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

Chun-Yu Ho
University at Albany, SUNY

Marc Rysman
Boston University

Yanfei Wang
Renmin University of China

January 21, 2020

Abstract

This paper evaluates Chinese restrictions on the number of foreign movies distributed domestically, particularly an increase in the quota in 2012. We estimate a structural model of consumer demand for movies. We solve a discrete choice model of consumer behavior that is dynamic in the sense that consumers may see movies only once. We find that the reliance on reduced-form age profiles is greatly reduced in our dynamic model relative to standard static approaches. Counterfactual experiments show that consumer welfare increases by 10% due to the import liberalization, and that there is relatively little substitution between foreign and domestic movies.

Keywords: Demand Estimation, Choice Set, Trade Liberalization.

JEL classifications: L10, L82, F13

1 Introduction

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, and how much this expansion led to substitution away from other movies, particularly distinguishing between the effect on foreign and domestic movies.

Evaluating welfare from movies is challenging because they are what we call *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. Ignoring these features can lead to misleading counterfactual calculations. Consumption durability is a feature of many cultural goods, such as books, museum exhibits, and albums.[1] Many of these goods exhibit stark declines in demand after introduction. Previous research has often estimated demand for these products with static models that contain an age profile, such as a set of dummy variable for age. Examples are Einav (2007) in movies and Hendricks & Sorensen (2009) in the context of album sales. While this may match the data well, it is puzzling from the perspective of economics why the utility from a cultural good would decline at a very rapid rate. A goal of our project is to show that much of this decline in sales can be explained by a model with consumption durability rather than a reduced-form age profile.

In our model, consumers face an exogenously evolving choice set. Consumers have heterogeneous preferences over movie characteristics, which do not change over time. We assume consumers can

[1] Consumption durability has long been considered in macroeconomic and finance literatures to understand consumption dynamics (Hayashi, 1985; Ferson & Constantinides, 1991).

see no more than one movie per week, reflecting consumers' limited time for attending cinemas. Further, we assume that consumers cannot see a movie more than once. Thus, the choice set of a given consumer evolves endogenously as the consumer makes choices over which movies to see. 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. While these assumptions are restrictive, we argue below that they are reasonable in our data and do not significantly impact our results. In estimation, we find the level of unobserved quality for each movie-week that rationalizes the observed market share, and form a GMM estimator around this term.

We apply our model to a data set covering 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. This survey data is useful because our model makes predictions about how often an individual goes to the movies and how this number is distributed across the population, but we cannot learn these outcomes just from data on aggregate movie market shares. Forcing our model to match this "micro-moment" significantly impacts the results.

For computational reasons, we restrict consumers to choose among six *named* movies, over which we track consumer histories. We further augment the choice set with three more options: a generic foreign movie, a generic domestic movie, and an outside option of not seeing a move in a cinema. When a movie falls out of the top six, we assume it enters one of the generic options. We argue that ticket sales are so concentrated on the top few movies that the limitation to six named movies is not important, and we plan to experiment with higher numbers of named movies.

We find that in a traditional static random coefficients logit model, the age profile is strongly significant and negative, reflecting the steep dropoff in sales over the life of a movie. However, estimating our dynamic model reduces the importance of the age profile, and in when we impose the micro-moment, we find that the coefficient on the age profile is insignificantly different from zero and precisely estimated. Thus, although the dropoff in sales that moves experience from week-to-week is extreme, it can be entirely explained by consumption durability. We also find a substantial heterogeneity in preference for foreign movies, suggesting that foreign and domestic movies are not close substitutes.

In addition, we consider a dynamic version of our model in which consumers have perfect foresight over what movies will be available in the weeks that follow. This context fits well into the setting that Magnac & Thesmar (2002) say allows for identification of the discount rate. Intuitively, we compare weeks with similar movie offerings but different movies available in following weeks. We estimate the discount rate to be zero. That is, movie-going behavior this week does not appear to respond the movie offerings in following weeks, and so myopia fits the data well. Below, we also discuss a straightforward extension to our model that allows for seeing a movie multiple times, but we do not believe it is important for our application.

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. We show that consumer welfare increases by about 10% due to the import liberalization. However, the welfare effects for producers are heterogeneous. 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 with the other foreign movies. In addition, we find that if the consumption durability in preferences is ignored, the welfare benefit for consumers is overestimated and the business stealing effects of extra foreign movies on competing foreign movies and domestic movies are also overestimated.

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 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 in particular affect movie production in terms of genre and content (see for instance Leung & Qi, 2019). We do not address that issue here, although that is not to say that it is not important.

2 Literature

Our work contributes to a growing empirical literature on trade in motion picture. Marvasti & Canterbery (2005) construct a trade barrier index for 33 countries and find that their trade barrier index is positively correlated with imports of U.S. motion pictures. Hanson & Xiang (2011) develop a heterogeneous firms model of trade for the motion picture industry. They find that average revenues per U.S. film vary widely across countries and are negatively correlated with geographic distance, linguistic distance, and other measures of trade barriers. Thus, these two papers find mixed results of trade barrier on imports of U.S. movies. Holloway (2014) examines 1,236 U.S. movies released between 1995 and 2004, and finds that movies with a higher quality, measured by their box office in the U.S., are more likely to enter into foreign countries. McCalman (2004) studies the role of protection of property rights in the international distribution of movies. Our work is closest to Ferreira, Petrin & Waldfogel (2013), in which they estimate a structural model of movie demand for 16,856 movies in 53 destination countries over the period 2000-2010. They then combine with the demand estimates with a quality production function of movie to examine the contribution of the increase in product quality to the gain from trade in motion picture. Our work differs from those studies in that it uses a structural demand model to examine the welfare effects from import liberalization of U.S. movies.

Our paper builds on the methodology developed by Berry, Levinsohn & Pakes (1995) to estimate demand system of differentiated products with market-level data. Our work also contributes to three strands of literature related to demand estimation based on Berry et al. (1995). First, we add to the empirical literature on demand estimation for movies. Davis (2006) and Sunada (2012) estimate the effect of spatial location of theatre on movie demand. Einav (2007) estimates the seasonality of movie demand. Moul (2007) estimates the effect of word-of-mouth on movie demand. Moul (2008) estimates the conduct of distributor on rental pricing and advertising. de Roos & McKenzie (2014) estimate the price elasticity of movie demand by exploiting the ticket discount offered by Australian theatres on Tuesday.

Second, we add to the literature evaluating the welfare benefit of new goods with the discrete choice demand model (Trajtenberg, 1989; Petrin, 2002). There are recent studies extending the demand model to accommodate some features of cultural goods, such as complementarity between existing offline version and new online version of the product (Gentzkow, 2007) and unpredictable product quality of new products (Aguiar & Waldfogel, 2018).

Third, we add to the literature of modelling heterogeneous choice sets across consumers in demand estimation. Bruno & Vilcassim (2008) show that demand estimates are biased if varying product availability across consumers is ignored. The existing literature suggests that there are two main reasons for having heterogeneous choice sets across consumers. First, the choice sets vary across consumers because some products stock out when they make purchase decision. Musalem, Olivares, Bradlow, Terwiesch & Corsten (2010) employ a Bayesian method to impute the entire sequence of sales to model product availability faced by each consumer. Conlon & Mortimer (2013) use an expectation-maximization (EM) algorithm to account for the missing data on product availability faced by each customer. Second, the choice sets vary across consumers because of the awareness of different brands. Goeree (2008) models the probability that a consumer would be aware of a given brand is expressed as a function of her demographics and exposure to advertising. Draganska & Klapper (2011) incorporate information on choice sets from consumer survey for demand estimation. Barroso & Llobet (2012) model the probability that a consumer would be aware of a given brand is expressed as a function of history of advertising expenditures.

In addition, we provide a model of consumption durability, in which consumer demand is a dynamic process. Our model is designed for aggregate data (that is, product-level market shares rather than individual choices) and our solution method is similar to Gowrisankaran & Rysman (2012). Relative to that paper, we focus on the durable nature of choice rather than forward-looking behavior, although the formation of choice sets is quite different. 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 (2019) and De Groote & Verboven (2019).

Our paper is related to the lengthy literature on the benefits of greater product variety in international trade.[2] However, some countries argue that cultural goods and services"encompass values, identity and meanings that go beyond their strictly commercial value" and request exceptions in protecting domestic cultural goods and services.[3] For example, Article IV of the GATT agreements in 1947 provides the conditions under which countries may impose quotas on foriegn movies.[4] The protection of national culture also played a role in Uruguay Round of the GATS ended in 1994 and the UNESCO Convention on the Protection and Promotion of the Diversity of Cultural Expressions (in particular Articles 6 and 8). There is particular concern for U.S. movies as U.S. producers rely more heavily on foreign revenues and U.S. movies dominate the market share in many foreign countries.[5]

The remainder of the paper is organized as follows: Section 2 provides the institutional background of the Chinese movie industry. Section 3 describes the data and descriptive statistics. Section 4 discusses the structural demand model. Section 5 presents the estimation procedures. Sections 6 and 7 report the empirical results and the results of counterfactual experiment, respectively, and Section 8 concludes.

[2]A leading example is Krugman (1979). There is a literature shows that the welfare gain from more product variety from trade is quantitatively large for manufacturing sectors, see Feenstra (1994), Broda & Weinstein (2006), Blonigen & Soderbery (2010) and Sheu (2014).

