al. (1995) and thus, we can think of parameter results in a similar way. Products with different characteristics attract different levels of market share depending on the presence of alternative products. To the extent that the product draws market share from products with a similar characteristic, estimation will find that the random coefficient on that characteristic has a large variance. To the extent that the product draws market share proportionally from all products, the variance will be small as in a standard logit model.

Like Gowrisankaran & Rysman (2012), and unlike Berry et al. (1995), the model makes use of market shares over time. In the period following the entrance of a popular foreign movie, observing high market shares for competing foreign films indicates that the random coefficient on *foreign* has high variance. That is, consumers that like foreign movies saw the first foreign movie and then, when it was out of the choice set, those consumers switched to another. The market share of a movie in any period depends on how long it has been on the market and which movies it faced in

those periods (and by extension, which movies those rivals faced in their time on the market, and so on). While we attempt to provide reduced-form analysis of these effects in Section 6, an advantage of a structural model in a setting like this is that it resolves these complex interactions in a coherent and parsimonious way.

Focusing specifically on the random coefficient on the constant term, this parameter is identified without micromoments by the extent of substitution between the outside good and the inside goods, such as due to calendar effects. In addition, the parameter is heavily affected by the micromoments. They show extensive repeat moviegoing, which the model matches by setting a high standard deviation on the random coefficient on the constant term. Repeat purchase is moderated by a highly negative recency coefficient, which also causes reductions in the overall movie-going share in the weeks following a popular release.

## 8 Empirical results

This section discusses the empirical results obtained from the demand model described in the previous section.

### 8.1 Parameter results and consumption durability

We present parameter results from estimating our model in Table 4. We apply the micromoments to all specifications. Column 1 reports estimates from using a standard Berry et al. (1995) model, i.e., a static random coefficients model. A striking feature of Column 1 is the large negative and significant age trend. Static models require a strong reduced-form age profile to match the kind of declines in market share that we see in the data (as evidenced in Figure 3).

Column 2 estimates our dynamic model without the *recency* term. This is the model with myopic consumers who experience consumption durability but with  $\rho = 0$ . Adding consumption durability causes the coefficient on *age* to become statistically insignificant and close to zero in magnitude. Thus, despite the enormous age effects in the raw data (as evidenced in Figure 3), the age profile can be entirely explained by the consumption durability of movie consumption.<sup>19</sup>

---

<sup>19</sup>The age trend is not separately identified from movie fixed effects and a week time trend, which is one reason we use a month trend. The results are robust to alternative treatments of the calendar time effects, such as using only

Table 4: Demand estimates

|                        |                      | 1                 | 2                 | 3                 |
|------------------------|----------------------|-------------------|-------------------|-------------------|
| Heterogeneity          | Constant             | 14.875<br>(1.920) | 10.38<br>(1.064)  | 19.314<br>(2.097) |
|                        | Enhanced(3D or IMAX) | 0.076<br>(0.419)  | 1.547<br>(1.405)  | 4.884<br>(0.858)  |
|                        | Foreign              | 3.877<br>(0.386)  | 3.242<br>(0.982)  | 3.926<br>(1.040)  |
|                        | Recency ( $\rho$ )   |                   |                   | -7.671<br>(1.514) |
|                        |                      |                   |                   |                   |
| Linear                 | Age                  | -0.85<br>(0.063)  | -0.016<br>(0.089) | -0.019<br>(0.128) |
|                        | Holiday              | 1.747<br>(0.276)  | 1.149<br>(0.183)  | 0.939<br>(0.203)  |
|                        |                      |                   |                   |                   |
| Consumption Durability |                      | No                | Yes               | Yes               |

Specifications include movie fixed effects, month-of-year fixed effects separately for foreign and domestic movies, year fixed effects, and a month time trend. *Consumption Durability* refers to whether consumers can see movies only once (Yes) or the model is static (No). 1,432 observations. 427 movies. 179 weeks.

Column 3 adds the *recency* term. Again, we find that the coefficient on the reduced-form age term is close to zero. We find that  $\rho$ , the parameter on *recency*, is negative and statistically significant. We take Column 3 to be our main results going forward. A feature of Column 3 is that the standard deviation parameters on the variables *enhanced* and *foreign* are statistically significant and economically large. This will drive our result in the next subsection that there is relatively muted substitution between foreign and domestic movies.

In thinking about identification, note that consumption durability does not necessarily imply that the *age* coefficient would be zero. Consumption durability implies that demand falls with age, but observed sales could be higher or lower than consumption durability would predict. However, we see that in our setting, consumption durability drives the coefficient on *age* to zero.

