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

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Abstract

This paper develops and estimates a structural model of consumer demand for movies in which consumer preferences are heterogeneous over movie attributes and durable on movies that watched before. Consumers do not consider the movies watched in the past as relevant choices contemporarily, which leads consumers to be heterogeneous in their choice sets. Our main finding is that consumers prefer movies with time slots in holiday, and have heterogeneous preferences on watching movies. Interestingly, consumers prefer less to watch movies with a longer time gap from releasing week is driven by the unavailability of those movies in their choice set due to consumption durability. We employ our model to analyze the import liberalization for U.S. movies to China since 2012. Counterfactual experiments show that consumer welfare increases by 10% due to the import liberalization. However, the import liberalization reduces the market share of competing foreign movies, but raises that of domestic movies. Finally, if the consumption durability in preferences is ignored, we show that the welfare benefit for consumers is overestimated and the business stealing effects of extra foreign movies on competing foreign movies and domestic movies are also overestimated.

Keywords: Demand Estimation, Choice Set, Trade Liberalization.

JEL classifications: L10, L82, F13

1 Introduction

Like many developing countries, China restricts the entry of cultural goods such as movies and books. We study the welfare implications of this restriction in the foreign film market from the perspective of consumer choice. We are particularly motivated by China's liberalization of the quota on foreign movies from 20 movies to 34 in early 2012. We ask how much consumer benefit resulted from this expansion, and how much movies already present in the market suffered from the increased choice set, 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 two 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, movies exhibit *consumption durability.*[1] Consumers typically receive significantly lower utility from seeing a movie a second time, so that consumers see most movies only once at most. Ignoring these features can lead to misleading counterfactual calculations. For instance, as we discuss further below, a standard static model without consumption durability will infer that the reason a movie that has been in theaters for a few weeks has low attendance is because it delivers low utility In contrast, a model with consumption durability may rationalize falling demand for older movies by finding that utility is unchanged but that many consumers have already seen the move.

Consumption durability is a feature of many cultural goods, such as books, museum exhibits, and albums. Many of these goods exhibit stark declines in demand after introduction. Previous research has often estimated demand for these products with static models that contain an age profile, such as a set of dummy variable for age. While this may match the data well, it is puzzling from the perspective of economics why the utility from a cultural good would decline at a very rapid rate. A goal of our project is to show that much of this decline in sales can be explained by a model with consumption durability rather than a reduced-form age profile.

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

In our model, consumers face an exogenously evolving choice set. Further, we assume that consumers cannot see a movie more than once. Thus, the choice set of a given consumer evolves endogenously as the consumer makes choices over which movies to see. Consumers have heterogeneous preferences over movie characteristics, which do not change over time. We assume that consumers choose myopically which movie to see. That is, consumers do not account for how seeing a movie today affects future outcomes. In estimation, we find an unobserved quality for each movie-week that rationalizes the observed market share, and form a GMM estimator around this term.

We apply our model to a data set covering national box office revenues by week from Chinese movie theaters from January 2012 to June 2015. We collect movie characteristics, such as whether the movie is foreign or domestic, the genre of the movie and the run-time. We augment the data with a survey from a consulting firm of how often people go to the movies. This survey data is useful because our model makes predictions about how often an individual goes to the movies and how this number is distributed across the population, but we cannot learn these outcomes just from data on aggregate movie market shares. Forcing our model to match this "micro-moment" significantly impacts the results.

For computational reasons, we restrict consumers to choose among six *named* movies, over which we track consumer histories. When a movie falls out of the top 6, we assume it is no longer available. We argue that ticket sales are so concentrated on the top few movies that this limitation is not important, and we plan to experiment with higher numbers of named movies. We further augment the choice set with three more options: a generic foreign movie, a generic domestic movie, and an outside option of not seeing a move in a cinema. Below, we discuss straightforward extensions to our model that would allow for seeing a movie multiple times and accounting for forward-looking behavior, but we do not believe they are important for our application.

Because the liberalization from going from 20 to 34 movies takes place just before the start of our data, we cannot evaluate the market before the policy change. Rather, we employ our structural model to determine outcomes in the counterfactual scenario. We show that consumer welfare increases by about 10% due to the import liberalization. However, the welfare effects for producers are heterogeneous. The import liberalization reduces the total market share of the competing foreign movies than domestic movies because the extra foreign movies are closer substitutes with the other foreign movies than domestic movies. If the consumption durability in preferences is ignored, the welfare benefit for consumers is overestimated and the business stealing effects of extra foreign movies on competing foreign movies and domestic movies are also overestimated. Finally, we suggest that the standard BLP model (Berry et al., 1995) has two biases in welfare evaluation when consumption durability is present. One bias originates from the omission of consumption durability for computing welfare. The other bias originates from demand estimation, which leads to underestimation of indirect utility provided by movies.

2 Literature

Countries may restrict the entry of cultural goods not just to protect domestic industries but also to protect the distinctive nature of their culture from global incursion, which is often seen as homogenizing. We evaluate only the economic implications of the quota, so that a policy maker considering such cultural protection would know the economic cost of a such a policy. In our counterfactual calculations, we assume the set of movies would not change. However, some research and popular press argue that Chinese policies in particular affect movie production in terms of genre and content. We do not address that issue here, although that is not to say that it is not important.

There is a growing trend of international trade in motion picture as the world becomes more integrated in trading goods and services. Although a great product variety has long been argued as a benefit of trade (Krugman 1979), an increasing trade in motion picture is criticized to undermine national culture in favour of their commercial aspects.[2] Many countries defend that cultural goods and services "encompass values, identity and meanings that go beyond their strictly commercial value" and request exceptions in protecting domestic cultural goods and services.[3] For example,

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

[3]Chu-Shore (2010) reports that there is a homogenization of cultural goods in response to trade liberalization. Maystre et al. (2014) provide a theory and evidences to support that trade integration leads to convergence in cultural values across countries.

Article IV of the GATT agreements in 1947 provides the conditions to use screen quota.[4] The protection of national culture also played a role in Uruguay Round of the GATS ended in 1994 and the UNESCO Convention on the Protection and Promotion of the Diversity of Cultural Expressions (in particular Articles 6 and 8).

There is a particular concern of U.S. movies in the debate of protecting national culture as the Hollywood relies more on the box office from foreign markets and U.S. movies dominate the market share in many foreign countries.[5] However, there has not been much discussion of how trade barrier on import of U.S. movies affect consumer welfare and surpluses of domestic and foreign producers. Supplying this discussion provides insights to policy makers for evaluating the welfare effects of import liberalization of motion picture.[6]

This paper examines an import liberalization of movie to China. This case of China has two features leading itself an important case study for the impacts of U.S. movies on foreign markets. First, China enlarged its quota for revenue sharing imports of foreign movies from 20 to 34 per year, with immediate effect in February 2012. These extra 14 movies need to be "enhanced " movies in 3D or IMAX format, which are mainly produced in the U.S. Second, China becomes the largest foreign market for U.S. movies as the annual box office in China has been accelerating faster than 20% during the past decade. Specifically, the box office of U.S. movies in China was at $USD 4.8 billion in 2014. Nonetheless, Figure 1 depicts that the share of domestic movies in box office remain at about 55%, which is higher than those in European countries documented in Hansan and Xiang (2009) and may relate to the import restriction of China on foreign movies.

