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

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Abstract

We evaluate 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 5.3% 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

*We thanks seminar audiences at BU, Carnegie Mellon, Wisconsin, Princeton and Stanford.

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. 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 typically estimated demand for these products with static models that contain an age profile, such as a set of dummy variables for age. Examples are Einav (2007) in movies and Hendricks & Sorensen (2009) for album sales. While this approach 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 this decline in sales is better 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 see no more than one movie per week, reflecting consumers' limited time for attending cinemas.

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

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 decisions over which movies to see. In estimation, we find the level of unobserved quality for each movie-week that rationalizes the observed market share, and form a GMM estimator around this term. For much of the paper, we assume that consumers choose myopically which movie to see. Under this assumption, consumers do not account for how seeing a movie today affects future outcomes. We also consider a model of perfect foresight but we show that myopia fits the data better.

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. Forcing our model to match this "micro-moment" significantly impacts the results.

Although the drop-off in sales that movies experience from week-to-week is extreme, our results show that it can be entirely explained by consumption durability. In particular, we estimate a traditional static random coefficients logit model with a reduced-form age profile and find that 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 with the age profile coefficients reduces the importance of the age profile, and when we impose the micro-moment, we find that the coefficient on the age profile is insignificantly different from zero and precisely estimated. We also find substantial heterogeneity in preferences for foreign movies, suggesting that foreign and domestic movies are not close substitutes.

Because the liberalization going from 20 to 34 movies takes place just before the start of our data, we cannot evaluate the market before the policy change. Rather, we employ our structural model to determine outcomes in the counterfactual scenario. In order to determine which of the 34 movies get dropped when switching to 20 movies, we estimate a simple probit model of the decision-making by the Chinese government over which movies will be chosen. We find that box office revenue is an important determinant, but the government also considers other criteria such as the rating (PG, R).

We use the results of this estimation to generate a distribution of possible movies in China if there was no liberalization. We show that consumer welfare increases by 5.3% due to the 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. This result raises questions for the value of infant industry policies, as substitution between the foreign and domestic products is limited. In addition, we find that if the consumption durability in preferences is ignored, the welfare benefit for consumers is overestimated and the difference in the business stealing effect of foreign movies on competing foreign movies and domestic movies is 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 static economic outcomes, such as consumer welfare. Thus, for a policy-maker considering such cultural or industry protection, we provide a measure of the economic cost. Note that in our counterfactual calculations, we assume the set of movies does not change. However, some research and popular press argue that Chinese policies 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 it may be important.

The remainder of the paper is organized as follows: The next section reviews the literature. Section 3 provides institutional background for the Chinese movie industry and our issues. Section 4 describes the data and descriptive statistics. Section 5 discusses the structural demand model. Section 6 presents the estimation procedures. Sections 7 and 8 report the empirical results and the results of the counterfactual experiments respectively, and are followed by a concluding section.

2 Literature

Our work contributes to a growing empirical literature on trade in motion pictures. 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 model of trade with heterogeneous firms 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. Ferreira, Petrin & Waldfogel (2013) estimate a structural model to evaluate the role of product quality in determining gains from trade in motion pictures. 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 a demand system for 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 the 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 Tuesdays.

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

Third, we add to the literature on modelling heterogeneous choice sets across consumers in demand estimation. 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. Conlon & Mortimer (2013) use an expectation-maximization (EM) algorithm to account for the missing data on product availability faced by each customer. 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. 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. Honka, Hortaçsu & Vitorino (2017) study demand for banks with survey data on consumer consideration sets. Draganska & Klapper (2011) also incorporate information on choice sets from a consumer survey. Barroso & Llobet (2012) model the probability of consumer awareness of a brand as a function of the history of advertising expenditures. Bruno & Vilcassim (2008) show that demand estimates are biased if varying product availability across consumers is ignored.

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, and 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] Some observers 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. A separate reason to restrict the entry of foreign goods is to support local producers, so-called infant industry protection. See Greenwald & Stiglitz (2006) and the literature that follows. Our result about limited substitute between foreign and domestic movies

[2] A leading example is Krugman (1979). The welfare gain from more product variety from trade appears quantitatively large for manufacturing sectors. See Feenstra (1994), Broda & Weinstein (2006), Blonigen & Soderbery (2010) and Sheu (2014).

suggests this concern is of limited importance. [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 the Uruguay Round of the GATS, which ended in 1994, and the UNESCO Convention on the Protection and Promotion of the Diversity of Cultural Expressions (in particular Articles 6 and 8). There is particular concern for U.S. movies as U.S. producers increasingly rely on foreign revenues and U.S. movies dominate the market share in many foreign countries.[5]

3 Institutional Background

This section discusses Chinese import policies for foreign movies. Until 1994, foreign movies were purchased mainly on a flat-fee basis. Between 1978-1993, the China Film Group was the only authorized agent to import and distribute these films. In each year, the China Film Group spent about USD $1 million to import about 30 foreign movies, and each foreign movie was purchased at about USD $30,000. As a result, the imported movies were usually considered "outdated and low-grade but cheap."[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 the WTO in 2001. Under the agreement, China increased the quota for revenue-sharing movies to 20. In order to diversify the imported films, in 2004, the State Administration of Radio, Film and Television (SARFT) reserved about six slots for non-U.S. movies.

[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 theory and evidence to support that trade integration leads to convergence in cultural values across countries.

[4] Many countries impose trade barriers on foreign 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 are 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 revenue in 19 European countries over the period 1995-2004. According to a report by the Motion Picture Association of America, the global box office for U.S. movies released in each country around the world reached $USD 36.4 billion in 2014, of which, $USD 26.0 billion was acquired from the international box office. Source: http://www.mpaa.org/wp-content/uploads/2015/03/MPAA-Theatrical-Market-Statistics-2014.pdf

[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.