One way to evaluate the importance of consumption durability is to ask how often consumers face a restricted choice set. If we consider consumer types (that is, draws  $\nu_i$ ) that expect to see at least one movie in a year, we find that on average, they face a restricted choice set in 29.65% of weeks. That is, in about three out of ten weeks, movie-going consumers have already seen one of the movies available. Naturally, consumption durability interacts with consumer heterogeneity, year dummies.

so durability is even more important for consumers that particularly value movies. Conditioning on types that see on average two or more movies in a year, consumers face a restricted choice set 41.77% of weeks. We do this calculation for the year February 2012 to January 2013, which matches our micro-moment sample frame. Overall, we find that consumption durability plays a role in a significant percentage of consumer decisions.<sup>20</sup>

## 8.2 Substitution patterns

We are interested in evaluating substitution patterns, both intertemporally and between foreign and domestic movies. To do so, we consider a decrease in utils of 0.738 for a single movie, which corresponds to a 10 RMB price increase if the price coefficient is -0.0738. We motivate this coefficient choice below, but it calibrates our model to reasonable price elasticities as measured by other papers. We change the utility of the top domestic movie at the midpoint of our dataset, which we number as movie 2207. This movie ranked second in weeks 94 and 95, fourth in week 96, and then dropped out of the top 6 thereafter. We change the utility of movie 2207 in week 94 only. We calculate the percentage change in ticket sales for movie 2207, for all other domestic movies (including the generic domestic option), and for all foreign movies (including the generic foreign option) for the week of the price change and the four weeks following. Results appear in Table 5.

Table 5: Substitution pattern for domestic movie

| Week     | Movie of Price Change | Other Domestic Movies | Foreign Movies |
|----------|-----------------------|-----------------------|----------------|
| 94       | -38.98%               | 14.38                 | 5.33           |
| 95       | 13.48                 | -5.35                 | -2.98          |
| 96       | 12.64                 | -1.5                  | -0.73          |
| 97       |                       | 0.29                  | 0.11           |
| 98       |                       | 0.11                  | 0.07           |
| Long-run | -22.68                | 11.63                 | 2.1            |

This table reports percentage quantity changes from a decrease in utils of movie 2207, a domestic movie, in week 94 (its first week on the market) to approximate a 10RMB price increase. The price increase lasts one period. The sales rank of the movie is 2 in weeks 94 and 95, 4 in week 96, and is out of the top 6 thereafter. The *Other domestic movies* and *Foreign movies* columns include the generic domestic and foreign options, respectively. The row *Long-run* sums the change in sales over the weeks 94-98 and divides by the quantity from week 94.

Focusing on the first column, the price change leads to a 39% decline in quantity in the period of

<sup>20</sup>We also regress movie fixed effects on movie characteristics. Discussion and results appear in Appendix C and Table C1.

the price change. However, that leads to a 13.5% increase in the next period, and a similarly large increase (over a relatively small base) in the following period. We are also interested in comparing the short and long-run elasticity. To calculate the long-run change, we sum the total change in quantity over five weeks and divide by the quantity from week 94. In this way, the denominators from the week 94 change and the long-run change are the same. The last row of the table reports the long-run change, and it is only -22.7%, less than 60% of the within-period change. Thus, as expected, the long-run elasticity is less than the short-run elasticity as consumers adjust by forgoing the movie that increased price and seeing it in later periods. Keep in mind that a model with only a reduced-form age profile and no consumption durability would predict no change in quantity in any periods following the price change.

We are also interested in substitution patterns to other movies. Table 5 shows that the price change leads to substantially more substitution to other domestic movies than foreign movies, with domestic movies increasing in the concurrent period by 14.4% and foreign movies increasing by only 5.3%. This difference is striking because the baseline sales of other domestic movies in this period is 2.78 million and foreign movies is 4.85 million, about 75% higher. That is, substitution is higher to domestic movies even though they have a substantially lower market share, which highlights the importance of the random coefficient approach to estimation.

Another way to evaluate substitution is with the diversion ratio (see Conlon & Mortimer, 2021, for a discussion of diversion ratios). Under the price increase, the number of tickets sold that period for movie 2207 goes from 2.18 million to 1.33 million, a decrease of 0.85 million. Other domestic movies increase from 2.78 to 3.18 million, an increase of 0.4 million. Thus, 47% (i.e.,  $0.4/0.85$ ) of the loss to movie 2207 goes to other domestic movies. In contrast, foreign movie admissions increase from 4.85 to 5.11 million, leading to a diversion ratio of 30.6%, and 22.4% going to no purchase.