[3]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 a theory and evidences to support that trade integration leads to convergence in cultural values across countries.

[4]Many countries impose trade barriers on foriegn movies. (Marvasti & Canterbery, 2005) shows that non-tariff trade barriers, such as quotas, are more commonly imposed than tariffs, especially for developing countries .

[5]Marvasti & Canterbery (2005) report that export revenues became an increasing portion of total revenue for U.S. 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 in 19 European countries over the period 1995-2004. According to a report by 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.mpaa.org/wp-content/uploads/2015/03/MPAA-Theatrical-Market-Statistics-2014.pdf

3 Institutional Background

This section discusses the import policies for foreign movies of China. 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, 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".[6]

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 approved to join 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% 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 are enhanced films in 3D or IMAX formats. In addition, revenue sharing was set at 25% of box office revenues instead of the previous scale of 13-17%. This agreement would be reviewed after 5 years to ensure that it is working as had envisioned. All the 34 revenue-sharing movies and all movies imported under the fixed fee plan are imported and distributed by China Film Group, and some are co-distributed by Huaxia, which is a state-owned enterprise established in 2003. There is no specific quota to import movies on a flat-fee basis, but is usually 20-30 per year.

A third option for movies to be distributed in China is for them to be co-produced. In a co-

[6] Stanley Rosen, "The Wolf at the Door: Hollywood and the Film Market in China," in Southern California and the World, eds. Eric J. Heikkila and Rafael Pizarro (Westport, CT: Praeger, 2002), 49–77.

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 (45%) terms 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 it was produced. The movie entered China under the fixed fee plan. Examples of movies that were successfully co-produced are *Looper* and *The Great Wall*.

All foreign films face censorship by SARFT [Marc: What about domestic movies? Also censored?], regardless of whether they are under a fixed fee plan, under revenue sharing or are co-produced. Review usually takes 30 days. Article 25 of the Regulation on the Administration of Movies effective in Februrary 2002 prohibits ten aspects of content that would not be allowed in any imported films. The list 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”.

Nonetheless, Figure 1 depicts that the share of domestic movies at the box office remain at about 55%, which is higher than those in European countries documented in Hanson & Xiang (2009) and may relate to the import restriction of China on foreign movies. 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 in pre-2012 data in the rest of the paper, and 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 the SARFT of China. The data contain information on box office revenue, number of tickets sold, and number of showing screens of all

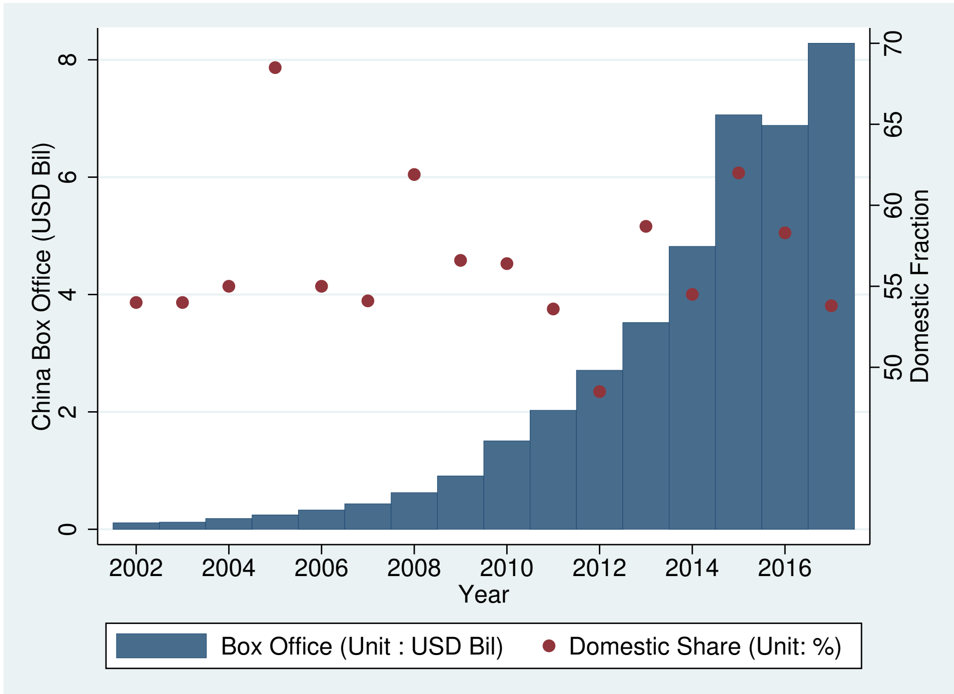

Figure 1: Chinese box office revenue and domestic share.

movies shown in 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. Our data is drawn from SARFT's program. Our empirical analysis includes the movies with annual admission share larger than 0.1% 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 releasing date, whether a movie is in 3D or IMAX format, whether a move is imported, genre and run time.

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 market share. 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. Movies in 3D represent 71% of foreign ticket sales. Similarly, 29% percent of foreign movies are in IMAX relative to 3% of domestic movies, and foreign IMAX movies represent 70% of foreign ticket sales.

Table 1: Movie characteristics

	Unweighted			Admission-Weighted		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	All	Domestic	Foreign	All	Domestic	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.

Foreign movies more likely to be action movies and less likely to be comedies or dramas, and this is even more extreme when we weight by market share.[7]

As is common for cultural goods such as books and music, market share for movies is highly skewed. For each week in our sample, we calculate the share going to each rank of movie, i.e. the top ranked movie, the second ranked movie and so on. We average this over the 181 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 6 movies cover 89.6% of the revenue, and the 7th ranked movie collects less only 4% of tickets, with percentages declining thereafter.

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 sales by movie and week on movie, year, month-of-year, and age fixed effects. 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 11 weeks (there are only two movies in the data that make it to 11 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.[8] The result appears in Figure 3. Predicted sales start around 95 million in the first week and drop to less than 50 million

[7] 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.

[8] 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).

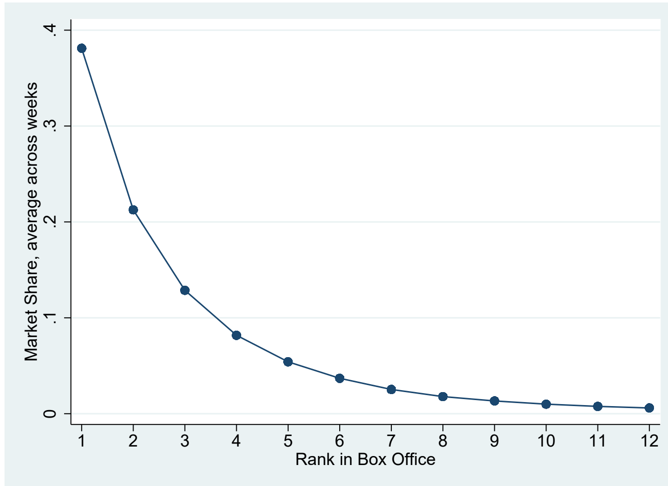

Figure 2: Average share of ticket sales by weekly sales rank

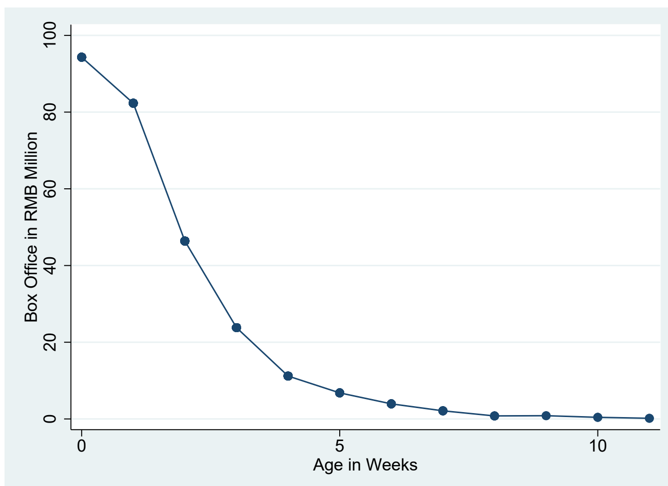

Figure 3: Age profile of movie revenue

by week 3, and are under 10 million by week 5, with continued declines afterwards.[9]

4.1 Time varying variables

Einav (2007) reports that there is a seasonality in movie demand. Thus, we use a dummy variable 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

[9]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.

observations belong to movies showing on holiday.

We further include a linear time trend in the week to capture the dramatic increase documented in Figure 1. We include a separate set of month-of-the-year dummies for foreign and domestic movies. Having two separate sets of month dummies is meant to capture how SARFT's treatment of foreign movies varies over the seasons.

4.2 Market Size and Market Share

In this subsection, we motivate several important modeling assumptions. An important restriction that we make for computational reasons is that consumers can select among 6 named movies in each period, in addition to a generic foriegn and generic domestic outside option. The model assumes that once a named movie has been chosen, it cannot be chosen again. We assume consumers can select among the 6 movies with the highest market share in each week.