Our work contributes to a growing empirical literature on trade in motion picture. Marvasti and Canterberry (2005) construct a trade barrier index for 33 countries and find that their trade

[4] Many countries impose trade barrier for importing movies, where non-tariff trade barriers, such as screen quota, are more commonly imposed than tariff by importing countries, especially for developing countries (Marvasti and Canterberry 2005).

[5] Marvasti and Canterbery (2005) report that export revenues become 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 and Xiang (2009) document that U.S. movies acquire more than 70% of box office in 19 European countries over the period 1995-2004. According to a report by Motion Picture Association of America, the global box office for U.S. movies released in each country around the world reached $USD 36.4 billion in 2014, of which, $USD 26.0 billion was acquired from the international box office. Source: http://www.mpaa.org/wp-content/uploads/2015/03/MPAA-Theatrical-Market-Statistics-2014.pdf

[6] Francois and van Ypersele (2002) and Rauch and Tridade (2009) argue that restrictions on trade in cultural goods can raise welfare.

barrier index is positively correlated with imports of U.S. motion pictures. Hanson and Xiang (2011) develop a heterogeneous firms model of trade for the motion picture industry. They find that average revenues per U.S. film vary widely across countries and are negatively correlated with geographic distance, linguistic distance, and other measures of trade barriers. Thus, these two papers find mixed results of trade barrier on import 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. Our work is closest to Ferreira et al. (2013), in which they estimate a structural model of movie demand for 16,856 movies in 53 destination countries over the period 2000-2010. They then combine with the demand estimates with a quality production function of movie to examine the contribution of increase in product quality in the gain from trade in motion picture. Our work differs from those studies in that it uses a structural demand model to examine the welfare effects from import liberalization of U.S. movies.

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

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

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

Our work differs from the previous three strands of literature in several ways. First, we model consumption durability in consumer's preferences on movies. Second, we exploit consumption durability in a way that consumers do not consider the movies watched in the past as relevant choices contemporarily to motivate the heterogeneous choice sets across consumers, and examine its impacts on welfare analysis. Third, since few numbers of movies accounts for the majority of sales in our dataset, we are able to keep track of the probability distribution of all choice sets over time. Our approach to model heterogeneous choice sets differs from those used in the previous studies, which rely on supplementary data or a model of choice set formation.

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

3 Institutional Background

This section discusses the import policies for foreign movies of China. Until 1994, foreign movies were purchased mainly on a flat-fee basis. Between 1978-1993, China Film Group was the only authorized agent to import and distribute these films. In each year, China Film Group spent about USD $1 million to import about 30 foreign movies, and each foreign movie was purchased at about USD $30,000. As a result, the imported movies were usually considered "outdated and low-grade but cheap".[7]

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 the declining movie attendance and solve the financial bottleneck of domestic studios. China Film Group was still the only authorized agent to import and distribute these films. Foreign studios were allowed to garner a certain share of box office revenue, roughly around 13-17%. The first ever revenue-sharing film imported to China was *The Fugitive* starring Harrison Ford, which was released in 6 major cities in China in November 1994. In a year after importing foreign movie with revenue sharing, the box office of China was about 50% higher than that in 1994. Later on, *Titanic* made the highest box office in 1998 at USD $43.5 million, and had held the record until 2009 broken by *Transformer 2*.

China was approved to join WTO on December 11, 2001. Under the agreement, China increased the quota for revenue-sharing movies to 20. Most of the 20 revenue-sharing slots were given to US movies. In order to diversify the imported films, in 2004, the State Administration of Radio, Film and Television (SARFT) decided to reserve about six slots for non-US movies.

In April 2007, the U.S. initiated the underlying WTO dispute, arguing that, by imposing more restrictive conditions on foreign companies, China was engaging in discriminatory practices and that China's state-owned enterprises and large joint ventures constituted a monopoly in film import and distribution. In January 2010, the WTO ruled that China had violated international trade rules and needed to end the government's monopoly on the distribution by 19 March 2010. China responded

[7]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.

that it disagreed but was willing to comply, but informed the U.S. at the deadline that this would not be possible (Su 2014).

In February 2012, China agreed to significantly increase market access for U.S. movies in order to resolve outstanding issues regarding the WTO dispute. With immediate effect, China enlarged its quota for revenue sharing imports of foreign films from 20 to 34 per year. The extra 14 films are enhanced films in 3D or IMAX formats. Besides, the terms on which revenues are shared with overseas right holders were changed. Revenue sharing was set at 25% of box office revenues instead of the previous scale of 13-17%. This agreement would be reviewed after 5 years to ensure that it is working as had envisioned.

Policy makers expect the additional import of U.S. movies into China will benefit both countries. After meeting with Chinese Vice President Jinping Xi in the Los Angeles, U.S. Vice President Joe Biden on 17 February 2012 indicated in his public speech that "This agreement with China will make it easier than ever before for U.S. studios and independent filmmakers to reach the fast-growing Chinese audience, supporting thousands of American jobs in and around the film industry...At the same time, Chinese audiences will have access to more of the finest films made anywhere in the world."[8]

All the 34 revenue-sharing movies are imported and distributed by China Film Group, and some are co-distributed by Huaxia, which is a state-owned enterprise established in 2003. All the imported films must go through the censorship by SARFT, which usually takes 30 days. Article 25 of the Regulation on the Administration of Movies effective in Februrary 2002 prohibits ten aspects of content that would not be allowed in any imported films. The list includes, among other things, "endangers the unity of the nation, sovereignty or territorial integrity", "propagating evil cult or superstition", and "propagating obscenity, gambling, violence, or instigates crimes".

Table 1 reports that the descriptive statistics of the imported movie from the U.S. in our sample.[9] About 63%, 18% and 20% of those movies are action, comedy and drama, respectively. The proportion of action (comedy and drama) movies among the imported movies from the U.S. is higher

[8] https://www.whitehouse.gov/the-press-office/2012/02/17/united-states-achieves-breakthrough-movies-dispute-china

[9] See the next section for more details of our data.