China has become the largest foreign market for U.S. movies as the annual box office in China has been accelerating faster than 20% annually during the past decade. Specifically, the box office of U.S. movies in China was at $USD 4.8 billion in 2014. In February 2012, China agreed to significantly increase market access for U.S. movies in order to resolve a WTO dispute that the U.S. had filed in 2007. With immediate effect, China enlarged its quota for revenue sharing imports of foreign films from 20 to 34 per year. The extra 14 films were specified to be in 3D or IMAX formats. In addition, revenue sharing was set at 25% of box office revenues instead of the previous rate of 13-17%. All of the 34 revenue-sharing movies and all movies imported under the fixed fee plan are imported and distributed by the China Film Group, and some are co-distributed by Huaxia, which is a state-owned enterprise established in 2003. There is no specific quota to import movies on a flat-fee basis, and it is usually 20-30 per year.[7]

A third option for movies to be distributed in China is for them to be co-produced. In a co-production agreement, a foreign producer collaborates with a Chinese investor. In addition, the movie must be sufficiently oriented towards the Chinese market, which SARFT interprets to mean that the movie must feature Chinese actors, Chinese settings and Chinese themes. Foreign producers obtain attractive revenue-sharing terms (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. The movie *Looper* had a similar experience. A successfully co-produced movie was *The Great Wall*. There were only 14 co-production movies from the U.S. over 2009-2015. [8]

All foreign films face censorship by SARFT, 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

[7] A small number of top movies have entered by fixed fee in recent years. The Appendix provides a list of top movies and their outcomes in China, whether imported by revenue-sharing, fixed fee or not at all. It does not appear that top movies that are not selected for revenue-sharing simply opt for fixed fee instead. Rather, these movies are never released in China.

[8] http://www.sanqin.com/2017/0418/292368.shtml

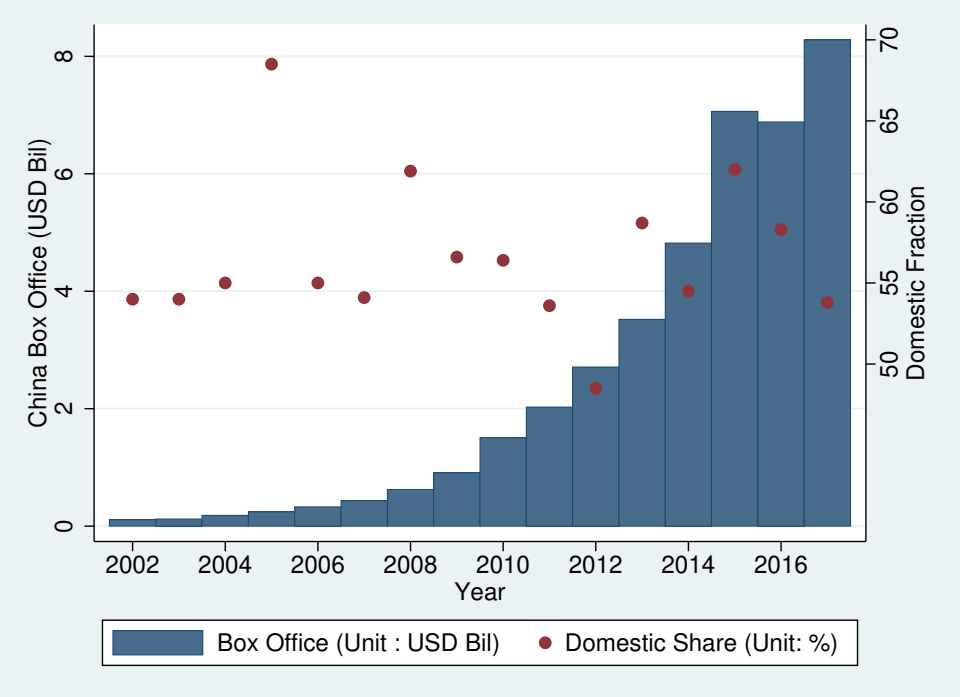


Figure 1: Chinese box office revenue and domestic share.

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."

Figure 1 depicts that the share of domestic movies at the box office remained at about 55% over a long period, 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 on pre-2012 data in the rest of the paper, as we view it as less reliable. However, this result foreshadows our finding that there is significant differentiation between foreign and domestic movies.

Similar to other markets, price variation in the Chinese movie market is limited. While prices vary by time of day, day of week and theater within a cinema, they do not tend to vary by movie, and which movie appears in which theater is a choice made by the cinema.[9] Similar to Einav

[9]Orbach & Einav (2007) discuss this issue in the U.S., which exhibits constant prices not only across movies but also across time of day and week.

(2007) and others in this literature, we do not attempt to estimate a price coefficient. We will capture the mean level of movie utility with a movie fixed effect, and present counterfactual results as percentage changes from the observed outcome. We compute a dollar value as a "back-of-the-envelope" calculation rather than as part of our formal estimation.

4 Data

The empirical analysis is based on a novel dataset from SARFT of China. The data contain information on box office revenue, number of tickets sold, and number of showing screens of all 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 genre, run-time, the release date, whether a movie is in 3D or IMAX format and whether a movie is imported.

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, which 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 represents 70% of foreign ticket sales. Foreign movies are more likely to be action movies and less likely to be comedies or dramas, and this is even more extreme when we weight by market share.[10]

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

[10]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.

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.

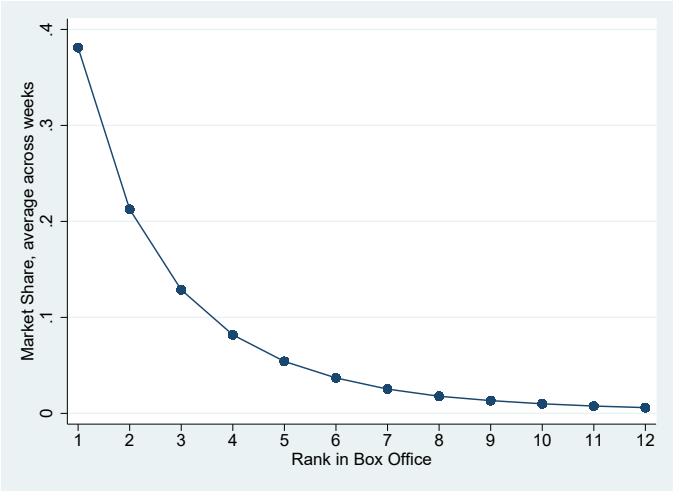


Figure 2: Average share of ticket sales by weekly sales rank

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 than 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