There are 427 movies that are one of the top 6 movies in at least one week. We calculate the box office share of the top 6 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 1,448 observations, which consists of the 6 top movies in each week and the two generic options (one foreign and one domestic) for 183 weeks. For 16 weeks, we observe no market share for foreign generic options, and we do not count those here, so we get $1,448 = (8 \times 183) - 16$. Counting those missing weeks as zero market shares would bring down the *Other foreign movies* market share slightly. We find that the top 6 movies have an average of 89.6% of the market. Thus, similar to what we saw in Figure 2, considering only the top 6 still captures most of the market. The generic foreign option gets about 3% and the generic domestic option gets about 6%. If we increased the top 6 movies to be the top 10, we capture 96.2%, an increase of less than 7 percentage points. Thus, there is little gain to expanding this number, and the computational cost would be high. Note that the characteristics presented in Table 1 are similar when using only the 427 movies that appear in the top 6. For completeness, we recalculate Table 1 for these movies and present the results in Table 7 in Appendix A.

A potentially restrictive assumption in our model is that agents are myopic. An important way

Table 2: Market Shares

Variables	(1) Mean	(2) SD	(3) Min	(4) Max
Box Office Share (%)				
Average movie	12.5	12.7	0.1	88.5
Top six movies	89.5	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

1,448 observations

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 6, the average percentage of their time that is spent in the top 6 is only 55.2% . That is, at the end of their time in the top 6, 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. Of course, a movie's time in the top 6 accounts for most of its revenue: For movies ever in the top 6, 85.7% of revenue is realized while in the top 6. Weighted by ticket sales to emphasize top sellers, the average percentage of time spent in the top 6 is still only 69%, whereas the percentage of revenue realized while in the top 6 is 95.4%. Overall, we find these descriptive statistics consistent with our assumptions that consumers are not forward looking, and that they choose among 6 top movies and 2 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) who analyzes the movie demand of the U.S. Because movie theatres are often located in urban area, thus we employ the population in urban area instead of total population to measure the market size. We use the annual figure of total urban population in year 2011, i.e. 354.256 million people, to measure the market size, and this size is denoted H. The population data is obtained from the China Statistical Yearbook. To compute the market shares, we divide the ticket sales of movie j in week t by the market size. Let q_{jt} be the ticket sales (quantity, not revenue) of movie j in week t. Then, $s_{jt}^{\texttt{data}} = q_{jt}/H$ 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 has 96%.

4.3 Data for Micro-moments

We employ the summary statistics reported from a survey conducted by a Chinese consulting firm on the movie industry called Entgroup. The survey was conducted in February and March of 2013. The 6,027 respondents are consumers who had watched at least one movie in the theater in the previous year. The survey shows that 23.2% of the respondents watched 1-3 movies, 19.2% of them watched 4-6 movies, and 57.6% watched more than 6 movies in the previous year.

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: rapidly exogenous evolution in choice 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 assume 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 discuss this assumption further below.

5.1 An overview

We present a simplified version of how the model works in Figure 4. The figure represents 4 time periods (weeks). The top row reports the time period and the set of exogenously available movies. In the first three periods, there are two movies available, A and B. 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.

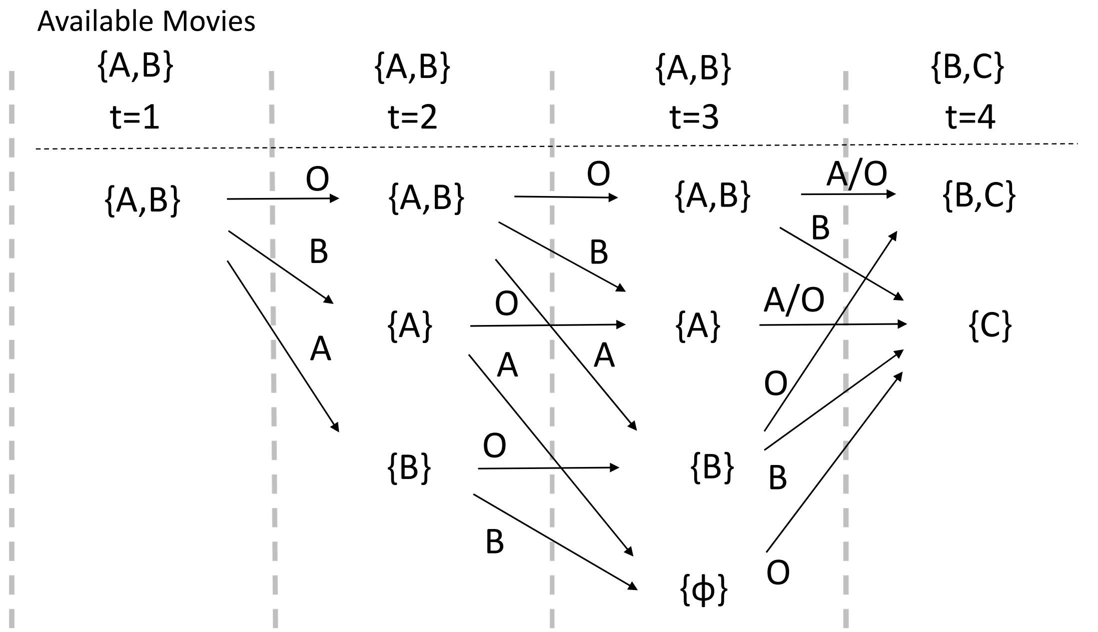

Figure 4: Simplified representation of the demand model.

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 for 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 period 1, 2, or 3, and choice set $\{B, C\}$ for consumers that have not yet seen B.

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 model. Also, there are typically multiple paths by which consumer 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 step. We compute the shares of consumers in each state exactly following the choice probabilities. In practice, we compute this for 6 movies per period rather than 2, for 3 non-dynamic options (the two generic movies plus the outside option) rather than 1, and for 183 time periods rather than 4, so the problem is numerically challenging. In addition, we allow for persistent consumer heterogeneity in the form of permanent random coefficients, and this 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 1 indexed by i face discrete finite time. The set of all movies ever available can be indexed by j from 1 to J. In our case, $J = 420$. A subset of 6 of these movies is available in any give 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 6 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 has high as 2^6. We denote the elements of $\mathcal{C}_t$ as C_{gt}, $g = 1, \ldots, G_t$. In Figure 4, $\mathbf{C}_t$ is the top row of a column, $\mathcal{C}_t$ is a column, and C_{gt} is each element of the column.

Denote the history of all movies seen by i up to period t as H_{it}. Let the function $C(H_{it}, \mathbf{C_t})$ return consumer i's choice set in t:

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

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 says that consumers always have three additional options. They may choose the outside option $j = 0$, or they may choose to see a generic foreign movie ($j = J + 1$) or 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. Below, we also apply a simplified specification for utility for the generic movies. Overall, it must be that $C(H_{it}, \mathbf{C_t}) \in \mathbf{C}_t$, so $C(H_{it}, \mathbf{C_t})$ must be equal to an element C_{gt}.

Let the utility to consumer i to choosing movie j in period t be denoted by u_{ijt}. Consumer i solves:

$$\max_{j \in C_{gt}} u_{ijt} \quad C_{gt} = C(H_{it}, \mathbf{C_t}).$$

We assume that utility takes on the functional form:

$$u_{ijt} = x_{jt}\beta + \xi_{jt} + \mu_{ijt} + \varepsilon_{ijt}.$$

The variables x_{jt} are K characteristics, observable to both the agent and the researcher. The scalar ξ_{jt} is observed by the agent but not the researcher. It represents unobserved quality, and will play the role of the econometric error term in our model. The term ε_{ijt} is distributed according to the Extreme Value distribution, and generates the familiar logit probability of choice. The term μ_{ijt} represents the consumer match to the product based on observable characteristics. Following Berry (1994) and Berry et al. (1995), we specify it as:

$$\mu_{ijt} = \sum_{k=1}^{K} x_{jkt}\sigma_k\nu_{ik}$$

where $\nu_{ik} \sim \mathcal{N}(0, 1)$. Thus, ν_{ik} 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. The parameters β and $\sigma_k,\ k = 1, \ldots, K$ are to be estimated. We refer to them together as $\theta = \{\beta, \sigma\}$. Furthermore, for convenience, we denote the mean utility of product j in period t as $\delta_{jt} = x_{jt}\beta + \xi_{jt}$.

5.3 Market shares

Given these assumptions, the conditional probability $P_{ijt}(C_{gt})$, the probability of i choosing j in t conditional on having choice set C_{gt} is:

$$P_{ijt}(C_{gt}) = \begin{cases} \dfrac{\exp(\delta_{jt} + \mu_{ijt})}{\sum_{k \in C_{gt}} \exp(\delta_{kt} + \mu_{ikt})} & j \in C_{gt} \\ 0 & \texttt{otherwise} \end{cases}. \tag{1}$$

In Figure 4, the $P_{ijt}(C_{gt})$ is the probability of being on each arrow given a 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 that lead 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 $\mathbf{C_t}$:

$$B_{gg't} = \left\{ j : C_{g't+1} = \underbrace{(C_{gt} \backslash \{j\})}_{\texttt{current}} \cup \underbrace{(\mathbf{C_{t+1}} \backslash \mathbf{C_t})}_{\texttt{entering}} \backslash \underbrace{(\mathbf{C_t} \backslash \mathbf{C_{t+1}})}_{\texttt{exiting}} \right\}. \tag{2}$$

Let s_{igt} be the share of consumers of type i with choice set g in period t. Thus, $\sum_{g=1}^{G_t} s_{igt} = 1$. We refer to s_{igt} as the unconditional probability or unconditional share. To compute s_{igt}, we assume that there is only one possible choice set in the first period: $\mathcal{C}_1 = \{\mathbf{C_1}\}$. Thus, $s_{i11} = 1$ for all i. Unconditional shares evolve as follows:

$$s_{ig't+1} = \sum_{g=1}^{G_t} \sum_{j \in B_{gg't}} P_{ijt}(C_{gt}) s_{igt} \;\; \forall g' = 1, \ldots, G_{t+1}, t = 1, \ldots, T-1. \tag{3}$$

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

$$\widehat{s}_{jt} = \int \sum_{g=1}^{G_t} P_{ijt}(C_{gt}) s_{igt} f(i) di \tag{4}$$

where $f(i)$ is the distribution of consumer types i, assumed to be the multivariate normal distribution.