Strikingly, market shares for rival movies decline in week 95. In this sense, movies are intertemporal complements rather than substitutes. This is in part because consumers that switch to other movies in week 94 can no longer see those movies in week 95. Quantity changes switch sign over the five weeks, although at very low magnitudes, as the implications of the price change and durability

Table 6: Substitution pattern for foreign movie

| Week     | Movie of Price Change | Domestic Movies | Other Foreign Movies |
|----------|-----------------------|-----------------|----------------------|
| 89       | -40.71%               | 4.77            | 11.58                |
| 90       | 11.62                 | -0.71           | -2.6                 |
| 91       | 4.21                  | -0.04           | 0.4                  |
| 92       |                       | 0.01            | 0.24                 |
| 93       |                       | 0               | 0.12                 |
| Long-run | -30.68                | 3.26            | 9.73                 |

This table reports percentage quantity changes from a decrease in utils of movie 1323, a foreign movie, in week 89 (its first week on the market) to approximate a 10RMB price increase. The price increase lasts one period. The sales rank of the movie is 1 in week 89, 4 in week 90, 6 in week 91, and is out of the top 6 thereafter. The *Domestic movies* and *Other foreign movies* columns include the generic domestic and foreign options, respectively. The row *Long-run* sums the change in sales over the weeks 89-93 and divides by the quantity from week 89.

work their way through the different options. As with the own-price effect, the long-run cross-price effects are lower than the short-run effects.

The effect is similar if we consider a price change to a foreign movie. We consider a change in price of the same level to movie 1323, an enhanced foreign movie, which appears in week 89 at number 1, and is then 4th, then 6th, and then drops out of the top 6. Results appear in Table 6. Results are similar, with a long-run own-price change less than the short-run, more substitution to foreign movies than domestic movies, and shifting signs over time.

### 8.3 Robustness

To establish robustness, we consider several alternative models. To show that our results on substitution between foreign and domestic movies is not driven by action movies, we add a random coefficient on the indicator variable for action movies. To show that our assumption of six named movies is not restrictive, we re-estimate the model with seven named movies. We also consider a version where our moment is based on first differences in the structural error term  $\xi_{jt}$  rather than the level, similar to Lee (2013). We also consider an importance sampling approach to integrating over draws rather than a Halton sequence. Additionally, a possible concern is that there is heterogeneity in age profiles. We address this by interacting the age variable with whether the movie is a top movie or not. We find that these specifications do not meaningfully change our results. Details are in Appendix D.

We also consider a model in which consumers have perfect foresight as to what movies will be available, as described in Section 5.4. The specification is otherwise identical to that in Column 3 of Table 4. For this specification, we include leads and lags of the instrumental variables in the instrument matrix. We find that the objective function is minimized at a discount rate of  $\lambda = 0$ .<sup>21</sup> Intuitively, consumers do not respond this week to the future availability of movies, which we believe is a reasonable result. Thus, our assumption of myopia fits the data well. Further discussion and results appear in Appendix D.

## 9 Counterfactual experiments

Since 2012, China increased the import quota for foreign movies from 20 to 34 per year. This section performs counterfactual experiments to evaluate this import liberalization on consumer and producer welfare. An assumption we make to perform these counterfactual experiments is that the producers do not revise the attributes of their movies in response to the import liberalization. We first discuss how to select the counterfactual set of 20 movies and then present results.

### 9.1 Selecting movies under counterfactual quotas

We consider several models of which 20 movies would have been selected if there had not been a liberalization. We compare taking 20 of the 34 movies from the bottom of the admissions (that is, the quantity sold in North America) distribution and from the top of the admissions distribution. In addition, we estimate a model of SARFT decision-making and use the results to predict SARFT's behavior in our counterfactual. For our model, we take the top 100 movies per year (for 2008-2015) by North American box office and then perform a probit regression, treating a movie as an observation, on which movies are accepted into China under revenue-sharing. We then use simulation techniques to construct an ordering of the movies by the latent value in the probit model and assume that SARFT would select in order of this latent variable. For explanatory variables in our probit regression, we use the log of North American box office, runtime, genre indicators, indicators for whether the movie is IMAX, 3D, rated R, the calendar year, and nationality of production. We find

---

<sup>21</sup>We find that including the leads and lags of instruments does not meaningfully change results, including at  $\lambda = 0$ , suggesting our main results would be robust to this change.

that box office revenue, IMAX, 3D, and being an action movie are all strong positive predictors of selection, whereas being rated R is negative, all as expected. A full presentation of this exercise, and our method for simulating the 20 movies chosen in the counterfactual, appears in Appendix E.