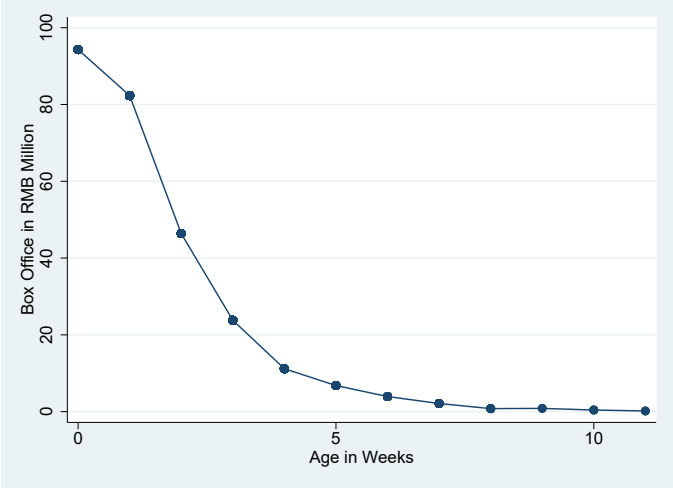


Figure 3: Age profile of movie revenue

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.[11] The result appears in Figure 3. Predicted sales start around 95 million in the first week and drop to less than 50 million by week 3, and are under 10 million by week 5, with continued declines afterwards.[12]

4.1 Time varying variables

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

We further include a linear time trend in the month to capture the dramatic increase in the Chinese movie market 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 anecdotal evidence that SARFT's treatment of foreign movies varies by season.

[11] 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).

[12] 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.

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	89.6	6.1	68.3	98.8
Other domestic movies	7.0	4.7	0.3	29.9
Other foreign movies	2.9	2.8	0.1	14.7
Market Share (%, out of potential market)				
Average over top six	0.5	0.6	0.0	8.5

1,448 observations

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 six *named* movies in each week, in addition to a generic foreign and generic domestic outside option. We assume consumers can select among the six movies with the highest market share in each week.

There appears to be little gain to adding more named movies to the choice set. We calculate the box office share of the top 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 1,464 observations, which consists of the 6 top movies in each week and the two generic options (one foreign and one domestic) for 183 weeks. [13] 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 7%. 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 8 in Appendix A.

A potentially restrictive assumption in our model is that agents are myopic. While we consider a dynamic model for robustness, we believe the myopic model is reasonable. An important way in

[13] For 16 weeks, we observe zero ticket sales for the foreign generic option, and we assume there was 1 ticket sold.

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. In contrast, 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) in the U.S. Because movie theatres are often located in urban areas, we employ the population in an urban area instead of total population to measure the market size. We use the annual figure of total urban population in the year 2011, i.e. 354.256 million people, to measure the market size, and this size is denoted M. The population data is obtained from the China Statistical Yearbook. To compute 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, $s_{jt}^{\texttt{data}} = q_{jt}/M$ is the market share of movie j. The outside good is defined as not watching a movie in a theater. The average market share of a movie is 0.5%, whereas the outside option averages 96%.

4.3 Data for Micro-moments

We employ the summary statistics reported from a survey conducted by a Chinese consulting firm 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% 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 for now that consumers make their current choice myopically. This assumption might be problematic in some performance markets, but we believe it is reasonable in our setting. We 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 four time periods (weeks). The top row reports the time period and the set of exogenously available movies. For this example, we assume only two movies are available rather than six. In the first three periods, movies A and B are available. In the fourth period, movie A drops out, and movie C arrives. A consumer starts in period 1 having not seen any movies, and so starts with the choice set $\{A, B\}$. The three arrows from $\{A, B\}$ represent the three choices the consumer may make: the consumer can choose to see A, B or choose not to see a movie.

The exogenously available movies stay the same in period 2, so consumers will face one of three choice sets in period 2 depending on what they choose in period 1. Consumers that saw A are in the set $\{B\}$ in period 2, consumers that saw B are in the set $\{A\}$, and consumers that did not see a movie are again in $\{A, B\}$. Consumers can reach one 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

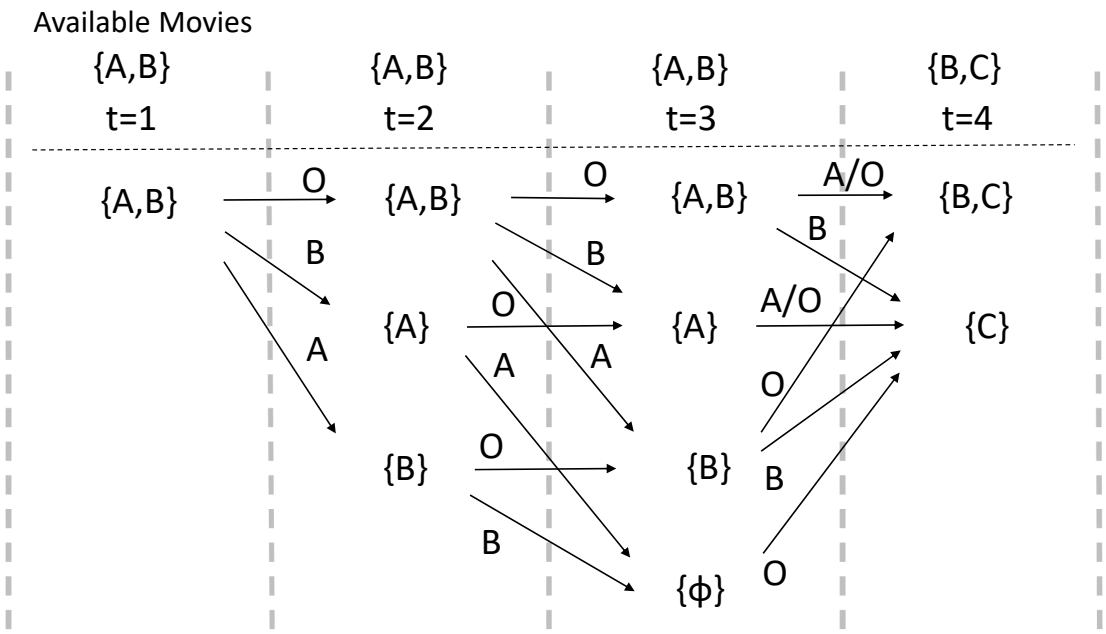


Figure 4: Simplified representation of the demand model.