(lower) than that documented in previous studies examining U.S. samples. For example, Redfern (2012) documents that about 28%, 19% and 11% of the top 50 grossing movies at the US box office each year from 2001 to 2010 are action, comedy and drama, respectively.[10] It suggests that the imported movies from the U.S to China gear towards to be action movies, which are in turn more likely to be shown in IMAX and 3D formats. Further, those action movies are more likely to enjoy a higher box office than the movies in other genres in the U.S. (Einav 2007; Moul 2007; Redfern 2012). Overall, these evidences suggest that the selection of action movies into China relates to its likelihood to pass the censorship by SARFT and to achieve high box office.[11]

Table 1: Descriptive Statistics of Imported U.S. Movies (Obs=127)

Varibles	**(1) Mean**	**(2) SD**	**(3) Min**	**(4) Max**
Product Attributes				
IMAX (Dummy)	0.504	0.502	0	1
3D (Dummy)	0.567	0.497	0	1
Action (Dummy)	0.630	0.485	0	1
Comedy (Dummy)	0.181	0.387	0	1
Drama (Dummy)	0.205	0.405	0	1

For the foreign movies cannot be allocated a quota for revenue sharing, they can only be imported based on a flat-fee. China Film Group and Huaxia are still the only agents allowed to distribute these films. They pay a lump sum fee for a film and the foreign studios cannot share the revenue afterwards. There is no specific quota to import movies on a flat-fee basis, but is usually 20-30 per year. Since the foreign distributors earn much less from flat-fee movies than revenue-sharing movies, the imported movies with flat-fee are usually lower in budget and quality and have a longer releasing gap from its first release in foreign markets. As a results, these movies usually have a small market share, about 10-15% of box office among foreign movies.[12] For example, China allowed a total of 58 foreign films into the country in 2015, but only 34 of those were permitted as revenue-sharing movies. Foreign revenue share films sold about USD $2.25 billion in tickets in 2015, which means foreign movie studio earned a maximum of USD $560 million from those 34 titles. The remaining

[10] The proportion of action movies in Moul (2008) is reported to be about 25%.

[11] 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 and Zhang (2011) report that, among the foreign movies shown in China, action and comedy movies enjoy a higher box office than drama movies.

[12] Cain, R. (2013, Mar 12). ‘Upside Down’ flips the script at China’s theaters. Retrieved from http://chinafilmbiz.com/2013/03/12/upside-down-flips-the-script-at-chinas-theaters/

24 imports were allowed in are flat-fee movies with USD $0.33 billion.[13]

4 Data

The empirical analysis is based on a novel dataset from the SARFT of China. The data contain information on box office, ticket admission and number of showing screens of all movies shown in each week. We supplement this dataset with the hand-collected information of movies, such as releasing date, whether a movie is in 3D or IMAX format, whether a move is imported, genre and run time. Our empirical analysis includes the movies with admission share larger than 0.1% from January 2012 to June 2015. There are 946 movies shown in 183 weeks.

Table 2: Descriptive Statistics (Obs=1455)

Varibles	**(1) Mean**	**(2) SD**	**(3) Min**	**(4) Max**
Box Office Share (%/100)				
A movie	0.126	0.134	0.001	0.906
Top six movies	0.910	0.058	0.706	0.994
Other domestic movies	0.061	0.043	0.002	0.279
Other foreign movies	0.031	0.030	0.001	0.172
Market Share (%/100)				
s_{jt}	0.005	0.006	0.000	0.085
Product Attributes				
Age (Week)	3.552	4.985	0	66
Holiday (Dummy)	0.203	0.402	0	1
IMAX (Dummy)	0.364	0.454	0	1
3D (Dummy)	0.249	0.419	0	1
Foreign (Dummy)	0.456	0.498	0	1
Action (Dummy)	0.400	0.460	0	1
Comedy (Dummy)	0.280	0.410	0	1
Drama (Dummy)	0.330	0.430	0	1
RunTime (Minute)	110.3	18.27	75	194

Table 2 reports the descriptive statistics of the variables that are used in the empirical analysis. We classfiy our sample movies into eight choices, namely six movies with the highest admissions in each week, other domestic movies and other foreign movies. Therefore, our sample includes 1,455 observations at the level of movie-week (There are 9 weeks without other foreign movies). Our sample movies account for more than 99% of weekly box office, in particular the top six movies,

[13] Los Angeles Times "Movie ticket sales jump 48% in China, but Hollywood has reason to worry." by Julie Makinen on Dec 29, 2015. Similarly, there were 67 foreign movies in 2014, where the box office of revenue-sharing movies is about 85% of USD $1.81 billion, total box offfice of foreign movies.

other domestic movies and other foreign movies account for about 89%, 7.1% and 3.1% of weekly box office, respectively.

4.1 Market Size and Market Share

We define China as a whole as the geographical market, which is analogous to Einav (2007) who analyzes the movie demand of the U.S. Since movie theatres are often located in urban area, thus we employ the population in urban area instead of total population to measure the market size. We use the annual figure of total urban population in year 2011, i.e. 354.256 million people, to measure the market size, and this size is denoted H. The population data is obtained from the China Statistical Yearbook. To compute the market shares, we divide the ticket admission of movie j in week t by the market size. Let q_{jt} be the admission of movie j in week t. Then, $S_{jt} = q_{jt}/H$ is the market share of movie j. The outside good is defined as all other movies and not watching a movie. The average market share of a movie is 0.5%, whereas the outside option has 96%.

4.2 Product Attributes

We use two time-varying product attributes of movies. First, we use the number of weeks since the movie released (Age_{jt}) to proxy the popularity of movies. Davis (2006) and Moul (2008) show that a movie enjoy a higher market share when it is closer to the releasing week. A movie has just released is expected to be more popular than a movie has been showing for several weeks. Second, Einav (2007) reports that there is a seasonality in movie demand. Thus, we use a dummy variable whether the current week has a holiday ($Holiday_t$) to capture the demand fluctuations of movies within a month. The holidays included are New Year's Day, Chinese New Year, Qingming Festival, May Day, Dragon Boat Festival, Mid-Autumn Day and National Day.

We also supplement our empirical analysis with a set of time-invariant movie attributes. We use dummy variables whether a movie is in 3D format ($3D_j$), whether a movie is in IMAX format ($IMAX_j$), and whether a movie is imported ($Foreign_j$). These movie attributes relate to the extra foreign movies due to the import liberalization in 2012. Further, we employ whether a movie is an action movie ($Action_j$), whether a movie is a comedy movie ($Comedy_j$), whether a movie is a drama movie ($Drama_j$) and the run time of a movie ($RunTime_j$).

Table 1 reports that the mean number of screens in a week allocated to show a movie is 17,936. In other words, since there are about 5,500 theaters, there are about 3 screens per theatre allocated to show a movie in a week. The mean and maximum numbers of weeks since the movie released is 0 and 66, respectively. On average, 20% of observations belong to movies showing on holiday. On average, 47% of observations are enhanced movies, in which 36% and 25% of observations are movies in IMAX and 3D formats, respectively. 46% of observations are foreign movies. In terms of genre, 40%, 20%, 33% of observations are action, comedy and drama movies, respectively. The average run time of our observations is 110 minutes.

4.3 Data for Micro-moments

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

5 Model

This section outlines a demand model for movies with consumption durability, where consumers do not consider the movies watched in the past as relevant choices contemporarily. The demand system is based on the structural model of demand for differentiated products, which is related to the indirect utility provided by each movie based on its attributes. The movie attributes represent the product quality provided by a movie, such as its convenience to watch and popularity. The novel feature of our model is consumption durability, which leads consumers to be heterogeneous in their choice sets depending on their previous choice. In other words, although our consumers maximize utility in static fashion by choosing one movie to watch from their choice sets or the outside option, the consumption durability introduces dynamics into their choice problem.

5.1 The Evolution of Choice Sets

There are nine available choices at each point of time, which includes the six movies with the highest admissions (Choice 1-6), the other domestic movies, the other foreign movies and the outside goods. Since the movies included in Choice 1-6, the other domestic movies and the other foreign movies account for more than 99% of box office, it is reasonable to assume that the outside option captures the choice of not watching any movie. Our model takes the set of available choices evolves exogenously.