## 9.2 Counterfactual estimates

Table 7 reports our results. We present our calculations on a per-year basis and use only the periods 2012 to 2014. While we also have data for 2015, we have data for only part of the year, which creates difficulty for our counterfactual calculations about which movies SARFT would keep or drop. The left panel shows the result in levels and the right panel shows percentage changes between the counterfactual and observed outcomes.<sup>22</sup> For instance, we observe an average of 638.13 million tickets sold per year over the three-year period from 2012-2014. According to our main specification, Column 3 of Table 4, we calculate that if the 14 movies with the lowest admissions of the 34 were removed, there would be 627.95 million tickets sold. The right panel indicates that going from 627.95 to 638.13 million tickets sold is a 1.62% increase. In contrast, eliminating the top 14 movies by admissions from the set of 34 would reduce ticket sales to 573.15 million, and going from this number of ticket sales to the observed level would be an increase of 11.34%. Obviously, even among the 34 foreign movies with revenue-sharing contracts, there is a large difference between the top and bottom movies.

We are particularly interested in the results using our model of SARFT behavior. Whether we use parameters from the post-2012 or pre-2012 period (columns 1 and 3 in Table E2 respectively) makes little difference, so we focus on the post-2012 outcome. SARFT heavily weights revenue so the impact of SARFT's choices is closer to the *Bottom 14* column than the *Top 14*. The results from modeling SARFT's decision-making lead to annual sales of 612.37 million tickets, so liberalization represents a percentage increase of 4.21%.

The extra movies significantly impact the foreign and domestic share. In Table 7, the second

---

<sup>22</sup>We have also calculated standard errors for this table, but we do not report them to make the presentation more readable. Standard errors are small, particularly for the percentages, and similar across columns. The standard errors are below 11 for the admissions numbers and below 0.5 percentage points for the percentages. We use the delta method in order to calculate standard errors, which accounts for confidence intervals in the demand parameters. Currently, our standard errors for Table 7 do not account for estimation or simulation error in the SARFT probit calculations, which would affect the middle columns of each panel.

row reports foreign movie admissions. The third row reports admissions to the non-excluded foreign movies when all movies are available. Total admissions for foreign movies when all movies are available is 280.91 million. When SARFT is restricted to 20 movies, foreign admissions are 228.79 million. These remaining movies had 206.42 million admissions (the third row) when all movies were available. Thus, the percentage change for foreign movies that compete with the newly introduced movies is  $(206.42-228.79)/228.79=-9.8\%$ , which appears in the third row of the right panel.

The SARFT model finds that liberalization leads to an overall admission increase of 4.21%, which is made up of a 22.84%, expansion in foreign movies (from 228.79 million to 280.91 million) and a reduction in domestic admissions 6.87% (from 383.58 to 357.22 million). The reduction of 6.87% compares to the reduction of 9.8% for foreign movies that were available without liberalization. The effect of liberalization is substantially larger on foreign movies than domestic movies, which is a result of the higher substitutability among foreign movies. This feature limits the impact of liberalization on domestic production, but domestic production still loses: liberalization leads to a reduction of 26.36 million tickets.

We can use our results to evaluate the contribution to revenue for the Chinese government and Chinese firms. Recall from Section 3 that the revenue allocation difference between a domestic and a revenue-sharing foreign movie is that whereas 100% of the revenue of a domestic movie stays in China, only 77% of revenue from a foreign movie stays in China (with the revenue going to tax receipts, distributors, and theaters). Thus, the Chinese movie industry as a whole gains from liberalization if domestic admissions decrease by less than 77% of the increase in foreign movies. Using the post-2012 SARF policy column, we saw that liberalization leads domestic admissions to fall from 383.58 to 357.22 million, a decrease of 26.36, whereas foreign movie admissions increase from 228.79 to 280.91, an increase of 52.12. The increase in foreign admissions is 97% more than the decrease in domestic sales, another manifestation of the low substitution between foreign and domestic movies. Assuming that movie prices are similar across foreign and domestic films, our result suggests that Chinese revenue benefited from liberalization, despite the losses felt by producers. This is consistent with the quota being driven either by cultural protection rather than just economic

protection or because the Chinese government puts a high weight on protecting domestic movie production relative to other parts of the industry.<sup>23</sup>

We are also interested in computing the dollar or yuan value of the change in consumer welfare. As discussed above, converting utility into a currency-valued number is not straightforward as a result of a lack of price variation in this market. We calibrate our price coefficient to match results in the literature. We focus on Gil et al. (2024), which studies moviegoing in China in a dataset related to ours during the same time period, and finds a product elasticity of 1.74. It is similar to Chen et al. (2024), which also studies moviegoing in China and finds an elasticity of 2.0. Calibrating our model to have a product elasticity of 1.74 leads to a price coefficient of -0.0738.<sup>24</sup> Using the post-2012 SARFT model of movie availability, we find that liberalization increases surplus by ¥1.185 billion (about US\$300 million in 2015). Details on how we calculate the price coefficient and the yuan-valued welfare change are in Appendix F, but we generally follow papers such as Petrin (2002). Note that none of the existing papers with price elasticities address consumption durability, so they are not perfect for our needs. But while establishing the correct price coefficient for these calculations is not the focus of our paper, it seems clear that our results are economically meaningful.<sup>25</sup>

We display the percentage change in consumer welfare in Table 7. We find that liberalization under the post-2012 SARFT model leads to an increase in utility of 7.71%.<sup>26</sup> Table 7 shows that the percentage change in utility is somewhat greater than the percentage change in quantities for the SARFT case, 7.71% relative to 4.21% in the post-2012 specification, implying that it is particularly high-quality movies that are affected by liberalization.