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 problem. Also, there are typically multiple paths by which a consumer may reach any given choice set. For instance, there are four arrows pointing to set $\{C\}$ in period 4, and there are multiple ways to reach each of the states that can lead to $\{C\}$.

In estimation, we assume a population of consumers starts in the first choice set in period 1, and then follows choice probabilities across each option (each arrow in Figure 4). Thus, we compute the share of the population that lands in each state in each period. Note that there is no simulation in this 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, $J = 427$. A subset of six of these movies is available in any given period. Denote the set of movies available in t as $\mathbf{C}_t$. We assume that $\mathbf{C}_t$ follows an exogenous process. The set of 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. It must be that $C\left(H_{it}, \mathbf{C_t}\right) \in \mathcal{C}_t$, so $C\left(H_{it}, \mathbf{C_t}\right)$ must be equal to an element C_{gt}.

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

solves:

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

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 characteristics reflect both movie characteristics, such whether a movie is foreign, and calendar characteristics such as the month of the year and whether it is a holiday weekend. 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 $\theta = \{\beta, \{\sigma_k\}_{k=1,\ldots,K}\}$. 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:

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

In Figure 4, $P_{ijt}(C_{gt})$ is the probability of being on each arrow leading from a given choice set.

As is clear from Figure 4, there may be multiple choices that lead from one choice set to another. Let $B_{gg't}$ be the set of products j such that choosing one leads from choice set g in period t to choice

set g' in period $t+1$. The set $B_{gg't}$ accounts for the deletion of j from C_{gt}, and any products that enter or exit $\mathbf{C_t}$:

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

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:

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

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.[14] In this sub-section, we provide a model that allows for forward-looking behavior. We assume 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 particular movies are arriving or leaving.

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

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 the same whether we use myopic or 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:

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

Here, we write $\tilde{g}'$ in the denominator to distinguish it from g' in the numerator, as different choices will lead the consumer to different choice sets. The rest of the model, such as the determination of s_{igt}, remains the same. We can estimate this model by backward induction. For a given guess of the parameters, we can calculate the utility and probability of each choice in the last period. We can then calculate the utility and probabilities of each choice in period $T-1$, accounting for the continuation value associated with each choice. We proceed backwards through each period sequentially.

We wish to estimate the 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. Perfect foresight models generate this kind of variation naturally. In our setting, movies that arrive or leave in future periods affect the future payoff but not otherwise the current payoffs.

In considering the discount rate, it is important to recognize that the discount rate we estimate is unlikely to correspond to the time value of money. The discount rate in our model reflects how

consumers adjust movie-going this week to changes in movie availability 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 (as in Gowrisankaran & Rysman, 2012) 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 with choice set $\{B\}$ to choose between both A and B, but assign A some reduction in utility, presumably a parameter to be estimated. We could assume that choosing to see a move that a consumer already say does not affect choice sets. This extension does not affect the overall dynamic process in our model, and thus would not be more difficult to estimate. This approach would be appealing if we had data on how often consumers saw individual movies, and the data showed that multiple viewings were important.

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 approach to the aggregate sales data, and then discuss micromoments.

6.1 Aggregate data 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 $s = 1, \ldots, S$.[15]

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 C_{gt} and movie j in the model, as described above in Equations 1 and 3. We do so separately for each draw of ν^s. We then replace Equation 4 with the discrete equivalent. In order to emphasize the dependence of the predicted market share on parameters and mean utilities, we write $\widehat{s}_{jt}(\theta, \delta)$, where $\boldsymbol{\delta}$ is the vector of elements δ_{jt}.

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

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

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 $\boldsymbol{\delta}$, compute $\boldsymbol{\delta}'$ and iterate until convergence. Note that the theorem in Berry (1994) that the fixed point equation is a contraction mapping does not necessarily apply to dynamic models. As in Gowrisankaran & Rysman (2012), our method is appropriate only under the assumption that the solution is unique. We have not experienced any problems with multiple solutions in practice.

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

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

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

and we assume a set of instrumental variables Z_{jt} is exogenous such that $E[m_1(\theta)] = E[\xi_{jt}|Z_{jt}] = 0$. We estimate via two-step GMM. We always assume that in the first period of the data, no consumers have seen a movie. In order to address this initial conditions problem, we drop the first four weeks of data in forming our moments. As there is frequent turnover in which movies are available, the "burn-in" period before consumers are reasonably distributed across choice sets is relatively short. As a result of dropping these observations, the tables of results in Section 7 list 1,432 observations rather than 1,464.

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 research 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, and so will be high only for enhanced movies.

6.2 Incorporating the Micro-moments

To improve the estimation, we incorporate two micro-moment conditions based on the survey data. Specifically, we use the information that, conditional on watching at least one movie, the probability of watching 1-3 movies is 23.5% and the probability of watching 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 $n_{it+1} = n_{it} + 1$. 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. We assume that n_{it} takes on a maximum of 7 to reflect our survey data, although a consumer with $n_{it} = 7$ can continue to go the movies.

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 $n = 0, 1, .., 6, 7+$. Conditional on watching at least one movie, the probability of watching 1-3 movies is then $P_{i1-3} = \sum_{n=1}^{3} P_{in} / \sum_{n=1}^{7+} P_{in}$ and the probability of seeing 4-6 movies is $P_{i4-6} = \sum_{n=4}^{6} P_{in} / \sum_{n=1}^{7+} P_{in}$. We take the average of P_{i1-3} and P_{i4-6}, i.e. $P_{1-3} = \frac{1}{S}\sum_{i=1}^{S} P_{i1-3}$ and $P_{4-6} = \frac{1}{S}\sum_{i=1}^{S} P_{i4-6}$. We postulate the micro-moment conditions as follows

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

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

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

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 $\min_\theta E[m(\theta)]'\Omega E[m(\theta)]$. We follow the two-step proce-

dure for 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.