Figure 1 illustrates a hypothetical example of the evolution of available choices for four weeks. Choices A and B are the two movies with the highest admissions in the first three weeks, whereas Choices B and C are the two movies with the highest admissions in the fourth week. We denote the set of available choices in week t as C_t, where $t = 1, 2, .., T$. In particular, $C_1 = C_2 = C_3 = \{A, B, Outside\ option\}$ and $C_4 = \{B, C, Outside\ option\}$.

A unique feature of our model is consumption durability, where consumers are heterogeneous in their choice sets because they do not consider the movies watched in the past as relevant choices contemporarily. We denote the potential choice sets in Week t as C_{gt}, where $g = 1, 2, .., G_t$. G_t is the number of choice set in Week t. For consistency, we define the choice set C_{1t} contains all available movies in Week t, which is the same as C_t.

In our example, there are three potential choice sets C_{12}, C_{22} and C_{32} in Week 2. The choice set C_{12} is available for consumers do not watch any movie in Week 1, whereas the choice set C_{22} and C_{32} are available for consumers watch movies B and A in Week 1, respectively.

As there are more movies overlap in top two choices over two consecutive weeks, there are more potential choice sets in the latter week. In Week 3, there are four potential choice sets C_{13}, C_{23}, C_{33} and C_{43}. The choice set C_{13} is available for consumers with C_{12} do not watch any movie in Week 2. The choice set C_{23} is available for consumers with C_{12} watch movie B in Week 2 and for consumers with C_{22} do not watch any movie in Week 2. The choice set C_{33} is available for consumers with C_{12} watch movie A in Week 2 and for consumers with C_{32} do not watch any movie in Week 2. Finally, the choice set C_{43} is available for consumers with C_{32} watch movie B in Week 2.

The number of choice set does not keep increasing over time because the median *Age* of our sample movies is 2. In our example, movie A exits after Week 3. There are only two potential choice sets C_{14} and C_{24} in Week 4. The choice set of C_{14} is available for consumers with C_{13} watch movie A or do not watch any movie in Week 3, and for consumers with C_{33} do not watch any movie in Week 3. The choice set of C_{24} is available for consumers with C_{13} watch movie B in Week 3, for consumers with C_{23} watch movie A or do not watch any movie in Week 3, for consumers with C_{33} watch movie B in Week 3, and for consumers with C_{43}.

5.2 The Consumers' Problem

In each period, consumers decide which movie to watch or stay with the outside goods, but these consumers face different choice sets, C_{gt}, $g = 1, .., G_t$. These consumers maximize the utilities to make their decisions. The utility of consumer i who choose to watch movie j from a choice set C_{gt} at time t is as follows:

$$\begin{aligned} u_{ijt} &= x_{jt}\beta + \sum_k x_{jt}^k \sigma_k v_{ik} + \xi_{jt} + \varepsilon_{ijt} \\ &\equiv \delta(x_{jt}, \xi_{jt}; \beta) + \mu(x_{jt}, v_i; \sigma) + \varepsilon_{ijt} \qquad (1) \\ &= \delta_{jt} + \mu_{ijt} + \varepsilon_{ijt} \end{aligned}$$

The utility is decomposed into two components, namely the mean utility $\delta(x_{jt}, \xi_{jt}; \beta) = x_{jt}\beta + \xi_{jt}$, which is independent of consumer characteristics, and a function of consumer heterogeneity, $\mu(x_{jt}, v_i; \sigma) = \sum_k x_{jt}^k \sigma_k v_i^k$. The x_{jt} is a K_1-dimensional vector of the observed product attributes affecting the mean utility of movie j and ξ_{jt} represents the unobserved product attributes of movie j. The $K_1 + K_2$ dimensional vector (β, σ) represents the demand parameters, in which β is the set of K_1 parameters that associates mean utility with movie characteristics, and σ is the set of K_2 parameters associated with consumer heterogeneity on a subset of movie characteristics, i.e. $K_1 \geqslant K_2$ or some σ_k are set to zero. The consumer-specific preference is captured by the idiosyncratic component, $\{v_i^k\}_{k=1,..,K_2}$ on product attributes, and a deviation specific to movie j, ε_{ijt}. The idiosyncratic component, $\{v_i^k\}_{k=1,..,K_2}$ is drawn from the multivariate standard normal distribution, and the deviation, ε_{ijt}, is assumed to be a mean zero stochastic term with iid extreme value Type 1 distribution. Moreover, the mean utility of choosing the outside good is normalized to zero, i.e., $\delta_{0t} = 0$.

5.3 Computing the Market Share

Market shares are determined by the choices made by consumers with different choice sets. For consumer i with choice set C_{gt}, the probability of consumer i choosing movie $j \in C_{gt}$ is

$$S_{ijt|C_{gt}} = \frac{\exp\left(\delta(x_{jt}, \xi_{jt}; \beta) + \mu(x_{jt}, v_i; \sigma)\right)}{1 + \sum_{k \in C_{gt}} \exp\left(\delta(x_{jt}, \xi_{jt}; \beta) + \mu(x_{jt}, v_i; \sigma)\right)} \quad (2)$$

The probability of consumer i of choosing movie $j \in C_t$ is computed by averaging the probability of consumer i choosing movie j across different choice sets, i.e.

$$s_{ijt} = \sum_{g=1,..,G_t} 1(j \in C_{gt}) S_{igt} S_{ijt|C_{gt}} \quad (3)$$

where S_{igt} is the probability of consumer i facing the choice set C_{gt}. The probability of consumer i facing a choice set in the following period is the total probability of consumer i transit from all choice sets to that choice set in next period (see Equation 4).

$$S_{ig,t+1} = \sum_{k=1,..,G_t} S_{ikt} P(C_{ikt} \to C_{ig,t+1}) \quad (4)$$

The market share of movie j in week t is computed by integrating the probability of choosing movie j over consumers

$$s_{jt} = \int s_{ijt} dF_i \quad (5)$$

where F_i is the distribution of consumers.

6 Estimation

This section specifies the parametric forms for the demand system and outlines the procedures used in the estimation. We simulate $ns_1 = 200$ consumers by drawing $\{v_i^k\}_{k=1,..,K_2}$ from the multivariate standard normal distribution. The estimation algorithm has three levels of non-linear optimization. In the inner loop, given the mean utility of each movie, the predicted market share of each movie is computed as the solution to the problem of consumers' choice. In the middle loop, for the fixed-point calculation, we compute the mean utility of each movie by matching the predicted market shares with the observed market shares. Then, we estimate the mean utility specification. In the outer loop, we estimate the demand parameters on consumer heterogeneity.

6.1 The Inner Loop

Given the set of parameters σ and the mean utility of movies δ_{jt} for all movie j and week t, we compute the week-by-week movie choice predicted by our model for consumers i with $\{v_i^k\}_{k=1,..,K_2}$.