We also compare these results to what we find when using a static model that ignores con-

---

<sup>23</sup>A fuller accounting of the benefits to China from liberalization would include Chinese investment in foreign movie production, which we do not address.

<sup>24</sup>There are other papers that calculate price elasticity for movies. de Roos & McKenzie (2014) exploit the presence of discounted tickets on Tuesdays in Australia, and finds the own-price elasticity is about 2.5. Using a nested logit model in data from Hong Kong, Ho, Liang, Weinberg & Yan (2018) find an elasticity in the range of 5 to 6.5. We focus on the results in China with related data.

<sup>25</sup>Mechanically, the price coefficient linearly scales the welfare increase we find. For instance, if we had found a price coefficient of -0.1467 instead of -0.0738 (i.e., double what we found), we would find a welfare increase of 3.86% instead of 7.71% (i.e., half of what we found). The relationship between the price coefficient we find and the elasticity we calibrate to is more complex, but still monotonic. That is, higher elasticities lead to higher (in absolute value) price coefficients.

<sup>26</sup>In this calculation, we display the ratio of the dollar-valued change in surplus to total industry revenue rather than starting or ending surplus. If we used surplus in the denominator, we would have to address the integrating constant in calculating consumer surplus. See Appendix F. Using observed industry revenue in the denominator addresses this issue. We do not display the levels (the left panel) because they are subject to the integrating constant.

sumption durability, i.e., the standard BLP results from Column 1 of Table 4. The results for this counterfactual are reported in the bottom panel of Table 7. We see that the static model generates a lower welfare gain from liberalization than the dynamic model, 6.76% relative to 7.71%. While this difference may not be large, there are important differences in the underlying quantities. The static model predicts liberalization would have a substantially larger effect on competing foreign movies (an 18.18% decline instead of a 9.8% decline) and a smaller effect on domestic movies (a 4.11% decline rather than a 6.87% decline). That is, the static model predicts less substitution between foreign and domestic movies.

Why is this the case? The size of the deviation of the random coefficient on *foreign* is similar in the static and dynamic results. In addition, the estimated random coefficient on *enhanced* is much larger in the dynamic model, and because more foreign movies are enhanced (i.e., 3D or Imax), that might suggest that the dynamic model would find foreign and domestic movies are *more* distant substitutes. Instead, the result appears to be due to dynamics: in the static model, consumers choose to see foreign movies every week, whereas the dynamic model predicts that consumers that prefer to see foreign movies still move on to domestic movies after seeing foreign movies. In this sense, consumption durability can lead the value to new product introduction to be higher. Keep in mind that the dynamic model could have matched the low substitutability in the static model by finding a much higher standard deviation in the random coefficient, whereas the static model cannot match the complex sequence of market shares predicted by the dynamic model.

Overall, the new foreign movies cannibalize the existing foreign movies less under the dynamic model and still have a limited impact on the domestic movies, so liberalization expands the quantity by more. Total admissions increase by 4.21% with the dynamic model and only 2.14% with the static model, which drives the higher welfare increase under the dynamic model.