7 Empirical Results

This section discusses the empirical results obtained from the demand model described in the previous section. Column 1 of Table 3 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 age trend is almost unchanged. The static model has no mechanism for matching the micromoment and so it does not qualitatively affect the results (although the coefficient on *foreign* drops substantially).

Column 3 estimates our dynamic model, in particular the model with myopic consumers who experience consumption durability. The coefficient on *age* drops almost in half. 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,

Table 3: Demand Estimates

Parameters		**Static**	**Static**	**Dynamic**	**Dynamic**	**Dynamic**
Non-linear	Constant	1.645	0.994	2.427	10.526	14.634
		(0.132)	(0.015)	(0.122)	(0.138)	(0.083)
	Enhanced(3D or IMAX)	0.881	0.353	0.038	1.531	1.203
		(0.169)	(0.165)	(0.044)	(0.097)	(0.057)
	Foreign	3.144	0.013	4.678	3.343	5.476
		(0.072)	(0.019)	(0.078)	(0.100)	(0.070)
	Discount Rate					
Linear	Age	-0.607	-0.545	-0.312	0.006	0.060
		(0.056)	(0.062)	(0.069)	(0.076)	(0.089)
	Holiday	0.405	0.404	0.450	1.300	1.244
		(0.388)	(0.415)	(0.387)	(0.401)	(0.464)
	Consumption Durability	No	No	Yes	Yes	Yes
	Micro-moments	No	Yes	No	Yes	Yes
	Forward Looking	No	No	No	No	No
	Importance Sampling	No	No	No	No	Yes

1,432 observations. Specifications include movie fixed effects, and month-of-year dummies separately for foreign and domestic movies.

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 to create the drop-off in sales with age. 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.[16]

In thinking about identification, note that consumption durability does not necessarily imply that the *age* coefficient would be zero. Consumption durability implies demand will fall with time, but observed sales could be higher or lower than consumption durability would predict. For instance, the *age* coefficient in column 3 is negative. However, when the micromoments are imposed, we see that coefficient on *age* driven to zero.

In Column 4, the random coefficient parameters on movies *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.

[16]The age trend is not separately identified from movie fixed effects and a week time trend, which is one reason we use a month trend. The results are robust to alternative treatments of the calendar time effects, such as replacing it with year dummies.

To establish robustness, we consider several alternative models. 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 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. The effect of changing from levels to differences is muted in our case because we have product fixed effects in the levels model. It is analogous to switching from fixed effects to first differences in a linear panel data estimation setting, which are asymptotically identical when using a flexible weighting matrix, such as we do. Not surprisingly, we find similar results. These appear in the Table 9 in Appendix A.

We also 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 of λ, we estimate the rest of the parameters as above. We find that the objective function is minimized at a discount rate of $\lambda = 0$.[17] Intuitively, consumers do not respond this week to the future availability of movies, which we believe is a reasonable result. Thus, our assumption of myopia fits the data well. Parameters are naturally the same as in column 4 but standard errors change because of the extra parameter.[18] This result appear in Table 9 in Appendix A.

Interestingly, for higher values of the discount rate (that is, more utility weight on the continuation value) we find a more negative age profile. For instance, when the discount rate λ is set to 0.5, we find the age profile coefficient increases in magnitude to -0.19 and is statistically significant. Intuitively, the model finds that forward-looking consumers see movies earlier because consumers anticipate that a movie will decline in value. Whereas consumption durability reduces the importance of the age profile, forward-looking behavior can increase the importance. Given our estimate of λ, this point is of only academic interest in our application, so we put this result in the Appendix (Appendix A, Table 9), but it may be interesting for other work on performance goods.

[17] Around $\lambda = 0$, we consider increments in the grid search as low as 5×10^{-5}.

[18] We find a standard deviation of λ of 0.023. 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

	Static	**Static**	**Dynamic**	**Dyanamic**
Enhanced	0.122	0.320	0.739	1.082
	(0.277)	(0.247)	(0.184)	(0.220)
Foreign	-0.484	-0.180	-0.854	-0.298
	(0.300)	(0.268)	(0.199)	(0.238)
Days since US release	-0.006	-0.005	-0.011	-0.013
	(0.004)	(0.004)	(0.003)	(0.004)
ln(runtime)	2.711	2.547	3.336	4.964
	(0.814)	(0.726)	(0.540)	(0.646)
Action	0.192	0.166	0.303	0.407
	(0.267)	(0.238)	(0.177)	(0.212)
Comedy	0.158	0.171	0.205	0.311
	(0.284)	(0.253)	(0.188)	(0.225)
Drama	-0.087	-0.064	-0.079	0.074
	(0.273)	(0.244)	(0.181)	(0.217)
Constant	-12.563	-12.019	-15.602	-23.777
	(3.759)	(3.355)	(2.495)	(2.986)

418 observations. The columns are defined analogously to Table 3. The first two columns implement a static demand model as BLP. The next two columns add consumption durability. The second and fourth columns implement micromoments.

As an additional robustness check on this issue, we estimate a model with no discounting (i.e. $\lambda = 1$) but in which consumers look only one period into the future. This might be a realistic approximation of forward-looking behavior in the market for movies. Results appear similar to the case with perfect foresight and $\lambda = 0.5$.

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 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. The coefficient on being foreign is insignificant, but the coefficient is difficult to interpret because of the separate foreign and domestic month-of-year fixed effects in the demand specification. The choice of which month to exclude from the month-of-year fixed effects in the estimation from Table 3 can greatly affect the coefficient on the indicator for being a foreign movie 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 movies in 3D or IMAX formats, which are mainly produced in the U.S. This section performs counterfactual experiments to evaluate this import liberalization on consumer and producer welfare. An assumption we make to perform these counterfactual experiments is that the producers do not revise the attributes of their movies in response to the import liberalization.

We first discuss how to select the counterfactual set of 20 movies, and then how to compute our welfare comparison. We then present the results.