For Week $t = 1$, we compute the movie choice for each consumer i from the choice set C_{11} according to Equation (2). Since there is only one choice set in Week 1, the movie choice of consumer i from C_{11} is the same as the movie choice of consumer i in Week 1, i.e. $s_{ijt} = S_{ijt|C_{gt}}$ for $t = 1$. Then, we compute the probability of consumer i transiting to C_{12} , .., $C_{G_2 2}$ according to Equation (4).

For Week $t = 2$, we compute the movie choice from the choice sets C_{12} , .., $C_{G_2 2}$ for each consumer i according to Equation (2), and then compute their choice probability of each movie s_{ijt} with Equation (3). Finally, we compute the share of consumers transiting to C_{13} , .., $C_{G_3 3}$ according to Equation (4).

For all remaining sample weeks, $t = 3, .., T$, we repeat these procedures to compute consumer i's probability to watch each movie j in week t, s_{ijt}.

6.2 The Middle Loop

For the middle loop of the estimation, we compute the mean utility of each movie shown in each week by matching the predicted market shares obtained from the inner loop to the observed market shares. First, we compute the marker share s_{jt} for movie j in each week t as follows:

$$s_{jt} = \frac{1}{ns_1} \sum_{i=1}^{ns_1} s_{ijt} \tag{6}$$

For a given set of parameters σ, we employ the contraction mapping proposed by Berry et al. (1995) to compute the mean utility δ_{jt} for all movie j and week t. Specifically, we compute the inner loop to update the predicted market share in each step of solving the contraction mapping.

After achieving convergence in the contraction mapping, we estimate the mean utility specification. Recall that the mean utility is postulated as follows:

$$\delta_{jt} = x_{1jt}\beta + \xi_{jt} = x_{1jt}\,\beta + \zeta_j + \zeta_{Year} + \zeta_{Month} + \zeta_{jt} \tag{7}$$

where β is the set of parameters to be estimated. The vector of the exogenous movie characteristics x_{1jt} is

$$x_{1jt} = \{Age_{jt}, Holiday_t\} \tag{8}$$

We decompose the unobserved product attributes into two terms, where ζ_j is a set of movie dummy variables that capture the time-invariant utility value of each movie; ζ_{Year} is a set of year dummy variables that capture the aggregate demand fluctuations for movies; ζ_{Month} is a set of month of the year dummy variables that capture the seasonal demand fluctuations for movies; and, ζ_{jt} represents the movie-week unobserved product characteristics. We estimate Equation (7) with the OLS.

6.3 The Outer Loop

For the outer loop of the estimation, we update the set of parameters σ with the Generalized Method of Moments (GMM) estimation procedure. The estimation procedure is as follows: Let X be the set of movie characteristics including Age_{jt}, $Holiday_t$, ζ_j, ζ_{Year} and ζ_{Month}. We assume X is exogenous and independent of the error terms in the demand equations, and therefore X is orthogonal to ζ. Utilizing the conditions $E(X'\zeta) = 0$, we construct the set of moments $m_1 = [X^{'}\zeta]$. The GMM estimator given our moment conditions is defined as $\min_\sigma m_1'\Omega m_1$. We follow the two-step procedure of GMM estimation proposed in Hansen (1982) and intialize it with an identity matrix as the weighting matrix Ω.

6.4 Incorporating the Micro-moments

To improve the identification of random coefficients, we incorporate two micro-moment conditions based on the survey data. Specifically, we use the information that, conditional on watching at least one movie, the probability to watch 1-3 movies is 23.5% and the probability to watch 4-6 movies is 19.2%.

We construct the sample analog by drawing another $ns_2 = 200$ consumers, with idiosyncratic preference components $\{v_i^k\}_{k=1,..,K_2}$ drawn from a standard multivariate normal distribution. These draws are independent of the draws for Equation (6). For each consumer i, we compute the movie choice for each possible choice set $S_{itg|C_{gt}}$. We count the the number of movies that each consumer i watch over the period between February 2012 and January 2013, i.e. $t = 6 - 57$ in our sample period. At $t = 57$, we compute the probability that consumer i watching different number of movies, i.e. P_{in} for $n = 0, 1, .., 6, 7+$. Then, we compute, conditional on watching at least one movie, the probability to watch 1-3 movies is $P_{i1-3} = \sum_{n=1}^{3} P_{in} / \sum_{n=1}^{7+} P_{in}$ and the probability to see 4-6 movies is $P_{i4-6} = \sum_{n=4}^{6} P_{in} / \sum_{n=1}^{7+} P_{in}$.

We then take the average of P_{i1-3} and P_{i4-6} over those ns_2 consumers, i.e. $P_{1-3} = \frac{1}{ns_2} \sum_{i=1}^{ns_2} P_{i1-3}$ and $P_{4-6} = \frac{1}{ns_2} \sum_{i=1}^{ns_2} P_{i4-6}$. We postulate the micro-moment conditions as follows

$$E[m_2(\theta)] \quad = \quad E\begin{bmatrix} I_{1-3} - P_{1-3}(\theta) \\ I_{4-6} - P_{4-6}(\theta) \end{bmatrix} \quad = \quad 0 \ , \tag{9}$$

The variables I_{1-3} and I_{4-6} are the indicators of a consumer watching 1-3 and 4-6 movies condition on she watched at least one movie in the previous year, respectively. Thus, the stacked moment conditions are

$$E[m(\theta)] \quad = \quad E\begin{bmatrix} m_1(\theta) \\ m_2(\theta) \end{bmatrix} \quad = \quad 0 \ . \tag{10}$$

The GMM estimator given our stacked moment conditions is defined as $\min_\sigma m'\Omega m$. We follow the two-step procedure of GMM estimation proposed in Hansen (1982) and intialize it with an identity matrix as the weighting matrix Ω. The weighting matrix is block-diagonal as in Petrin (2002) because the two moment conditions are computed from different samples. 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, i.e. $\begin{bmatrix} \sum_{i=1}^{N_2}(I_{1-3,i} - P_{1-3}(\theta)) \\ \sum_{i=1}^{N_2}(I_{4-6,i} - P_{4-6}(\theta)) \end{bmatrix} \begin{bmatrix} \sum_{i=1}^{N_2}(I_{1-3,i} - P_{1-3}(\theta)) \\ \sum_{i=1}^{N_2}(I_{4-6,i} - P_{4-6}(\theta)) \end{bmatrix}'$ where $N_2 = 6,027$.

6.5 The Price Coefficient

We do not estimate the price coefficient with the movie-week level data because the price variations at that level may not represent those are faced by consumers. Appendix A discusses the details of estimating price coefficient α with a more disaggregate dataset at movie-theater-day level.[14] That data provides more credible price variations over time and across theaters. We employ that price coefficient in our counterfactual experiment to convert the welfare estimates into monetary value.

7 Empirical Results

This section discusses the empirical results obtained from the demand model described in the previous section. Table 3 reports the demand estimates from the random coefficient specifications, in which Column 1 is our preferred specification. For Column 1, the coefficients of Age and $Holiday$ are significantly negative and positive, respectively. It suggests that consumers prefer to watch movies near the releasing week and consumers' movie demand increases in weeks with holiday. The coefficients of $\sigma_{Foreign}$ is positive and significant, which suggest that there is consumer heterogeneity in watching foreign movies, and reject the use of simple logit model.