Table 7: Welfare and market share effects of the import liberalization from 2012

|                                               | Quantities |           |             |           |        | Percentage Increase from Liberalization |             |           |        |
|-----------------------------------------------|------------|-----------|-------------|-----------|--------|-----------------------------------------|-------------|-----------|--------|
|                                               | All movies | Bottom 14 | SARFT Model |           |        | Bottom 14                               | SARFT Model |           |        |
|                                               |            |           | Pre-2012    | Post-2012 | Top 14 |                                         | Pre-2012    | Post-2012 | Top 14 |
| <b>Dynamic Model with Recency</b>             |            |           |             |           |        |                                         |             |           |        |
| Annual Admissions                             | 638.13     | 627.95    | 614.34      | 612.37    | 573.15 | 1.62                                    | 3.87        | 4.21      | 11.34  |
| Annual Admissions of Foreign Movies           | 280.91     | 256.36    | 231.92      | 228.79    | 162.24 | 9.58                                    | 21.17       | 22.84     | 73.15  |
| Annual Admissions of Competing Foreign Movies |            | 246.83    | 211.41      | 206.42    | 110.51 | -3.72                                   | -8.86       | -9.8      | -31.88 |
| Annual Admissions of Domestic Movies          | 357.22     | 371.59    | 382.43      | 383.58    | 410.91 | -3.87                                   | -6.59       | -6.87     | -13.07 |
| Annual Consumer Welfare (Util)                |            |           |             |           |        | 3.66                                    | 7.17        | 7.71      | 19.19  |
| <b>Static Model</b>                           |            |           |             |           |        |                                         |             |           |        |
| Annual Admissions                             | 638.13     | 632.94    | 625.9       | 624.75    | 602.64 | 0.82                                    | 1.95        | 2.14      | 5.89   |
| Annual Admissions of Foreign Movies           | 280.91     | 268.97    | 254.07      | 252.22    | 203.86 | 4.44                                    | 10.59       | 11.4      | 37.8   |
| Annual Admissions of Competing Foreign Movies |            | 246.83    | 211.41      | 206.42    | 110.51 | -8.23                                   | -16.8       | -18.18    | -45.79 |
| Annual Admissions of Domestic Movies          | 357.22     | 363.98    | 371.83      | 372.53    | 398.79 | -1.86                                   | -3.93       | -4.11     | -10.42 |
| Annual Consumer Welfare (Util)                |            |           |             |           |        | 2.53                                    | 6.16        | 6.76      | 18.58  |

The left panel presents the outcome in levels in millions, averaged across the three years from 2012-2014. The column *All movies* is the observed outcome when 34 movies are selected for revenue-sharing. The rest present counterfactual restrictions to 20 movies. *Bottom 14* removes the lowest 14 movies by Chinese box office admissions, the *SARFT Model* columns make use of the Probit model estimated in Table E2 as described in Section 9.1. The *pre-2012* column uses Column 3 and the *post-2012* column uses Column 1. The *Top 14* column eliminates the top 14 movies by admissions. The percentage changes in the right panel are the percentage increase going from the restricted choice set to the *All Movies* choice set on the left panel. *Annual Admissions of Competing Foreign Movies* is the quantity sold for the remaining movies when all movies are available (i.e, under liberalization). It is from raw data and the same across panels. The top panel (Dynamic Model) uses the model with consumption durability based on Column 3 of Table 4. The bottom panel (Static Model) uses a standard static model and parameters from Column 1 of Table 4. We do not report standard errors for readability's sake but they are below 11 for all items in the left panel and below 0.05 for all items in the right panel.

As a robustness check, we also consider these counterfactuals under the model without recency (based on Column 2 of Table 4). We present this result in the Appendix in Table A2. In this case, we find consumer welfare increases somewhat more, 8.88% relative to 7.71%, with other results scaled up similarly. As expected, the recency term moderates demand.

An issue with our calculations is that they assume consumers have fewer choices in the counterfactual settings due to foreign movies being excluded. In a logit-based model such as ours, this implies that consumers draw fewer logit error terms, which can impact choices and the level of welfare for consumers.<sup>27</sup> In order to evaluate the importance of this issue, we recalculate the counterfactual calculations, but this time, we replace lost movies in the consumer choice set with the next most popular movie so consumers always have six named movies available. The changes in counterfactual quantities are quite small, and we conclude that our results are not driven by the mechanics of counting logit error terms. Results and further discussion appear in Appendix G.

## 10 Conclusion

We study demand for movies. We propose a model that recognizes movies as *performance goods*: Choice sets rapidly evolve, consumers have limited time to devote to seeing movies in theaters, and consumers rarely want to see movies multiple times, which we term *consumption durability*. We propose a dynamic model of consumer demand that captures these features.

We apply the model to detailed administrative data on ticket sales drawn from a Chinese government agency. Like movie markets in other countries and other cultural goods products, ticket sales in China exhibit a stark decline in sales soon after their introduction. Whereas previous research used coefficients on age in static and reduced-form models to match this feature, we find that coefficients on age go essentially to zero when estimating with our model. Thus, it appears that consumption durability can well explain this feature of the data without relying on reduced-form age coefficients. We focus on a model with consumption durability and myopic consumers, which we show fits the data better than a forward-looking model in which consumers account for future movie releases.

---

<sup>27</sup>Akerberg & Rysman (2005) address this issue in estimation by introducing a term that controls for the number of products in the choice set, motivated by a model of product crowding in unobserved utility space. However, we set the number of inside products to six throughout estimation, so this is not an issue for estimation, and we do not have the variation to estimate such a term.