8.1 A model of movie selection by SARFT

As stated above, we consider several models of which 20 movies would have been selected if there had not been a liberalization from 34 to 20 movies. We compare taking the 20 movies from the bottom of the revenue distribution, the top of the revenue distribution, and from an empirical model designed to estimate how the Chinese government chooses which movies to select. In this subsection, we discuss this model and its predictions.

Our approach to modeling SARFT's decision-making is to form a list of the top 100 movies per year by North American box office, and then perform a probit regression movie-by-movie on which ones are accepted into China under revenue-sharing. We then use simulation techniques to construct an ordering of the movies by the latent value in the probit model, and assume that SARFT would select in order of this latent variable.

In more detail, we select the top 100 movies by North American box office revenue according to Boxofficemojo.com. We do so for each year from 2008-2015, which allows us to study SARFT decisions before and after the policy change in 2012. We assign movies to years based on the date of release in North America and use their lifelong revenue, so even a movie released in late December may be among the highest earners. We assume each movie is governed by a Probit model:

$$Y^* = z\alpha + \eta, \;\; Y = \mathbb{1}\{Y^* \geq 0\}.$$

Table 5: Share of top movies that are selected for revenue-sharing movies by SARFT

Year	% of Top 100	% of Top 50	% of Top 10
2008	19	33	56
2009	22	41	67
2010	21	35	78
2011	25	43	89
2012	30	52	80
2013	27	42	70
2014	29	50	80
2015	27	48	100

Top movies are ordered by North American box office revenue.

where $\eta \sim \mathcal{N}(0,1)$ and $Y = 1$ if the movie is selected for revenue sharing by SARFT. In selecting the top 100 movies in a year, we do not include movies that enter by co-production. Also, we assume that movies that enter by fixed fee would have entered by revenue-sharing if they could have. Thus, we assign movies that enter by fixed fee to have $Y = 0$.

In considering what variables should be included in z, North American revenue appears to be of primary importance. However, there are other factors. To see this, consider Table 5, which reports the share of top movies (ordered by North American box office) selected for revenue-sharing by SARFT.[19] Practically every movie comes from the top 100. The share coming from the top 50 though is always less than double the share coming from the top 100, so some movies are being selected from outside the top 50. While SARFT selected 7 or more of the top 10 in every year since 2010, SARFT selects all of the top 10 movies in only one year, 2015. That is, SARFT is regularly passing on movies in the top 10 and top 50.[20] For explanatory variables, we use the log of North American box office , runtime, genre indicators, and indicators for whether the movie is IMAX, 3D, or rated R.[21] We also include indicators for year.

Results from estimating the probit model appear in Table 6. We provide separate regressions

[19]Note that movies are organized by release year, not selection year. So for instance, 25 of the top 100 movies are selected from the 2011 release year even though only 20 movies are selected in 2011 because some 2011 movies are selected in 2012, when the quota increased to 34.

[20]For movies with Chinese release dates close to their US release dates, North American revenue would be unknown the SARFT at the time of their decision. We ignore this issue. Box office revenue can often be predicted with at least some level of accuracy.

[21]We do not attempt to measure other factors that SARFT appears to account for, such as whether the movie glorifies foreign military, or is about religion or the occult. These are difficult to quantify. We briefly explored a machine-learning approach based on movie reviews, but with only a limited number for observations in each regression, and with much of the outcome explained by box office revenue, it did not appear that we had a data set suitable for such an approach.

for the four years after the policy, 2012-2015, and the four years before, 2008-2011. Starting with column 1, which gives results for the 2012-2015 period, we see that box office revenue, IMAX, 3D, and being an action movie are all strong positive predictors of selection, whereas being rated R is negative, all as expected. These parameters generate reasonable magnitudes of these effects. For instance, the effect of increasing box office by 1% is to increase the probability of selection by 0.2 percentage points.[22]

Given the primacy of box office revenue, we consider a model that adds the square of log box office revenue in column 2. Results for the other variables are quite similar. We find a concave effect for box office revenue, with a peak at about 90th percentile of box office revenue. The fit of the models is quite similar in terms of which models are selected (results available upon request).

As an alternative, we also estimate the Probit model using the period before the policy change, when only 20 movies were selected. Results are in column 3. Box office appears less important, with a coefficient about half of what we found in the post period, and a marginal effect of only 0.08 percentage points. The other coefficients, such as on IMAX, 3D, Action and Rated R, are all about 50% larger. Indeed, although the liberalization specified that the increase from 20 to 34 movies was to include 14 movies that were 3D or IMAX, we do not find the constraint on 3D and IMAX to be binding. As we can see from column 3, there was a significant preference for IMAX and 3D movies before the policy change. Note that the lower coefficient on box office revenue in the pre-2012 period reflects the joint decisions of both SARFT and movie producers. Producers of internationally popular movies may have been less eager to release movies in China when its box office tended to generate less revenue and piracy was more of an issue.

Now we turn to selecting which movies would have been selected by SARFT if there had been no liberalization. We assume the 20 movies it would have selected come from the 34 movies it actually did select under liberalization. In both the pre and post period, SARFT stated that it would select at least six non-US movies. In fact, we observe less than 6 movies without the involvement of a US

[22]This data set includes two movies, *Iron Man 3* and *Looper* that aimed for co-production status but were turned down after they were produced, and entered China on a fixed-fee contract. Arguably, these movies never were considered for revenue-sharing and should not be included in this regression. When we drop these two observations, results are almost identical. One change is that the coefficient on *Action* increases slightly, as these are both action movies that are recorded as $Y = 0$.