5.4 Forward-looking behavior

In some performance goods settings, our assumption of myopic behavior may not be reasonable.[10] In this sub-section, we provide a model that allows for forward-looking behavior. We assume

[10] 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

consumers have perfect foresight over all future values of δ_{jt} but not over ε_{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 a particular movies is 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 from making a choice from set g in period t to be:

$$V_{igt} = \ln \left(\sum_{j \in C_{gt}} \exp\left(\delta_{jt} + \mu_{ijt} + \lambda V_{ig't+1}\right) \right).$$

where g' is the choice set in $t+1$ that a consumer will realize when they start in g, t and pick j (which is written out formally in the brackets in Equation 2). The variable λ is the discount rate. For this calculation, we assume that $V_{igT+1} = 0$ for all i and g. Thus, for a consumer in the final period T, the choice problem is unchanged under forward-looking behavior.

Thus, we can define the utility to i from movie j as:

$$u_{ijt} = \delta_{jt} + \mu_{ijt} + \lambda V_{ig't+1} + \varepsilon_{ijt}$$

Rewriting Equation 1, the new choice probability is:

$$P_{ijt}(C_{gt}) = \begin{array}{cc} \dfrac{\exp\left(\delta_{jt} + \mu_{ijt} + \lambda V_{ig't}\right)}{\sum_{k \in C_{gt}} \exp\left(\delta_{kt} + \mu_{ikt} + \lambda V_{i\tilde{g}'t}\right)} & j \in C_{gt} \\ 0 & \texttt{otherwise} \end{array}.$$

Here, we write $\tilde{g}'$ in the denominator to distinguish it from g' in the numerator. The rest of the model, such as the determination of s_{igt}, remains the same.

We wish to estimate discount rate. Magnac & Thesmar (2002) argue that identification of the discount rate requires variation in the continuation value that is not reflected in the current values. In our setting, movies that arrive or leave in future periods affect the future payoff but not otherwise the current payoffs. Indeed, perfect foresight models generate this kind of variation naturally.

evidence of dynamic behavior in exhibit attendance.

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. While the discount rate is at the level of the week, it reflects how consumers adjust movie-going this week to changes in movie availability next week. Our prior belief is that consumers heavily discount this continuation value, and indeed we find it to be so 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 and does not require a fixed-point algorithm. In contrast, limited information models typically require an assumption of stationarity as well as assumptions on the information set that consumers have. Researchers may wish to invoke Inclusive Value Sufficiency (Gowrisankaran & Rysman, 2012, as in) but that introduces multiple fixed point algorithms, as well as questions about how to discretize or otherwise approximate the state space.

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 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 a movie that has already been seen is equivalent to choosing a generic movie in terms of how it affects the evolution of a consumer's choice set. This extension does not affect the overall dynamic process in our model. This approach would be appealing if we had data on how often consumers saw individual movies, and it showed the multiple viewings were important.

Note that 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 Estimation

This section discusses estimation of the model. We first discuss the BLP-type moments, and then discuss micromoments.

6.1 BLP moments

First, we cannot compute Equation 4 analytically. For this step, we use simulation. We draw S values of ν_{ik}^s, $k = 1, \ldots, K$ and $s = 1, \ldots, S$.[11]

For a given set of parameters θ and a guess of mean utilities δ_{jt}, we compute $P_{ijt}(C_{gt})$ and then s_{igt} for each draw of ν^s as described above in Equations 1 and 3. 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 $\widehat{s}_{jt}(\theta, \delta)$, where δ is the vector of elements δ_{jt}.

As in Berry et al. (1995), we recover δ for any set of parameters θ via the fixed point equation:

$$\delta'_{jt} = \delta_{jt} + \ln\left(s_{jt}^{\texttt{data}}\right) - \ln\left(\widehat{s}_{jt}(\theta, \delta)\right).$$

As above, $s_{jt}^{\texttt{data}}$ are the market shares observed in the data. For any guess of parameters θ, we solve this equation by successive approximation. That is, we plug in a guess of δ, compute δ' 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.

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

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

[11] Using s for both samples and market shares is somewhat confusing, but it is clear in context. In practice, we draw ν_{ik}^s from a Halton sequence, setting $S = 200$.

and we assume a set of instrumental variables Z_{jt} is exogenous such that $E[\xi_{jt}|Z_{jt}] = 0$. We estimate via two-step GMM.

In practice, we include a full set of movie fixed effects, so we do not estimate β for any variables that do not vary over time. The generic domestic and foreign outside option each have a dummy variable indicating their type, and are subject to the time varying explanatory variables (time trend, holiday, and month-of-year effects) but are not further parameterized. Our base specification places random coefficients on three variables: the constant term, a dummy for whether a movie is foreign, and a dummy for whether a movie filmed in either IMAX or 3D, which we call *enhanced*. These are the most important variables for our question. We experiment with other specifications as well.

We assume that all explanatory variables are exogenous. Recall that price is not an explanatory variable. However, the presence of consumer heterogeneity terms (σ_k) means we still need additional instrumental variables to achieve identification. Our first set of instruments follows Berry et al. (1995). Because we take product introductions as exogenous, we use sums over the characteristics of other movies in the top 6 in the same week. 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 past since the movie's release, and the movie's runtime. Additionally, Gandhi & Houde (2019) recommend instruments that emphasize how differentiated a product is from others on the market. We construct these for the instruments based on dummy variables. We do so by interacting the Berry et al. (1995) instruments with the dummy variable in question. Thus, the sum over the *enhanced* dummy will be interacted with whether the movie in question is enhanced, so will be high only for enhanced movies.

6.2 Incorporating the Micro-moments

To improve the identification of random coefficients, 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 to watch 1-3 movies is 23.5% and the probability to watch 4-6 movies is 19.2%.

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, but also how times they have been to the movies. That is, we denote the state of a consumer as $\{C_{gt}, n_{it}\}$ where n_{it} is the number of movies that i has seen in the previous year. When a consumer chooses to see a movie and $n_{it} < 7$, then $n_{it+1} = n_{it} + 1$. We assume that n_{it} takes on a maximum of 7 to reflect our survey data. 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 C_{gt}. Tracking n_{it} 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 $n = 0, 1, .., 6, 7+$. Then, we compute, conditional on watching at least one movie, the probability to watch 1-3 movies is $P_{i1-3} = \sum_{n=1}^{3} P_{in} / \sum_{n=1}^{7+} P_{in}$ and the probability to see 4-6 movies is $P_{i4-6} = \sum_{n=4}^{6} P_{in} / \sum_{n=1}^{7+} P_{in}$.

We then 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

$$E[m_2(\theta)] \quad = \quad E \begin{bmatrix} P_{1-3}^{\texttt{data}} - P_{1-3}(\theta) \\ P_{4-6}^{\texttt{data}} - P_{4-6}(\theta) \end{bmatrix} \quad = \quad 0 \ , \tag{5}$$

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

$$E[m(\theta)] \quad = \quad E \begin{bmatrix} m_1(\theta) \\ m_2(\theta) \end{bmatrix} \quad = \quad 0 \ . \tag{6}$$

Here, $m_1(\theta)$ are the BLP moments, as discussed in Section 6.1. The GMM estimator given our stacked moment conditions is defined as $\min_\theta m'\Omega m$. We follow the two-step procedure of GMM estimation proposed in Hansen (1982) and intialize it with an identity matrix as the weighting matrix Ω. We draw a new sample of draws ν_k^s for the micromoment calculation. Thus, the weighting matrix is block-diagonal as in Petrin (2002). In the second stage of the GMM optimization routine, the weighting matrix of the micro moment conditions is computed using a variance-covariance matrix of the micro-moment conditions.

It is difficult to know how to weight the two sets of moments in estimation. Although formally, the survey data has more observations, we believe it is less reliable than the administrative ticket data. Following Li, Mazur, Park, Roberts, Sweeting & Zhang (2019), we impose that the two sets of moments are weighted equally. Formally, we impose that the sum of the weights within each set of moments (the BLP moments and the micromoments) are equal. In the second stage of GMM, we impose that the weighting matrix is diagonal and we allow the relative weights within each set of moments to reflect the relative inverse of the variance of the moment, but we still normalize so that the weight on each set of moments is equal.