Then, we regress the movie-specific effects on time-invariant movie characteristics and report the results in Column 1 of Table 4.[15] The coefficients of $IMAX$, $3D$ and $ln(RunTime)$ are positive and significant, which suggests consumers are more prefer to watch movies in $IMAX$ and $3D$ formats and movies with longer run time. The coefficients of $Foreign$ is negative and significant, which suggests that, on average, consumers are less prefer to watch foreign movies.

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

[15] We use 1,455 observations to invert the mean utility from market share. Only 986 observations are used in the mean utility regression with 314 movie fixed effects. Thus, there are 986 observations of residual from the mean utility regression for constructing the sales moments. In Table 4, we use 314 movie fixed effects used as the dependent variable to estimate the coefficients of time-invariant movie attributes.

Table 3: Demand Estimates

Model	(1) Dynamic	(2) Dynamic	(3) Static	(4) Dynamic
Linear Part				
Age	-0.485^{***} [0.055]	-0.450^{**} [0.201]	-0.566^{***} [0.017]	0.005 [0.099]
Holiday	0.265^{***} [0.017]	0.271^{***} [0.098]	0.242^{***} [0.007]	1.660^{***} [0.374]
Movie FE	*Yes*	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*
Month FE	*Yes*	*Yes*	*Yes*	*Yes*
No. of Movies	315	315	315	315
Observations	986	986	986	986
Non-linear Part				
σ_C				7.807^{***} [1.425]
$\sigma_{Foreign}$	2.587^{*} [1.569]	3.368^{*} [1.719]	2.222^{***} [0.778]	2.131^{***} [0.719]
σ_{IMAX}		0.387 [9.600]		
σ_{3D}		0.709 [5.574]		
Consumption Durability	*Yes*	*Yes*	*No*	*Yes*
Micro-moments	*No*	*No*	*No*	*Yes*
No. of Movies	946	946	946	946
Observations	1455	1455	1455	1455

Data variation at the movie-week level. The label of each column report demand specification used. The dependent vaiable is the mean utility δ_{jt}. The linear part has fewer observations than the non-linear part because it only includes movies with repeated observations. The standard errors are in parentheses. ***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level.

Next, we perform a robustness check of including the random coefficients for $IMAX$ and $3D$. Since there is a higher probability for foreign movies shown in $IMAX$ and $3D$ formats, this brings up a concern, namely that $IMAX$ and $3D$ formats rather than $Foreign$ are the sources of consumer heterogeneity.[16] To address this issue of confounding factors, we extend our model to include the random coefficients of $IMAX$ and $3D$, and report the results in Column 2 of Table 3. The random coefficients of $IMAX$ and $3D$ are insignificant, which suggests that consumers' heterogeneous preferences are driven by whether a movie is foreign instead of those two enhanced formats.

Column 3 of Table 3 reports the results from a standard BLP model with no consumption durability and only with a random coefficient on $Foreign$. Compared to our main results in Column 1, the coefficient of Age becomes smaller and estimated at -0.566. It is because the standard BLP

[16] The probability of a movie shown in $IMAX$ format are 0.48 and 0.15 for foreign and domestic movies with the top six weekly admission. Similarly, the probability of a movie shown in $3D$ format are 0.58 and 0.27 for foreign and domestic movies with the top six weekly admission.

model assumes that available movies are all in the choice set of consumers. It requires *Age* exerting a more negative effect on consumer utility in order to match the decreasing trend of market share of a movie over time. On the other hand, our model with consumption durability assumes that some movies released before do not appear in the choice sets of some consumers, which in turn reduce the market share of those movies. As a result, our model relies less on *Age* to match the decreasing trend of market share of a movie over time. Further, we regress the estimated movie-specific fixed effects on time-invariant characteristics and report the results in Column 3 of Table 4. The results are similar to those reported in Column 1 of Table 4.

Table 4: Estimates of Movie Characteristics

	(1)	(2)	(3)	(4)
Varibles	**Dynamic**	**Dynamic**	**Static**	**Dynamic**
Consumption Durability	**Yes**	**No**	**No**	**Yes**
Micro-Moments	**No**	**No**	**No**	**Yes**
Foreign	-3.914^{***}	-5.371^{***}	-3.372^{***}	-1.395^{***}
	[0.195]	[0.190]	[0.214]	[0.453]
IMAX	0.793^{***}	0.813^{***}	0.656^{**}	2.297^{***}
	[0.247]	[0.241]	[0.271]	[0.574]
3D	0.555^{***}	0.496^{**}	0.530^{**}	1.540^{***}
	[0.208]	[0.202]	[0.228]	[0.482]
Action	-0.032	-0.028	-0.060	-0.164
	[0.195]	[0.190]	[0.214]	[0.453]
Comedy	0.351	0.369^{*}	0.322	0.925^{*}
	[0.215]	[0.209]	[0.235]	[0.498]
Drama	-0.167	-0.187	-0.173	-0.447
	[0.198]	[0.193]	[0.217]	[0.459]
ln(RunTime)	1.605^{***}	1.697^{***}	1.506^{**}	3.951^{***}
	[0.619]	[0.603]	[0.678]	[1.436]
Constant	-5.466^{*}	-4.500	-5.594^{*}	-18.83^{***}
	[2.8882]	[2.810]	[3.160]	[3.160]
R2	0.579	0.736	0.459	0.176
Observations	314	314	314	314

Data variation at the movie level. The label of each column report demand specification used. The dependent vaiable is the movie FE ζ_j.
The standard errors are in parentheses. ****Significant at the 1% level;* ***Significant at the 5% level;* **Significant at the 10% level.*

Column 4 of Table 3 re-estimates our preferred specification with the micro-moments. The coefficients of σ_C and $\sigma_{Foreign}$ are positive and significant, which suggest that there are consumer heterogeneities in watching a movie and in watching foreign movies. Column 4 of Table 4 reports consistent results with Column 1 of Table 4, except most of the positive coefficients on time-invariant movie attributes, such as $IMAX$, $3D$, $Comedy$ and $\ln(RunTime)$, become larger in magnitude by about 3 times. The positive coefficient σ_C and those larger positive coefficients on time-variant attributes suggest that the model matches the majority fraction of consumers with more than six visits to theater by generating more consumer heterogeneity, that increases the set of consumers who have higher utility from watching movie, and by increasing the positive impact of movie attributes. Interestingly, compared to our main results in Column 1, the coefficient of *Age* becomes insignificant, which suggests that the dynamics of choice set captures most of the explantory power of *Age* on movie demand.

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 allows there are extra 14 foreign enhanced movies in 3D or IMAX formats, which are mainly produced in the U.S. This section performs counterfactual experiments to evaluate such import liberalization on consumer and producer welfare. An assumption we make to perform these counterfactual experiments is that we assume the producers do not revise the attributes of their movies in response to the import liberalization.

8.1 Welfare Computation

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

Second, we take away the movies listed in Appendix B from the choice sets of consumers. We denote the counterfactual choice sets as $\widetilde{C}_{gt}$, $g = 1, .., G_t$. Some choice sets $\widetilde{C}_{gt}$ have the same set of movies as C_{gt} because they do not include any movies listed in Appendix B. For example, $\widetilde{C}_{11} = C_{11}$. But, for the choice sets including the movies listed in Table B1, $\widetilde{C}_{gt}$ is a subset of C_{gt}.