In our results, a static model leads to lower substitution between foreign and domestic products, and to lower welfare gains from increasing the choice set. In the static model, consumers can purchase the same product every period, but consumption durability leads consumers to switch to new products after they have consumed their favorite product. We use the model to consider policy-relevant counterfactual scenarios. In particular, China effectively places a quota on the number of foreign movies that may be imported. This quota was increased from 20 to 34 in 2012. We evaluate the consumer welfare increase from this change, and we find it to be significant, leading to a 7.71% increase in consumer welfare. Further, we find that the Chinese government and firms benefit from liberalization because losses to Chinese movie production are more than offset by gains to tax receipts, distribution, and cinemas. This result is driven by our finding low substitution between foreign and domestic movies. Our paper provides a measure of the economic cost of these types of quotas, hopefully to be accounted for in policies designed to protect domestic culture or local industries.

Our results are explained in part because we find that there is relatively little substitution between foreign and domestic movies. Low substitution raises questions about the role of the quota as a tool for infant industry protection, as we find that relaxing the quota would have a relatively low impact on domestic film production. Consumption durability appears to be an important factor in this market, and likely related markets such as books and theater performances. Future work exploring the implications of consumption durability in other contexts, such as for release strategy, appears valuable.

## References

- Akerberg, D. A. & Rysman, M. (2005). Unobservable product differentiation in discrete choice models: Estimating price elasticities and welfare effects. *RAND Journal of Economics*, 36, 771–788.
- Berry, S. (1994). Estimating discrete choice models of product differentiation. *RAND Journal of Economics*, 25, 242–262.
- Berry, S., Gandhi, A., & Haile, P. A. (2013). Connected substitutes and invertibility of demand. *Econometrica*, 5, 2087–2111.
- Berry, S., Levinsohn, J., & Pakes, A. (1995). Automobile prices in market equilibrium. *Econometrica*, 63, 841–890.
- Blonigen, B. A. & Soderbery, A. (2010). Measuring the benefits of product variety with an accurate variety set. *Journal of International Economics*, 82, 168–180.
- Broda, C. & Weinstein, D. E. (2006). Globalization and the gains from variety. *Quarterly Journal of Economics*, 121, 541–585.
- Chen, L., Yi, L. X., & Yu, C. (2024). The welfare effects of vertical integration in China’s movie industry. *American Economic Journal: Microeconomics*, 16, 204–235.
- Chu-Shore, J. (2010). Homogenization and specialization effects of international trade: Are cultural goods exceptional? *World Development*, 38, 37–47.
- Conlon, C. & Gortmaker, J. (2025). Incorporating micro data into differentiated products demand estimation with `pyblp`. *Journal of Econometrics*, Article 105926.
- Conlon, C. & Mortimer, J. H. (2021). Empirical properties of diversion ratios. *RAND Journal of Economics*, 52, 693–726.
- Dalton, C. M., Gowrisankaran, G., & Town, R. J. (2020). Salience, myopia, and complex dynamic incentives: Evidence from Medicare Part D. *The Review of Economic Studies*, 87, 822–869.
- De Groote, O. & Verboven, F. (2019). Subsidies and time discounting in new technology adoption: Evidence from solar photovoltaic systems. *American Economic Review*, 109, 2137–2172.
- de Roos, N. & McKenzie, J. (2014). Cheap Tuesdays and the demand for cinema. *International Journal of Industrial Organization*, 33, 93 – 109.
- Duan, N. (1983). Smearing estimate: A nonparametric retransformation method. *Journal of the American Statistical Association*, 78, :605–610.
- Einav, L. (2007). Seasonality in the U.S. motion picture industry. *The RAND Journal of Economics*, 38, 127–145.
- Feenstra, R. C. (1994). New product varieties and the measurement of international prices. *American Economics Review*, 84, 157–177.
- Ferreira, F., Petrin, A., & Waldfogel, J. (2016). Preference externalities and the rise of China: Measuring their impact on consumers and producers in the global film market. Working paper, University of Minnesota.
- Ferson, W. E. & Constantinides, G. M. (1991). Habit persistence and durability in aggregate consumption: Empirical tests. *Journal of Financial Economics*, 29, 199–240.
- Francois, P. & van Ypersele, T. (2002). On the protection of cultural goods. *Journal of International Economics*, 56(2), 359–369.
- Gandhi, A. & Houde, J.-F. (2020). Measuring substitution patterns in differentiated-products industries. Unpublished manuscript, University of Wisconsin-Madison.
- Gil, R., Ho, C.-Y., Xu, L., & Zhou, Y. (2024). Vertical integration and market foreclosure in media markets: Evidence from the Chinese motion picture industry. *Journal of Law and Economics*, 67, 143–193.