6.3 The Price Coefficient

Estimating the price responsiveness in movies is very challenging. Prices are often based on the theater and the time of day but not the individual movie, so we do not typically observe product-specific variation in prices. For instance, Einav (2007) does not use a price coefficient, and it instead focuses on summary statistics that do not rely on such a coefficient. The Chinese market is similar to the U.S. in these regards. We propose a method for estimating the price coefficient in Appendix B that relies on a more disaggregate dataset at the movie-theater-day level.[12] However, the part of our paper is still very much work in progress. We employ that price coefficient in our counterfactual experiment only to convert the welfare estimates into monetary value, but the rest of our results are of interest even without that computation.

7 Empirical Results

This section discusses the empirical results obtained from the demand model described in the previous section. Table 3 reports the demand estimates from the random coefficient 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 can match the kind of declines in market share that we see in the data (as evidenced in Figure 3) only with a strong reduced-form age profile. Column 2 adds the micromoment but the

[12]Note that the use of plug-in parameter α is also employed in Aguiar & Waldfogel (2018), in which they do not have price variation to estimate σ.

Table 3: Demand Estimates

		BLP	BLP	Dynamic	Dynamic
Non-linear	Constant	1.0233***	0.9775***	0.7214***	12.3469***
		(0.0783)	(0.0549)	(0.0748)	(0.0465)
	Enhanced(3D or IMAX)	1.9467***	0.5192***	1.3067***	0.8207***
		(0.0722)	(0.0524)	(0.0762)	(0.0704)
	Foreign	4.2040***	0.7219***	3.2650***	2.6482***
		(0.0300)	(0.0474)	(0.0272)	(0.1144)
Linear	Age	-0.5788***	-0.5470***	-0.4564***	0.0150
		(0.0357)	(0.0261)	(0.0284)	(0.0486)
	Holiday	0.3167**	0.3269***	0.3164**	1.3720***
		(0.1305)	(0.1201)	(0.1242)	(0.2564)
	WeekTrend	0.0050***	0.0041***	0.0044***	0.0280***
		(0.0005)	(0.0004)	(0.0005)	(0.0011)
	Consumption Durability	No	No	Yes	Yes
	Micro-moments	No	Yes	No	Yes
	First Difference Moments	No	No	No	No
	Differentiation IVs	Yes	Yes	Yes	Yes

1,448 observations. Specifications include movie fixed effects, and month-of-year dummies separately for foreign and domestic movies.

age trend is almost unchanged. The static model has no mechanism for matching the micromoment and so it does not qualitatively affect the results.

Column 3 estimates our dynamic model. Here again, the parameters do not change much, although the coefficient on age is reduced towards zero at least somewhat. Note that the standard deviation on the constant term is relatively small, and this specification implies that relatively few people see movies more than once or twice per year.

Our preferred specification is Column 4, in which the micromoments are imposed on the dynamic model. This specification leads to a dramatic increase in the random coefficient on the constant term. That is, the way to match the repeat viewing in the survey data is to greatly increase consumer heterogeneity, so some consumers highly value going to the movies and go repeatedly. Because the movie-going population is much smaller in this specification, the age profile is no longer necessary. In Column 4, the coefficient on age is 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.[13]

[13]The age trend is not separately identified from movie fixed effects and a week time trend. Results across the four

In Column 4, the random coefficient parameters on movies being enhanced and foreign are also statistically significant. The parameter on foreign in particular is fairly large. That will drive our result in the next section that there is relatively muted substitution between foreign and domestic movies.

As described in Section 6, we construct our moments based on the assumption that $E[\xi_{jt}|Z_{jt}] = 0$. However, it might be more natural in a dynamic framework to assume that $E[\xi_{jt} - \xi_{jt-1}|Z_{jt}] = 0$. This approach is the approach of Lee (2013). This "differenced" model focuses on changes over time rather than levels. For this specification, we also first-difference the instruments. Because we use product fixed effects in our main specification, this change is analogous to switching from fixed effects to first differences, which are asymptotically identical. Not surprisingly, we find very similar results. These appear in the Table 8 in Appendix A.

As a robustness check, we consider a model in which consumers have perfect foresight as to what movies will be available, as described in Section 5.4. We perform a grid search over values of the discount rate λ from 0 to 1. The specification is otherwise identical to that in Column 4 of Table 3, which includes the micro-moment. For each value, we estimate the rest of the parameters as above. Interestingly, for higher values of the discount rate (that is, more utility weight on the continuation value) we find a more negative age profile. The model allows forward-looking consumers to see movies earlier because consumers anticipate that a movie will decline in value.

More importantly, we evaluate the objective function for different values of the discount rate. As discussed above, we believe the discount rate is well-identified in our setting. We find that the objective function is minimized at a discount rate of $\lambda = 0$. We find a standard error of 0.023.[14] Intuitively, consumers do not respond this week to movies available in future weeks, which we find to be a reasonable result. Thus, our assumption of myopia fits the data well.

Next, we regress the movie-specific effects from the demand estimation on time-invariant movie characteristics and report the results in Table 4. Focusing on column 4, our preferred specification, we see that enhanced movies and action movies have positive and significant coefficients. We further

weeks are robust to alternative treatments of the calendar time effects, such as replacing it with year dummies.

[14] We calculate the standard error with the usual sandwich estimator for optimal GMM. In this calculation, we do not address the issue that the parameter is on an inequality constraint.

Table 4: Regression of movie fixed effects on movie characteristics

	BLP	**BLP**	**Dynamic**	**Dynamic**
enhanced	-0.2328	0.2389	0.1322	1.3429
	[0.2611]	[0.2415]	[0.2110]	[0.2218]***
foreign	5.0032	4.6871	4.7875	25.1577
	[0.2827]***	[0.2615]***	[0.2285]***	[0.2402]***
gap(release delay)	-0.0078	-0.0046	-0.007	-0.0133
	[0.0040]*	[0.0037]	[0.0032]**	[0.0034]***
ln(runtime)	2.3495	2.1083	2.4535	4.3412
	[0.7640]***	[0.7066]***	[0.6175]***	[0.6491]***
action	-0.0326	0.111	0.0966	0.3549
	[0.2517]	[0.2328]	[0.2034]	[0.2138]*
comedy	0.2155	0.1152	0.1786	0.1813
	[0.2660]	[0.2460]	[0.2150]	[0.2260]
drama	-0.1822	-0.0642	-0.1197	0.0928
	[0.2568]	[0.2375]	[0.2076]	[0.2182]
constant	-16.4619	-15.1312	-16.9498	-48.3785
	[3.5311]***	[3.2659]***	[2.8542]***	[3.0003]***
R2	0.540	0.575	0.644	0.978

427 observations.

control for the time since U.S. release, and it is negative. Thus, Chinese consumers are more likely to see movies released close to their international release. This may be because there is significant marketing close to the release day, or because release delay allows counterfeit versions of the movie to reach consumers. We also find a large positive coefficient for being foreign, but note that this is difficult to interpret because of the separate foreign and domestic month-of-year fixed effects. The choice of which month to exclude from the month-of-year fixed effects can greatly affect the coefficient on foreign in Table 4.

8 Counterfactual Experiments

Since 2012, China has agreed to increase the import quota for foreign movies from 20 to 34 in each year. The import liberalization specifies an extra 14 foreign enhanced movies in 3D or IMAX formats, which are mainly produced in the U.S. This section performs counterfactual experiments to evaluate such 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.

8.1 Welfare Computation

First, we assume that the foreign movies that belong to the extra 14 imported foreign movies are the bottom (or top) 14 foreign "enhanced" movies by box office annually. Consequently, we identify a total of 49 such imported foreign movies, in which there are 14 movies in 2012, 2013, 2014 and 7 movies in the first half-year of 2015. Appendix C lists the movies that belong to this category in our sample.

Second, we take away the movies listed in Appendix C from the choice sets of consumers. We denote the counterfactual choice sets as $\widetilde{C}_{gt}$, $g = 1, .., G_t$. Some choice sets $\widetilde{C}_{gt}$ have the same set of movies as C_{gt} because they do not include any movies listed in Appendix C. For example, $\widetilde{C}_{11} = C_{11}$. But, for the choice sets including the movies listed in Tables 9 and 10, $\widetilde{C}_{gt}$ is a strict subset of C_{gt}. Third, we employ the estimated mean utility and follow Equations 1-4 to compute the market share of each remaining movies week by week, solving for new choice probabilities and transitions.

Fourth, to evaluate the welfare benefit of import liberalization on consumer welfare, we compute the welfare benefit of consumer after including these extra movies in consumers' choice sets as follows

$$\begin{aligned} \%\Delta CS &= \int \frac{CS_i - \widetilde{CS}_i}{\widetilde{CS}_i} dF_i \\ where & \\ & CS_i = \sum_t \sum_{g \in G_t} s_{igt} \ln \left(1 + \sum_{j \in C_{gt}} e^{\delta_{jt} + \mu_{ijt}} \right) \\ & \widetilde{CS}_i = \sum_t \sum_{g \in G_t} \widetilde{s}_{igt} \ln \left(1 + \sum_{j \in \widetilde{C}_{gt}} e^{\delta_{jt} + \mu_{ijt}} \right). \end{aligned} \tag{7}$$

That is, we first compute the welfare for each consumer i facing a choice set $\widetilde{C}_{gt}$ in each week t. Second, we sum up the welfare for each consumer i facing different choice sets according to her probability facing each choice set, $\widetilde{s}_{igt}$. Third, we aggregate consumer welfare for each consumer i over all weeks to obtain $\widetilde{CS}_i$. Finally, we aggregate the consumer welfare over all consumers. We compare the counterfactual consumer welfare to the sample consumer welfare to compute the percentage change in consumer welfare.