Third, we employ the estimated mean utility and follow Equations (2)-(5) to compute the market share of each remaining movies week by week. Starting from Week 1, we compute the movie choice $\widetilde{S}_{ijt|C_{gt}}$ for each consumer i for the choice set $\widetilde{C}_{11}$ according to Equation (5). Since there is only one choice set in Week 1, the movie choice from $\widetilde{C}_{11}$ is the same as the market share in Week 1, i.e. $\widetilde{s}_{ijt} = \widetilde{S}_{ijt|C_{gt}}$ for $t = 1$. Then, we compute the share of consumers transiting to $\widetilde{C}_{12}$,.., $\widetilde{C}_{G_2 2}$ according to Equation (4), and market share according to Equation (5). In Week 2, we compute the movie choice $\widetilde{S}_{ijt|C_{gt}}$ for the choice sets $\widetilde{C}_{12}$,.., $\widetilde{C}_{G_2 2}$ according to Equation (2), and then compute the movie choice $\widetilde{s}_{ijt}$ for each consumer i of each movie with Equation (3). Finally, we compute the share of consumers transiting to $\widetilde{C}_{13}, .., \widetilde{C}_{G_3 3}$ according to Equation (4), and market share according to Equation (5). We repeat these procedure for all sample weeks.

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

$$
\begin{aligned}
\%\Delta CS &= \int \frac{CS_i - \widetilde{CS}_i}{\widetilde{CS}_i} dF_i \\
where & \\
& CS_i = \sum_t \sum_{g \in G_t} S_{igt} \ln \left(1 + \sum_{j \in C_{gt}} e^{\delta_{jt} + \mu_{ijt}} \right) \\
& \widetilde{CS}_i = \sum_t \sum_{g \in G_t} \widetilde{S}_{igt} \ln \left(1 + \sum_{j \in \widetilde{C}_{gt}} e^{\delta_{jt} + \mu_{ijt}} \right)
\end{aligned} \tag{11}
$$

To compute consumer welfare, we first compute the welfare for each consumer i facing a choice set $\widetilde{C}_{gt}$ in each week t. Second, we sum up the welfare for each consumer i facing different choice sets according to her probability facing each choice set, $\widetilde{S}_{igt}$. Third, we aggregate consumer welfare for each consumer i over all weeks to obtain $\widetilde{CS}_i$. Finally, we aggregate the consumer welfare over all consumers. We compare the counterfactual consumer welfare to the sample consumer welfare to compute the percentage change in consumer welfare. To compute the monetary value of welfare benefit from including these extra movies, we compute the following expression of compensating variation

$$
CV = \int \frac{CS_i - \widetilde{CS}_i}{\alpha} dF_i \tag{12}
$$

Turning to the supply side, we compute the total market share of all movies after including those extra movies to examine the extent of consumers switching from the outside option to watching a movie.[17] We then compute the total market share of domestic movies in each week after including those extra movies. The change in total market share of domestic movies shows the business stealing effect of those extra movies from domestic movies. Also, we compute the total market share of remaining foreign movies in each week after including those extra movies. The change in market share of remaining foreign movies shows the business stealing effect of those extra movies from the remaining foreign movies.

We conclude this sub-section by using Figure 1 to illustrates an advantage of using our model to evaluate the welfare benefits of new movies. Suppose movie B would not be imported if the trade liberalization did not take place. Our model with consumption durability allows that consumers with choice sets C_{22} and C_{23} would not be affected because movie B was not in their choice sets. Further, the inclusion of other domestic movies and other foreign movies are important for evaluating welfare benefit of new movies. Consumers would have switched to those two choices instead of the outside option if those new movies had removed.

8.2 Welfare Estimates

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

Lower panel of Table 5 reports the results from our counterfactual experiment of adding top 14

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

foreign enhanced movies. The results reported in Column 1 are consistent with those reported in the upper panel. The main difference between these two sets of results is that the lower panel exhibits a larger impact on consumer and produce welfare as the newly included movies have higher mean utility. The import liberalization in 2012 increases consumer welfare by 40.8%, annual consumer welfare by RMB 580 per year and marker share of all movies by 34.8%. The market shares of competing foreign movies and domestic movies reduce by 9.31% and 0.76%, respectively.

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

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

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

8.3 Welfare Estimates without accounting for Consumption Durability

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

In this counterfactual experiment, we compare two situations with all sample movies available. First, we compute consumer welfare and movie admission with our model (Specification RC) and report the results in Column 1 of Panel A, Table 6. Second, we compute consumer welfare and movie admission with a counterfactual model have the same set of demand estimates as our model

(Specification RC) but do not incorporate consumption durability. In this model, all consumers have the common choice set C_t, which contains all movies available to consumers, in each week t. We report the results in Column 2 of Panel A, Table 6. The consumer welfare and movie admission estimates between these two models are reported in Column (2)-(1). We find

that the welfare benefit for consumers are overestimated if consumption durability is ignored. It is because that demand model assumes consumers considering the movie watched before as a part of their choice sets, which overestimates the consumer welfare from watching movies. In turn, it overestimates the movie admission all movies regardless of their country of origin.

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

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

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

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

8.4 Welfare Estimates from a Standard BLP

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

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

We also compute consumer welfare and movie admission with Model *Static* for the other two sets of movies. One is all movies except the bottom 14 enhanced movies (reported in Panel B, Table 6) and the other is all movies except the top 14 enhanced movies (reported in Panel C, Table 6). Although the consumer welfare and movie admission of our model is higher than those of Model *Static* in those two scenarios, the differences in consumer welfare and movie admission between our model and Model *Static* vary across those two scenarios. Finally, Model *Static* underestimates the consumer welfare gain and biases market share change due to the introduction of bottom or top 14 enhanced movies (see Column 3 of Panel A-B, Table 5).