Table 6: Probit model of SARFT's decision to select movies for revenue-sharing

	Period 2012-15		Period 2008-2011	
ln(Box Office)	0.748	18.110	0.476	17.090
	(0.142)	(6.074)	(0.170)	(7.862)
ln(Box Office)^2		-0.471		-0.451
		(0.164)		(0.213)
IMAX	0.442	0.500	0.661	0.735
	(0.229)	(0.234)	(0.254)	(0.256)
3D	0.844	0.924	1.236	1.257
	(0.209)	(0.215)	(0.299)	(0.303)
Action	0.656	0.682	0.968	0.971
	(0.216)	(0.223)	(0.221)	(0.226)
Comedy	-0.159	-0.181	-0.460	-0.487
	(0.233)	(0.240)	(0.234)	(0.238)
Drama	-0.197	-0.172	-0.741	-0.746
	(0.218)	(0.222)	(0.255)	(0.257)
In(RunTime)	1.084	1.130	2.933	3.057
	(0.667)	(0.676)	(0.821)	(0.835)
Rated R	-0.924	-0.993	-1.323	-1.396
	(0.228)	(0.235)	(0.341)	(0.356)
2009			0.047	0.0602
			(0.274)	(0.279)
2010			-0.404	-0.433
			(0.287)	(0.290)
2011			-0.419	-0.489
			(0.295)	(0.301)
2013	-0.300	-0.278		
	(0.246)	(0.249)		
2014	-0.162	-0.211		
	(0.247)	(0.253)		
2015	-0.143	-0.109		
	(0.255)	(0.260)		
Constant	-19.5	-179.5	-23.16	-176.5
	(3.491)	(56.270)	(4.155)	(72.850)

400 observation for each column, consisting of the top 100 movies by the lifetime of North American box office revenue among all movies released in each of four years. The dependent variable is equal to 1 if the movie was selected for revenue sharing. Standard errors are in parenthesis.

firm in all but one year, 2014. Perhaps SARFT counts movies with at least some non-US production, of which there are many. We assume that all of the entirely non-US produced movies that appear in the 34 for a given year are selected to be among the 20. From 2012 to 2015, this accounts for 4,5, 6 and 2 movies.

Second, we construct $z\hat{\alpha}$ for each of the remaining 34 movies, where $\hat{\alpha}$ comes from the Probit estimation in column 1 of Table 6. We draw values of η from the standard normal distribution, and thus simulate an ordering of SARFT's preferences over the movies it can select from. We assume that it fills up what remains of the 20 slots based on this preference ordering. We repeat this process 100 times, thus generating a distribution of the set of 20 movies that SARFT would have selected without liberalization. In order to better understand our model and our results, we also present results if instead of using the ordering from the Probit model, we assumed that SARFT selected from its set of 34 strictly based on box office revenue. We consider both orderings, from the top and bottom of the box office revenue variable.

In constructing these sets, we ignore that the constraint to pick a certain number of IMAX and 3D movies existed only under liberalization. As we stated above, the constraint did not appear binding and SARFT exhibited a strong preference for such movies even before the constraint existed. Another potential drawback of our approach is that it ignores any portfolio effects in SARFT's decision-making. We do not allow the government to prefer a mix of movies, such as a certain number of comedies relative to action movies. These kinds of preferences would be difficult to estimate given our sample size, and more importantly, we are not aware of SARFT having such preferences.

8.2 Welfare Computation

For each year, we compare market shares and welfare from the observed choice set with 34 foreign movies to the welfare from a counterfactual choice set of 20 foreign movies, where the selection of the 20 movies is as described in the previous sub-section. In this subsection, we take the counterfactual choice set as given and define how to compute the resulting welfare change.

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 that have been excluded. But, for the choice sets C_{gt} that include an excluded movie, $\widetilde{C}_{gt}$ is a strict subset of C_{gt}. For the counterfactual set of choice sets, we employ the estimated mean utility and follow Equations 1-4 to compute the market share of each of the remaining movies week by week, solving for new choice probabilities and transitions.

To evaluate the welfare benefit of import liberalization on consumer welfare, we compute the welfare to consumers with and without the excluded movies, as follows:

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

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 of 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 consumer welfare over all consumers. We compare the counterfactual consumer welfare to the consumer welfare from the observed data to compute the percentage change in consumer welfare.

In a similar way, we compute the total market share of all movies in the observed and counterfactual scenarios to examine the extent of consumer switching from the outside option to watching a movie.[23] Similarly, we compute the total market share of domestic movies in each week. The change in total market share of domestic movies shows the business stealing effect of those extra movies from domestic movies. We perform a similar computation for foreign movies.

8.3 Welfare Estimates

Table 7 reports our results. The left panel shows the result in levels and the right panel shows percentage changes between the counterfactual and observed outcomes. For instance, we observe an

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

average of 638.13 million tickets sold per year over the four year period from 2012-2015. According to our main specification, Column 4 of Table 3, we calculate that if the lowest 14 movies of the 34 selected movies by North American box office were removed, there would be 625.96 million tickets sold. The right panel indicates that going from 626.96 to 638.13 million tickets sold is a 1.9% increase. In contrast, eliminating the top 14 movies by revenue the from set of 34 would reduce ticket sales to 549.04 million, and going from this number of ticket sales to the observed level would be an increase of 16.2%. Obviously, even among the 34 foreign movies with revenue-sharing contracts, there is a big difference between the top and bottom movies.

We are particularly interested in the results using our model of SARFT behavior. Whether we use parameters from the pre-2012 or post-2012 period (columns 3 and 1 in Table 6 respectively) makes little difference, so we focus on the post-2012 outcome. Although SARFT heavily weights revenue, SARFT's choices lead to substantially more impact than the *Bottom 14* column. The results from modeling SARFT's decision-making leads to annual sales of 605.81 tickets, and going from 605.81 to 638.13 is percentage increase of 5.3%.

The extra movies significantly impact the foreign and domestic share. The SARFT model generates a percentage increase of foreign ticket sales of 23.7%, with foreign movies that compete with the newly introduced foreign movies experiencing a decline in ticket sales of 8.8%. That compares with domestic movies, which lose only 5.7% of tickets when the 14 foreign movies are added to the market. In this sense, foreign movies are a closer substitute amongst each other than with domestic movies.