- Gowrisankaran, G. & Rysman, M. (2012). Dynamics of consumer demand for new durable goods. *Journal of Political Economy*, 120, 1173–1219.
- Gowrisankaran, G. & Rysman, M. (2020). A framework for empirical models of dynamic demand. Unpublished manuscript, Boston University.
- Greenwald, B. & Stiglitz, J. E. (2006). Helping infant economies grow: Foundations of trade policies for developing countries. *American Economic Review*, 96, 141–146.
- Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica*, 50, 1029–1054.
- Hanson, G. H. & Xiang, C. (2009). International trade in motion picture services. In *International Trade in Services and Intangibles in the Era of Globalization*, NBER Chapters (pp. 203–222). National Bureau of Economic Research, Inc.
- Hanson, G. H. & Xiang, C. (2011). Trade barriers and trade flows with product heterogeneity: An application to US motion picture exports. *Journal of International Economics*, 83, 14–26.
- Hayashi, F. (1985). The permanent income hypothesis and consumption durability: Analysis based on Japanese panel data. *Quarterly Journal of Economics*, 100, 1083–1113.
- Hendricks, K. & Sorensen, A. (2009). Information and the skewness of music sales. *Journal of Political Economy*, 117, 324–369.
- Ho, J. Y., Liang, Y., Weinberg, C. B., & Yan, J. (2018). An empirical study of uniform and differential pricing in the movie theatrical market. *Journal of Marketing Research*, 55, 414–431.
- Hodgson, C. & Sun, S. (2025). Heterogeneity in vertical foreclosure: Evidence from the Chinese film industry. Unpublished manuscript, Yale University.
- Holloway, I. (2014). Foreign entry, quality, and cultural distance: Product-level evidence from US movie exports. *Review of World Economics*, 150, 371–392.
- Kokas, A. (2017). *Hollywood Made in China*. University of California Press.
- Krugman, P. R. (1979). Increasing returns, monopolistic competition, and international trade. *Journal of International Economics*, 9, 469–479.
- Kwak, J. & Zhang, L. (2011). Does China love Hollywood? An empirical study on the determinants of the box-office performance of the foreign films in China. *International Area Studies Review*, 14, 115–140.
- Lee, F. (2006). Cultural discount and cross-culture predictability: Examining the box office performance of American movies in Hong Kong. *Journal of Media Economics*, 19, 259–278.
- Lee, R. (2013). Vertical integration and exclusivity in platform and two-sided markets. *American Economic Review*, 103, 2960–3000.
- Leung, T. C. & Qi, S. (2023). Globalization and the rise of action movies in Hollywood. *Journal of Cultural Economics*, 47, 31–69.
- Magnac, T. & Thesmar, D. (2002). Identifying dynamic discrete decision processes. *Econometrica*, 70, 801–816.
- Marvasti, A. & Canterbury, E. R. (2005). Cultural and other barriers to motion pictures trade. *Economic Inquiry*, 43, 39–54.
- Maystre, N., Olivier, J., Thoenig, M., & Verdier, T. (2014). Product-based cultural change: Is the village global? *Journal of International Economics*, 92, 212–230.
- McCalman, P. (2004). Foreign direct investment and intellectual property rights: Evidence from Hollywood’s global distribution of movies and videos. *Journal of International Economics*, 62, 107–123.
- Mehta, A., Rysman, M., & Simcoe, T. (2010). Identifying the age profile of patent citations. *Journal of Applied Econometrics*, 25, 1179–1204.

- Moul, C. C. (2007). Measuring word of mouth's impact on theatrical movie admissions. *Journal of Economics and Management Strategy*, 16, 859–892.
- Orbach, B. Y. & Einav, L. (2007). Uniform prices for differentiated goods: The case of the movie-theater industry. *International Review of Law and Economics*, 27(2), 129–153.
- Petrin, A. (2002). Quantifying the benefits of new products: The case of the minivan. *Journal of Political Economy*, 110, 705–729.
- Rauch, J. E. & Trindade, V. (2009). Neckties in the tropics: A model of international trade and cultural diversity. *Canadian Journal of Economics*, 42(3), 809–843.
- Rosen, S. (2002). The wolf at the door: Hollywood and the film market in China. In E. J. Heikkila & R. Pizarro (Eds.), *Southern California and the World* (pp. 49–77). Westport, CT: Praeger.
- Sheu, G. (2014). Price, quality, and variety: Measuring the gains from trade in differentiated products. *American Economic Journal: Applied Economics*, 6, 66–89.
- Sun, S. (2022). The vertical spillover effect of import liberalization: A study of the Chinese movie theater industry. Unpublished manuscript, University of Wisconsin.
- Trajtenberg, M. (1989). The welfare analysis of product innovations, with an application to computed tomography scanners. *Journal of Political Economy*, 97, 444–479.