8.5 Welfare Estimates from the model with Micro-moments

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

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

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

9 Conclusion

To be written

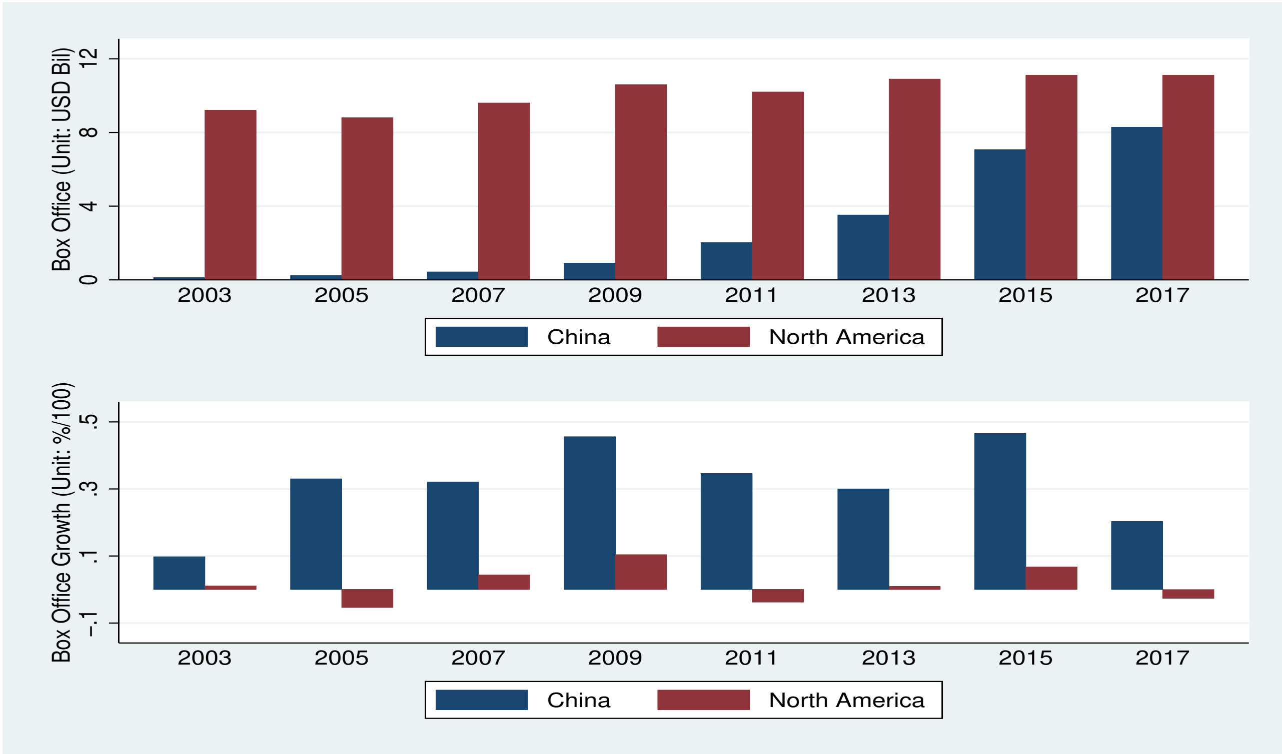

Figure 1: Figure 1: An Example of the Evolution of Choice Sets

Note: We denote the set of available choices in week t as C_t, where $t = 1, 2, .., T$. In particular, $C_1 = C_2 = C_3 = \{A, B, Outside\ option\}$ and $C_4 = \{B, C, Outside\ option\}$. We denote the potential choice sets in Week t as C_{gt}, where $g = 1, 2, .., G_t$. G_t is the number of choice set in Week t. In Week 2, there are three potential choice sets C_{12}, C_{22} and C_{32}. The choice set C_{12} is available for consumers do not watch any movie in Week 1 (Arrow O), whereas the choice set C_{22} and C_{32} are available for consumers watch movies B (Arrow B) and movie A (Arrow A) in Week 1, respectively. In Week 3, there are four potential choice sets C_{13}, C_{23}, C_{33} and C_{43}. In Week 4, there are only two potential choice sets C_{14} and C_{24} becuase movie A exits after Week 3.

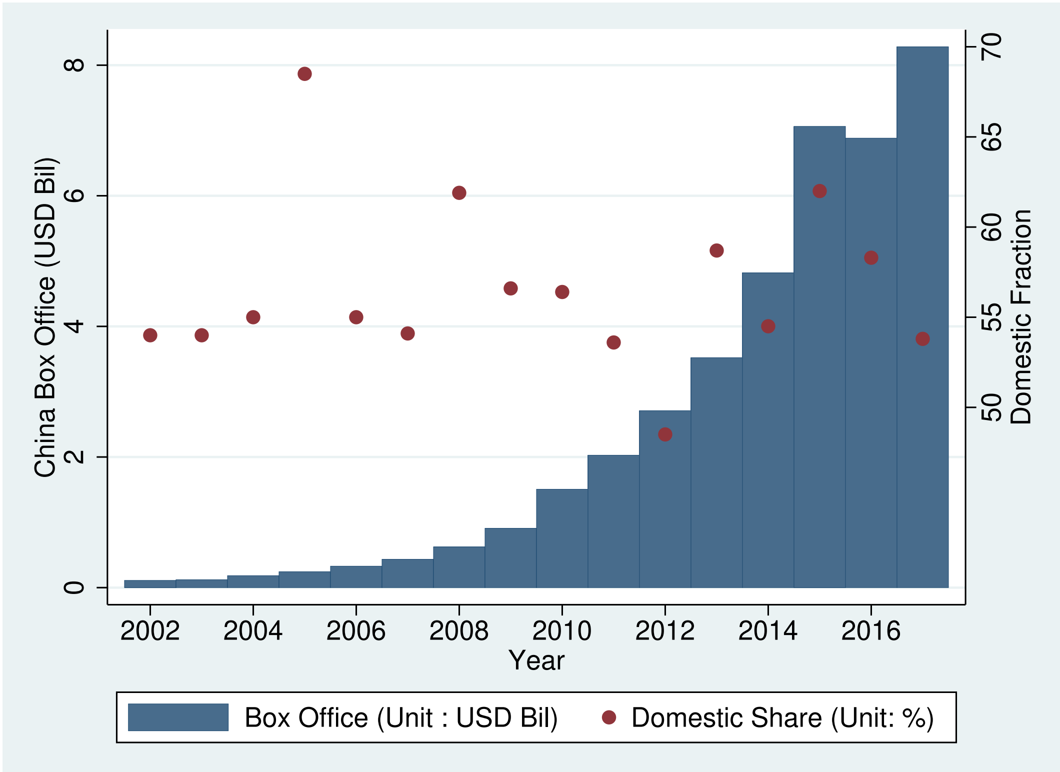

Figure 2: Figure 2: Box Office 2002-17.
Source: Various sources.

Figure 3: A Snapshot of Movie Ticket Price of a Theater (Date: 12/29/2011)

Appendix A - The Estimation of Price Coefficient

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

Market Definition

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

Box Office

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

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

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

Movie Characteristics

We construct nine variables on movie characteristics based on the website Douban, which is the most popular website on movie information in China.[18] We define dummy variables Foreign, 3D, Comedy, Action and Sequel for whether a movie is foreign, three-dimensional, comedy, action, sequel to movies shown before, respectively. We define Rater as the number of online raters (in thousands) for each movie as an measure of popularity. Although this measure includes feedback after the release of movies, this measure is mostly determined during the movies' run. To measure the quality of a movie, we construct two variables, namely Director and Star. Director is computed as the average rating of a director's top three movies, and Star is computed as the average of the average rating of the top three movies casted by the movie's top four leading actors and actresses. Further, we construct the variable Budget, which takes 1 if a film's budget exceeds RMB 80 million, and zero otherwise. For Chinese movies, we obtain this information from news on movie press conferences and http://baike.baidu.com, while for foreign movies, we obtain the estimated budget from www.imdb.com, and then convert to RMB using the average USD-RMB exchange rate in 2013.

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

Demand Model

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

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

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

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

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

Identification and Estimation

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

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

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

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

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

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

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

Results

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

Table A1: Nested Logit Model with Disaggregate Data

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

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

Appendix B - The List of Imported Enhanced Movies

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

Table B1: 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 B2: 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

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