To compute the monetary value of welfare benefit from including these extra movies, let α be the marginal utility of money (estimated in the Appendix B. We compute the following expression of compensating variation

$$CV = \int \frac{CS_i - \widetilde{CS}_i}{\alpha} dF_i \tag{8}$$

We compute the total market share of all movies after including those extra movies to examine the extent of consumers switching from the outside option to watching a movie.[15] We then compute the total market share of domestic movies in each week after including those extra movies. The change in total market share of domestic movies shows the business stealing effect of those extra movies from domestic movies. Also, we compute the total market share of remaining foreign movies in each week after including those extra movies. The change in market share of remaining foreign movies shows the business stealing effect of those extra movies from the remaining foreign movies.

8.2 Welfare Estimates

Upper panel of Table 5 reports the results from our counterfactual experiment of adding the bottom 14 foreign enhanced movies. With the import liberalization in 2012, consumer welfare increased by 10.3% (see Column 1). After converting the consumer welfare gain into monetary value, it is equivalent to RMB 188 million, i.e. RMB 0.53 per consumer, per year. Consistently, the market share of all movies increases by 8.33% because consumers enjoy a higher welfare from choosing to watch a movie after including those extra movies. Nonetheless, the welfare effects for producers are heterogeneous. The import liberalization reduces the total market share of competing foreign movies by 2.69% and the total market share of domestic movies by 0.22%. The impact of extra foreign movies on competing foreign movies is larger than that on domestic movies because they are closer substitutes of competing foreign movies as indicated by the positive and significant random coefficient $\sigma_{Foreign}$.

Lower panel of Table 5 reports the results from our counterfactual experiment of adding top 14 foreign enhanced movies. The results reported in Column 1 are consistent with those reported in the upper panel. The main difference between these two sets of results is that the lower panel exhibits

[15] This market share is calculated basing on all the admissions.

Table 5: Welfare and Market Share Effects of the Import Liberalization from 2012

	(1)	(2)	(3)	(4)
Model	**Dynamic**	**Dynamic**	**Static**	**Dynamic**
Consumption Durability	**Yes**	**No**	**No**	**Yes**
Micro-Moments	**No**	**No**	**No**	**Yes**
Panel A: Add Bottom 14 Enhanced movies				
$\%\Delta$*Consumer Welfare*	10.3%	9.01%	9.40%	5.85%
Δ*Annual Consumer Welfare (Million RMB)*	188	181	170	448
$\%\Delta$*Market Share of All Movies*	8.33%	7.37%	8.02%	3.38%
$\%\Delta$*Market Share of Competing Foreign Movies*	−2.69%	−4.13%	−3.42%	−6.42%
$\%\Delta$*Market Share of Domestic Movies*	−0.22%	−0.21%	−0.21%	−5.26%
Panel B: Add Top 14 Enhanced movies				
$\%\Delta$*Consumer Welfare*	40.8%	47.3%	39.9%	22.5%
Δ*Annual Consumer Welfare (Million RMB)*	580	703	565	1492
$\%\Delta$*Market Share of All Movies*	34.8%	37.9%	33.7%	21.6%
$\%\Delta$*Market Share of Competing Foreign Movies*	−9.31%	−18.1%	−12.5%	−22.8%
$\%\Delta$*Market Share of Domestic Movies*	−0.76%	−0.88%	−0.75%	−8.74%

Note: The table shows the results of our counterfactual experiment based on alternative demand specifications. The plug-in estimate of α *is -0.391.*

a larger impact on consumer and produce welfare as the newly included movies have higher mean utility. The import liberalization in 2012 increases consumer welfare by 40.8%, annual consumer welfare by RMB 580 per year and marker share of all movies by 34.8%. The market shares of competing foreign movies and domestic movies reduce by 9.31% and 0.76%, respectively.

8.3 Welfare Estimates without accounting for Consumption Durability

In this sub-section, we present a counterfacutual experiment that eliminates the consumption durability, where consumers is bounded rational in the sense that they consider to watch the movies that they watched previously. We aim to illustrate how the heterogeneous choice sets driven by consumption durability affect the welfare estimates.

In this counterfactual experiment, we compare two situations with all sample movies available. First, we compute consumer welfare and movie admission with our model (column 4 of Table 3) and report the results in Column 1 of Panel A, Table 6. Second, we compute consumer welfare and movie admission with a counterfactual model with the same set of demand estimates, but we do not incorporate consumption durability. In this model, all consumers have the common choice set $\mathbf{C}_t$, which contains all movies available to consumers, in each week t. We report the results in Column 2

Table 6: Welfare and Movie Admission Estimates under Alternative Sets of Available Movies

	(1)	**(2)**	**(3)**	**(4)**	**(2)-(1)**	**(3)-(1)**
Model	**Dynamic**	**Dynamic**	**Static**	**Dynamic**		
Consumption Durability	**Yes**	**No**	**No**	**No**		
Micro-Moments	**No**	**No**	**No**	**Yes**		
Panel A: All Movies						
Annual Consumer Welfare (Util)	782.6	856.2	775.0	3171	73.65	-7.6
Annual Consumer Welfare (RMB)	2001	2190	1982	8111	188.4	-19
Annual Admissions of All Movies	697.8	734.7	697.8	697.8	36.90	0
Annual Admissions of Foreign Movies	309.3	342.5	309.3	309.3	33.17	0
Annual Admissions of Domestic Movies	388.5	392.2	388.5	388.5	3.72	0
Panel B: All Movies except Bottom 14 Enhanced movies						
Annual Consumer Welfare (Util)	709.2	785.4	708.4	2996	76.23	-0.8
Annual Consumer Welfare (RMB)	1814	2009	1812	7663	195	-2
Annual Admissions of All Movies	644.2	684.3	646.0	675.0	40.15	1.8
Annual Admissions of Foreign Movies	254.8	291.3	256.7	264.9	36.47	1.9
Annual Admissions of Domestic Movies	389.4	393.0	389.3	410.1	3.69	-0.1
Panel C: All Movies except Top 14 Enhanced movies						
Annual Consumer Welfare (Util)	555.9	581.2	554.1	2588	25.38	-1.8
Annual Consumer Welfare (RMB)	1422	1487	1417	6619	64.90	-5
Annual Admissions of All Movies	517.6	532.9	522.1	573.9	15.27	4.5
Annual Admissions of Foreign Movies	126.1	137.2	130.7	148.2	11.05	4.6
Annual Admissions of Domestic Movies	391.5	395.7	391.4	425.7	4.23	-0.1

Note: The table shows the results of our counterfactual experiment based on alternative demand specifications. The plug-in estimate of α is -0.391. Unit: Million

of Panel A, Table 6. The change in consumer welfare and movie admissions are reported in columns 5 and 6. We find that the welfare benefit for consumers are overestimated if consumption durability is ignored. It is because the demand model assumes consumers have a wider choice set than they actually do. In turn, it overestimates the movie admission all movies regardless of their country of origin.

We also compute consumer welfare and movie admission with our model and the counterfactual model for the other two sets of movies. One is all movies except the bottom 14 enhanced movies (reported in Panel B, Table 6) and the other is all movies except the top 14 enhanced movies (reported in Panel C, Table 6). The top and bottom movies are determined by total revenue. The consumer welfare and movie admission of our model is smaller than those of the counterfactual model in those two scenarios. However, the differences in consumer welfare and movie admission between our model and the counterfactual model vary across those two scenarios. As a result, the counterfactual model underestimates the consumer welfare gain and biases market share change due to the introduction of bottom 14 enhanced movies (see Column 2 of Panel A, Table 5). However, the counterfactual model overestimates the consumer welfare gain and biases market share change due to the introduction of top 14 enhanced movies (see Column 2 of Panel B, Table 5).

8.4 Welfare Estimates from a Standard BLP

In this sub-section, we present a counterfacutual experiment with a standard BLP model using the parameter estimates reported in Column 1 of Table 3. There are two biases in welfare evaluation when we employ the BLP model. First, the BLP model does not incorporate consumption durability, which potentially overestimates the welfare benefit from extra foreign movies. It is the same issue as we discuss in the previous sub-section. Second, the BLP model underestimates the indirect utility (excluded the error term ε_{ijt}) provided by extra foreign movies. The extra foreign movies do not appear in all choice sets of consumers in our model, whereas they appear in all choice sets of consumers in the BLP model. As a result, the BLP model requires lower indirect utilities of extra foreign movies to match their observed market shares than our model does. It leads to an underestimation of welfare benefit from extra foreign movies.

Results with all movies appear in in Column 3 of Panel A, Table 6. In this model, all consumers have the common choice set C_t, which contains all movies available to consumers, in each week t. We find that this model underestimates the welfare benefit for consumers because it underestimates the indirect utility provided by movies to consumers. Columns 2 and 3 of Panel A, Table 6 provide evidence for the underestimation of indirect utility relative to our model because they use the same model to compute the consumer welfare and movie admission but with different sets of demand estimates. Interestingly, there is no difference in ticket sales computed between our model and this one because both models form the moment conditions by matching predicted market share to observed market share.