Table 7: Welfare and Market Share Effects of the Import Liberalization from 2012

		Exclusion based on				Percentage Change due to Exclusion			
			SARFT Model				SARFT Model		
Dynamic Model	All movies	Bottom 14	pre-2012	post-2012	Top 14	Bottom 14	pre-2012	post-2012	Top 14
Annual Admissions	638.13	625.96	608.83	605.81	549.04	1.9%	4.8%	5.3%	16.2%
Annual Admissions of Foreign Movies	280.91	257.00	230.92	227.04	149.35	9.3%	21.6%	23.7%	88.1%
of Competing Foreign Movies						-4.0%	-8.1%	-8.8%	-26.0%
Annual Admissions of Domestic Movies	357.22	368.96	377.92	378.77	399.68	-3.2%	-5.5%	-5.7%	-10.6%
Annual Consumer Welfare (Util)	2616.92	2549.37	2481.41	2474.53	2265.67	2.6%	5.5%	5.8%	15.5%
Static Model									
Annual Admissions of All Movies	638.13	618.85	595.73	592.26	522.03	3.0%	7.1%	7.7%	22.2%
Annual Admissions of Foreign Movies	280.91	259.74	234.77	231.25	155.14	8.2%	19.7%	21.5%	81.1%
of Competing Foreign Movies						-4.97%	-11.72%	-13.76%	-28.77%
Annual Admissions of Domestic Movies	357.22	359.11	360.96	361.01	366.89	-0.5%	-1.0%	-1.0%	-2.6%
Annual Consumer Welfare (Util)	933.55	894.38	845.06	837.35	685.89	4.4%	10.5%	11.5%	36.1%

The left panel presents the outcome in levels in millions, averaged across the four years from 2012-2015. The right side presents percentage changes of the left side. The column *All movies* is the observed outcome when 34 movie are selected for revenue-sharing. The rest present counterfactual restrictions to 20 movies. *Bottom 14* removes the lowest 14 movies by North American box office revenue, the *SARFT Model* columns make use of the Probit model estimated in Table 6 as described in Section 8.1. The *pre-2012* column uses Column 3 and the *post-2012* column uses Column 1. The *Top 14* column eliminates the top 14 movies by revenue. The percentage changes in the right panel are the percentage increase going from the restricted choice set to the *All Movies* choice set on the left panel. The top panel (Dynamic Model) uses the model with consumption durability based on Column 4 of Table 3. The bottom panel (Static Model) uses a standard static model and parameters from Column 1 of Table 3.

This result is particularly striking when we consider the *Top 14* column. Going from the market without the top 14 movies to the *All Movies* column increases foreign ticket sales by 88.1%, with competing foreign movies experiencing a decline of 26%, as compared to a decline in domestic movies of only 10.6%. These large differences in the effect on foreign and domestic are driven by the standard deviation in the random coefficient on *Foreign* in Table 3. In this sense, it appears that foreign and domestic movies are not very close substitutes for each other. This result calls into question the value of import quotas as a way to protect the domestic movie industry, as it does appear the foreign movies greatly impact domestic movie-going.

We are also interested in comparing these results to what we find when using a static model that ignores consumption durability. i.e. the standard BLP results from Column 1 of Table 3. The results for this counterfactual are reported in the bottom panel of Table 7. We see that the static model generates larger results for welfare gains of liberalization than the dynamic model. Ticket sales of foreign movies are slightly higher under the counterfactual scenario under the static model than the dynamic model. But the biggest difference is in the domestic movies: the static model predicts that sales of domestic movies hardly changes at all, a 1% change when using the SARFT model. Note that the size of the deviation of the random coefficient on *Foreign* is similar in the static and dynamic results.

Instead, the result appears to be due to dynamics: in the static model, consumers choose to see foreign movies every week, whereas the dynamic model predicts that consumers that prefer to see foreign movies still move on to domestic movies after seeing foreign movies. Keep in mind that the dynamic model could have matched the low substitutability in the static model by finding a much higher standard deviation in the random coefficient, whereas the static model cannot match the complex sequence of market shares predicted by the dynamic model. We find the low substitutability for the static model in Table 7 implausible, and we view this as evidence in favor of the dynamic model.

We also compute the effect on consumer utils using the discrete choice model. Naturally, given that we effectively assume that price is constant, the change in utils closely tracks the change

in quantities. However, Table 7 shows that the percentage in utils is somewhat higher than the percentage change in quantities, implying that it is particularly high quantity movies that are affected by liberalization. As discussed above, converting utils into dollar numbers is not straightforward as a result of a lack of price variation in this market. However, some previous research suggests a reasonable price coefficient would be 0.399. That implies the movie market generates welfare of ¥19 billion. With such a large number, relatively small changes become important. Going from the restricted choice set implied by the post-2012 SARFT model to the observed choice set implies an increase in surplus of ¥1.076 billion. While establishing the correct price coefficient for these calculations is not the focus of the paper, it seems clear that the results are economically meaningful.

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, which we term consumption durability. We propose a dynamic model of consumer demand that captures these features.

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

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, leading to a 5.3% increase in ticket sales. 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 8: 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.

Appendix B The List of Imported Enhanced Movies

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

Table 9: Robustness results for Table 3

Parameters		**Differences**	**Perfect Foresight**	**Perfect Foresight**	**1-week foresight**
Non-linear	Constant	9.189	10.526	10.425	9.645
		(0.731)	(0.126)	(0.135)	(0.248)
	Enhanced(3D or IMAX)	1.437	1.531	1.524	1.509
		(2.054)	(0.201)	(0.138)	(0.310)
	Foreign	2.821	3.343	3.316	3.038
		(1.100)	(0.164)	(0.114)	(0.148)
	Discount Rate		0.000	0.500	
			(0.023)		
Linear	Age	-0.117	0.006	-0.190	-0.330
		(0.632)	(0.081)	(0.072)	(0.072)
	Holiday	1.121	1.300	1.252	1.166
		(0.616)	(0.413)	(0.395)	(0.405)
	Consumption Durability	Yes	Yes	Yes	Yes
	Micro-moments	Yes	Yes	Yes	Yes
	Forward Looking	No	Yes	Yes	Yes

These models provide robustness checks for Table 3. The first column uses the first difference in ξ to form moments rather than the level. The second column allows for perfect foresight and estimates the discount rate to be zero. The third column imposes the discount rate $\lambda = 0.5$. The fourth column imposes $\lambda = 1$ and allows consumers to look only one period into the future.

Table 10: 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 11: 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