We also compute consumer welfare and ticket sales for the other two sets of movies. One is all movies except the bottom 14 enhanced movies (reported in Panel B, Table 6) and the other is all movies except the top 14 enhanced movies (reported in Panel C, Table 6). Although the consumer welfare and ticket sales of our model is higher in those two scenarios, the differences in consumer welfare and movie admission between our model and this one vary across those two scenarios. Finally, this model underestimates the consumer welfare gain and biases market share change due to the introduction of bottom or top 14 enhanced movies (see Column 3 of Panel A-B, Table 6).

8.5 Welfare Estimates from the model with Micro-moments

In this sub-section, we present a counterfacutual experiment with our dynamic model with micro-moments reported in Column 4 of Table 3. We employ that model to compute consumer welfare and movie admission and report the results in Column 4 of Panel A, Table 6. In this model, consumer welfare is higher than that in our benchmark model reported in Column 1 of Panel A, Table 6 because the indirect utility from watching a movie is increased by the consumer heterogeneity σ_C.

We also compute consumer welfare and movie admission using the Model *Dynamic* with micro-moments for the other two sets of movies. Since the consumer welfare of this model is higher than those of Model *Dynamic* without micro-moments, there is a larger increase in monetary value of consumer welfare due to adding the bottom or top 14 enhanced movies. Nonethelesss, the percentage change in utility for those two scenario is smaller because the base utility is higher.

Further, the dynamic model with micro-moments finds that the addition of the bottom or top 14 enhanced movies has a weaker impact on movie admission or market share of all movies because consumers have a higher indirect utility from watching a movies. Consumers' decision to watch a movie relies less on the availability of those enhanced movies. Consistent with the dynamic model, the substitution between foreign movies is stronger than that between foreign and domestic movies.

9 Conclusion

We study demand for movies in China. 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. We propose a dynamic model of consumer demand that captures these features, and we further assume that consumers make decisions myopically.

We apply the model to detailed administrative data on ticket sales drawn from a government agency. Like movie markets in other countries and other cultural goods products, ticket sales in China exhibit a stark decline in sales early after their introduction. Whereas previous research have 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 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 welfare increase from this change, and we find it to be significant. Our results provide a measure of the consumer welfare cost of these types of quotas, hopefully to be accounted for in policies designed to protect domestic culture or local industries.

In addition, we find that there is relatively little substitution between foreign and domestic movies. This result raises questions about the role of the quota as a tool for infant industry protection, as it appears that relaxing the quota would have relatively low impact on domestic film production.

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Appendices

Appendix A Additional Tables

Table 7: Movie characteristics for movies that ever appear in the top 6 for a week

	Unweighted			Admission-Weighted		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	All	Domestic	Foreign	All	Domestic	Foreign
Age (Week)	3.26	3.48	2.95	4.34	4.96	3.66
RunTime (Minute)	108.5	104.8	114.0	118.7	112.3	125.8
Indicator variables:						
IMAX	0.21	0.08	0.40	0.45	0.20	0.72
3D	0.34	0.21	0.54	0.51	0.32	0.72
Foreign	0.41	0	1	0.48	0	1
Action	0.38	0.25	0.58	0.51	0.33	0.71
Comedy	0.28	0.33	0.21	0.26	0.34	0.16
Drama	0.33	0.37	0.26	0.34	0.49	0.19

427 observations, 253 domestic and 174 foreign.

Table 8: Main results using first difference

		BLP	**BLP**	**Dynamic**	**Dynamic**
Non-linear	Constant	0.2728	0.9775***	0.0067	11.2775***
		(0.3127)	(0.2788)	(0.3150)	(1.1150)
	Enhanced(3D or IMAX)	0.3498	0.5171**	0.2235	0.8993***
		(0.5699)	(0.2641)	(0.4207)	(0.7394)
	Foreign	3.1508***	0.7274*	2.8986***	2.2821***
		(0.8511)	(0.4170)	(0.8203)	(1.1263)
Linear	Age	-0.5602***	-0.5471***	-0.4786***	-0.0378
		(0.1682)	(0.1891)	(0.1556)	(0.3279)
	Holiday	0.2951	0.3269	0.3071	1.2632
		(0.3307)	(0.3329)	(0.3432)	(0.8636)
	WeekTrend	0.0048	0.0041	0.0043	0.0252
		(0.1682)	(0.1891)	(0.1556)	(0.3279)
	Consumption Durability	No	No	Yes	Yes
	Micro-moments	No	Yes	No	Yes
	First Difference Moments	Yes	Yes	Yes	Yes
	Differentiation IVs	Yes	Yes	Yes	Yes

671 observations. These models are identical to Table 3 except we use $E[\xi_{jt} - \xi_{jt-1}|Z_{jt}] = 0$.

Appendix B Estimation of Price Coefficient

The estimation of price coefficient is based on a proprietary dataset that matches the information of box office information at theater-movie-day level to movie characteristics.

Market Definition

We expect consumers to watch movies in nearby area, thus we define market as a district. District is the smallest geographical unit that our data can be analyzed. As a matter of fact, we use theater-week fixed effects in our demand estimation, so that the choice of market size becomes irrelevant as long as the market size only varies at the district level.

Box Office

A unique feature of our data is that the price has variations at movie-theater-day level. Here, we first illustrate that prices are different across movies with Figure 3. It shows that there are six screens in the theater, in which Screen 1 and 2 show the same movies. Usually, prices range between RMB 40 and RMB 50 for showing in the afternoon. Prices range between RMB 60 and RMB 100 for shows in the evening. The prices are determined by the demand of each movie at each point of time. As a result, there are price variations of a movie across screens, theaters and days.

Our data source obtains box office and ticket sold of all movies shown in each theater on each day. The sample of box office contains 947,108 observations at the level of theater-movie-day. It contains 98 movies displayed in February and March of 2013. The movies were shown in 3,075 theaters located in 1,382 districts of 325 cities across all Chinese provinces. For each observation, we have the information of box office, admission and number of screens shown of a movie in a theater on a specific day. We compute average price as the ratio of box office to admission and age as the day since its first date of release in each theater, which vary at movie-theater-day level.

On each day, on average, a movie is shown in 4 screens of a theater, is priced at RMB 32, and is watched by 104 consumers. They have shown for 8.83 days, on average.

Movie Characteristics

We construct nine variables on movie characteristics based on the website Douban, which is the most popular website on movie information in China.[16] We define dummy variables Foreign, 3D, Comedy, Action and Sequel for whether a movie is foreign, three-dimensional, comedy, action, sequel to movies shown before, respectively. We define Rater as the number of online raters (in thousands) for each movie as an measure of popularity. Although this measure includes feedback after the release of movies, this measure is mostly determined during the movies' run. To measure the quality of a movie, we construct two variables, namely Director and Star. Director is computed as the average rating of a director's top three movies, and Star is computed as the average of the average rating of the top three movies casted by the movie's top four leading actors and actresses. Further, we construct the variable Budget, which takes 1 if a film's budget exceeds RMB 80 million, and zero otherwise. For Chinese movies, we obtain this information from news on movie press conferences and http://baike.baidu.com, while for foreign movies, we obtain the estimated budget from www.imdb.com, and then convert to RMB using the average USD-RMB exchange rate in 2013.

For our sample movies, 31% is comedy, 27% is action, 19% is foreign, 10% is 3D, 19% is sequels, and 31% with a large budget. The number of raters varies from 0 to 376,058. Director varies from 0 to 8.97 and Star varies 0 to 8.59.

Demand Model

We use whether a movie belongs to the genre of comedy or not as the nesting structure (Moul, 2007). We estimate the following nested logit model for movie j in theater c at day t as follows:

$$\ln(\frac{s_{jcmt}}{s_{0cmt}}) \quad = \quad \alpha p_{jcmt} + \sigma \ln(s_{jcmt|g}) + x_{jcmt}\beta + \xi_{Age} + \xi_{cw} + \xi_{day} + \xi_{jcmt}$$

The indices j, c, m and t denote movie, theater, market and day, respectively. The variable of interest is p_{jcmt}, which is the average price of movie j shown in theater c in day t. There is a K-dimensional row vector of observed characteristics with variations at theater-movie-day and movie level. The variable at theater-movie-day level is screening of movie j shown in theater c in day t, and the variables at movie level are Foreign, 3D, Action, Comedy, Sequel, Budget, Rater, Director and Star. We also control for age, theater-week and day of the week fixed effects.

[16] http://movie.douban.com

We do not incorporate consumption durability in this specification for two reasons. First, Table 3 reports that the coefficients of most variables do not change substantially between dynamic and static demand models if there is no micro-moment. Second, in principle, the sets of available movies across districts are different from each other. Thus, there is a need to model the dynamics of chocie set in each district. This model extension is beyond the scope of our paper.

Identification and Estimation

We discuss the identification of α, β_{Screen} and σ, which are potentially subject to endogeneity. Our identification relies on the cross-sectional variation across movies within a theater and across movies shown in other theaters within a market.

Since theaters set prices for each movie on each day, we assume that a theater acts as a multi-products firm to set prices and screens of various movies maximizing profit. The pricing and screening decisions of a movie depend on the exogenous attributes of other movies shown in the same theater. Further, since their attributes are set previously, they are uncorrelated with unobserved attributes of the focal movie. This identification assumption suggests that the attributes of other movies shown in the same theater can be used as instruments because they affect the price and screen of the focal movie through the theaters' decisions. Therefore, we construct the first set of instruments (IV-Set 1) with the average of rival movies' attributes shown in the same theater on the same day of the focal movie. We take averages on each of the following nine variables, namely Comedy, Action, Foreign, 3D, Budget, Sequel, Rater, Director and Star, over movies in the set of rival movies with the same genre shown in the same theater. There are nine potential instruments constructed for each genre. This set of potential instruments varies at movie-theater-day level and takes the form below:

$$IV1_{jcmt} \quad = \quad Mean_{k \neq j, k \in g}(x_{kcmt}) \qquad g = \{Comedy, Action\}$$

Turning to the nesting parameter, we rely on the exogenous attributes of movies shown in other theaters in the same market, which are associated with competition and therefore should be related to the within-group market share, the endogenous variable. Further, since their attributes are also set previously, they are uncorrelated with unobserved attributes of the focal movie. This identification assumption suggests that the attributes of movies shown in the other theaters in the same market can be used as instruments because they affect the within-market share of the focal movie through competition. Therefore, we construct the second set of intruments (IV-Set 2) with the average movie attributes shown in other theaters. There are nine potential instruments constructed for each genre and all movies. This set of potential instruments varies at theater-day level and takes the following form below.

$$IV2_{cmt} = Mean_{k\in g,h\neq c,h\in m}(x_{khmt}) \qquad g = \{All, Comedy, Action\}$$

Although those movie attributes may seem endogenous if high quality movies are released in together in high-demand weeks, we capture those factor with theater-week fixed effects and day of the week fixed effects.

We estimate the demand system with the instrumental variable method. In practice, we do not use all potential instrumental variables because not all of them pass the over-idenfication test. We employ the subset of IV-Set 1 with Action, Budget, Director and Star to identify the parameters of price and screen. We employ the subset of IV-Set 2 with Star of all rival movies and 3D of all rival comedy movies to identify the nesting parameter.

Results

Table A1 reports the demand parameters. The price coefficient is negative and significant at -0.391. About 0.01% of observations with price elasticity smaller than one, and the average price elasticity is about 16.5. The coefficient of within-group market share is positive and significant at 0.311, which suggests that movies within the same group are more substitutable than movies across groups. Foreign, 3D and action movies, and movies with more screens, more reputable director and more popular stars have a higher demand, whereas comedy, sequal and large-budget movies have a lower demand.

Table A1: Nested Logit Model with Disaggregate Data			
	(1)		(2)
Varibles	**Coefficient**	**Varibles**	**Coefficient**
Price	-0.391^{***} [0.024]	*Age FE*	*Yes*
Screen	0.474^{***} [0.025]	*Theater-Week FE*	*Yes*
$ln(s_{jcmt\|g})$	0.311^{***} [0.044]	*Day of the Week FE*	*Yes*
Foreign	0.087^{***} [0.015]	*Observations*	946,721
3D	2.571^{***} [0.159]	**Diagnosis**	**P-value**
Action	0.426^{***} [0.027]	*Under-identification*	0.000
Comedy	-0.683^{***} [0.031]	*Weak-identification*	< 0.05
Sequel	-0.673^{***} [0.018]	*J-Stat*	0.338
Budget	-0.359^{***} [0.018]		
Rater	0.000 [0.000]		
Director	0.022^{***} [0.002]		
Star	0.069^{***} [0.006]		

Data variation at the theater-movie-day level. The dependent vaiable is $ln(s_{jcmt}/s_{0cmt})$. The heteroskedasticity-robust standard errors are in parentheses. ***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level.

Appendix C The List of Imported Enhanced Movies

This appendix reports the list of extra 14 enhanced movies imported from 2012 to 2015-June.

Table 9: The Extra 14 ”Enhanced” Movies Imported from 2012-2015 June (from the bottom)

Year	**Name**	**Country**	**Total Admissions**
2012	Hugo	USA	329117
2012	Brave	USA	499413
2012	Rise of the Guardians	USA	712414
2012	The Pirates! In an Adventure with Scientists!	UK USA	990433
2012	Happy Feet Two	Australia	1278797
2012	Wreck-It Ralph	USA	1612182
2012	2012	USA Canada	3637135
2012	Wrath of the Titans	USA	3872170
2012	Madagascar 3	USA	4639001
2012	The Hunger Games	USA	4663878
2012	Prometheus	USA UK	5350118
2012	John Carter	USA	6478148
2012	The Amazing Spider-Man	USA	7526159
2012	The Dark Knight Rises	USA UK	8918613
2013	Jack the Giant Slayer	USA	1308871
2013	Epic	USA	1445346
2013	Stalingrad	Russia	1724534
2013	The Great Gatsby	USA Australia	1903653
2013	The Lone Ranger	USA	2237816
2013	Turbo	USA	3136888
2013	The Smurfs 2	USA	3401186
2013	Oz: The Great and Powerful	USA	4018735
2013	Oblivion	USA	4209237
2013	Elysium	USA	4489111
2013	White House Down	USA	5046894
2013	Monsters University	USA	5508499
2013	After Earth	USA	6451851
2013	The Wolverine	USA UK	6528809
2014	Ice Age: The Meltdown	USA	814261
2014	Hercules	USA	1881858
2014	Transcendence	USA UK Mainland	2913717
2014	Mr. Peabody & Sherman	USA	3434888
2014	Ender's Game	USA	3985895
2014	The Maze Runner	USA Canada UK	4727580
2014	Jack Ryan: Shadow Recruit	USA Russia	4854034
2014	Rio 2	USA	6585903
2014	Penguins of Madagascar	USA	7245766
2014	Maleficent	USA UK	7320639
2014	Frozen	USA	7497391
2014	RoboCop	USA	8313051
2014	Teenage Mutant Ninja Turtles	USA	1.04E+07
2014	Need for Speed	USA UK Ireland Phllipines	1.05E+07
2015	Insurgent	USA	2765940
2015	Tomorrowland	USA Spain	3503748
2015	Seventh Son	Mainland USA UK Canada	4395115
2015	Home	USA	4493869
2015	Taken 3	USA France	5036256
2015	The Hunger Games: Mockingjay - Part 1	USA	5273498
2015	Jupiter Ascending	USA UK	7475382

Table 10: The Extra 14 “Enhanced” Movies Imported from 2012-2015 June (from the top)

Year	Name	Country	Total Admissions
2012	Titanic(3D)	USA	2.11E+07
2012	Mission: Impossible - Ghost Protocol	USA	1.85E+07
2012	Life of Pi	USA UK Canada TW	1.45E+07
2012	The Avengers	USA	1.35E+07
2012	Men in Black III	USA	1.21E+07
2012	Ice Age: Continental Drift	USA	1.17E+07
2012	Battleship	USA	9016784
2012	Journey 2: The Mysterious Island	USA	8936251
2012	The Dark Knight Rises	USA UK	8918613
2012	The Amazing Spider-Man	USA	7526159
2012	John Carter	USA	6478148
2012	Prometheus	USA UK	5350118
2012	The Hunger Games	USA	4663878
2012	Madagascar 3	USA	4639001
2013	Pacific Rim	USA	1.70E+07
2013	Furious 6	USA	1.23E+07
2013	The Croods	USA	1.07E+07
2013	Skyfall	UK USA	1.05E+07
2013	Gravity	USA UK	1.04E+07
2013	Man of Steel	USA UK	9528079
2013	Jurassic Park(3D)	USA	8921621
2013	Thor: The Dark World	USA	8747259
2013	Star Trek Into Darkness	USA	8546433
2013	G.I. Joe: Retaliation	USA	8426234
2013	The Hobbit: An Unexpected Journey	USA New Zealand	7023161
2013	The Wolverine	USA UK	6528809
2013	After Earth	USA	6451851
2013	Monsters University	USA	5508499
2014	Transformers: Age of Extinction	USA Mainland	4.74E+07
2014	Interstellar	USA UK	2.09E+07
2014	X-Men: Days of Future Past	USA UK	1.93E+07
2014	Dawn of the Planet of the Apes	USA	1.92E+07
2014	Captain America: The Winter Soldier	USA	1.83E+07
2014	Guardians of the Galaxy	USA UK	1.52E+07
2014	The Amazing Spider-Man 2	USA	1.47E+07
2014	Godzilla	USA Japan	1.26E+07
2014	The Hobbit: The Desolation of Smaug	USA New Zealand	1.13E+07
2014	Edge of Tomorrow	USA Canada	1.08E+07
2014	How to Train Your Dragon 2	USA	1.07E+07
2014	Need for Speed	USA UK Ireland Phllipines	1.05E+07
2014	Teenage Mutant Ninja Turtles	USA	1.04E+07
2014	RoboCop	USA	8313051
2015	Furious 7	USA Mainland Japan	6.25E+07
2015	Avengers: Age of Ultron	USA	3.66E+07
2015	The Hobbit: The Battle of the Five Armies	USA New Zealand	1.88E+07
2015	San Andreas	USA Australia	1.67E+07
2015	Big Hero 6	USA	1.42E+07
2015	Kingsman: The Secret Service	UK USA	1.42E+07
2015	Cinderella	USA UK	1.38E+07