Strategic Decision-Making in Hollywood Release Gaps*

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November 2016

Abstract

Hollywood blockbusters are usually released in the U.S. before other foreign markets. The release gaps have declined significantly over time and varied greatly across countries. While movie piracy has been suggested as an important determinant for the release gap decision of distributors, theory and evidence suggest there are other important determinants. In this paper, we use a discrete choice release gap decision game model to disentangle the impacts of the i) release gap effect, which includes factors that provide incentives for a distributor to shorten the release gap; ii) word-of-mouth effect, which provides incentives for a distributor to lengthen the release gap; and iii) competition effect, which accounts for the incentives blockbusters have to avoid each other. We obtain box office and release gap data from the private industry source Boxofficemojo.com. We provide results on the economically significant impact of these three factors on distributors' release gap decisions and box office revenue.

JEL Classification: F14, L82, 034
Keywords: Hollywood, movie exports, release gap, intellectual property rights

*We thank Liran Einav for sharing his codes, Christina Marsh Dalton for her many helpful comments, and Douglas Cheng, Caitlin Dourney, Hannah Sheffield, and Alex Yiu for their valuable research assistance. We also thank seminar participants at 6th APIC, Hong Kong Baptist University, Peking U HSBC School, and Wake Forest University for their many suggestions and comments. We thank three anonymous referees for their many comments and suggestions leading to substantial improvements in the paper. Financial support from the Farr Funds at Wake Forest University is gratefully acknowledged. The usual disclaimer applies.

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1 Introduction

Movie executives fear the collapse of Hollywood exports in the face of rising worldwide piracy rates. Yet box office sales growth remains stable. According to the Motion Picture Association of America (MPAA), U.S./Canadian and international box office sales grew 12% and 32% between 2008 and 2012.[1]

One characteristic of the movie industry often mentioned in connection with piracy is the release gap between when a movie appears in the U.S. and a foreign market. Hollywood studios try to preempt piracy by releasing movies as quickly as possible. Industry observers often note the decline in movie release gaps worldwide, a point made by Eliashberg, Elberse, and Leenders (2006). Looking at the years 1980, 1990, 2000, and 2010, for example, we observe this trend when comparing the average release gap for those top ten box office hits from the U.S. which were also released in Hong Kong. The average release gap declines from 168 days in 1980, a year which saw the hits *Star Wars: Episode V - The Empire Strikes Back* and *The Blues Brothers*, to 149 days in 1990 to 43 days in 2000 to 20 days in 2010. Out of the top ten movies in 2010, two were released first in Hong Kong, one was released on the same day in both the U.S. and Hong Kong, and one was released less than a week later in Hong Kong.[2] McCalman (2005) provides evidence that the release gap has a non-linear relation to the level of intellectual property rights in a country: either very weak or very strong protection of intellectual property rights is associated with a longer release gap.

Although piracy affects release gaps, it is only one of many possible factors contributing to the release gap decisions made by Hollywood studios. Studios are notoriously tight-lipped about what determines their release schedules. A recent article exploring the topic ends without a clear answer: "Why did the studios select those dates? After much to-ing, fro-ing and dithering about whether to comment on the record, neither studio would say."[3] In addition to factors such as seasonality and the movie decay pattern, we categorize the factors contributing to release gap

[1] We use the MPAA's *Theatrical Market Statistics 2012* for various statistics throughout the paper. This report currently resides at `http://www.mpaa.org/policy/industry`.

[2] The numbers for this example were constructed from information accessed from Boxofficemojo.com and IMDb.com.

[3] Buckley, Cara 2015. "Why This Movie Now? Planning Release Dates, From 'Straight Outta Compton' to 'Meru'." August 11. `http://www.nytimes.com/2015/08/12/movies/why-this-movie-now-planning-release-dates-from-straight-outta-compton-to-meru.html`

variation observed in the data into three main effects: the release gap effect, word-of-mouth effect, and competition effect.

The release gap effect refers to factors that provide incentives for a distributor to shorten the release gap. These include i) the prevalence of digital cinema, which can significantly reduce the duplication and delivery cost of a movie, estimated to be approximately 3.5% of the total cost to create and distribute a movie (Husak (2004)), and ii) movie piracy, which has become more important after the spread of Peer-to-Peer (P2P) file sharing technology.

The word-of-mouth effect refers to the effect of longer release gaps on box office performance. In particular, a longer release gap allows a movie more time to accumulate (both positive and negative) reviews on the Internet and, thus, more (both positive and negative) word-of-mouth in the foreign market. Moul (2007) shows word-of-mouth has a positive impact on domestic box office performance. Elberse and Eliashberg (2003) argues that U.S. releases act as a filter which selects the more successful movies to be released abroad.

The competition effect refers to the interactions among Hollywood distributors. Distributors want to release movies on popular movie-going weekends, like the Fourth of July in the U.S., but also want to avoid competition from other blockbusters. Krider and Weinberg (1998) cites, for example, a Vice President of Warner Brothers:

> ...all studios, including Warner Brothers, are constantly moving their opening dates, and we shift the pictures around the calendar in an effort to find the ideal release date for each picture on our schedule. Because the opening weekend is so critical, it is even more critical that we find exactly the right date for each movie.

This same Vice President cites the primary concern about the release date as being competition from other movies with a similar target audience. Krider and Weinberg (1998) relates an example of a studio adjusting its release date in the face of competition during the Christmas season of 1992. Columbia Pictures moved its release date of *A Few Good Men* from December 18 to December 11, which coincided with the release date of Twentieth Century Fox's *Hoffa*. Both movies star the actor Jack Nicholson. Twentieth Century Fox feared losing ticket sales and moved the release of *Hoffa* to December 25. Strategy regarding release dates may also apply to foreign markets.

In this paper, we develop and estimate a model of discrete games, which allows us to disentangle the three effects when analyzing the release gap decision. Our theoretical modeling takes two steps. First, we model demand for movies as a function of movie quality, movie demand decay pattern, and seasonality underlying demand for a movie, as in Einav (2010). Second, we build on Einav (2010) to construct a private information sequential-move game on the release gap decision. In the model, we take the movie decay pattern and seasonality as given and re-parameterize the movie's quality as a function of the length of release gap and the number of positive and negative reviews on International Movie Database (IMDb) to account for the release gap effect and word-of-mouth effect. We then take the season in which a movie is released as given and focus on the strategic decision of the release gap within the season.

We estimate the model using data on box office performance and release dates from the U.S. and 18 other countries between 2008 and 2014. For computational concerns, we choose four annual release seasons (Presidents' Day, Memorial Day, Fourth of July, and Thanksgiving), all at around a dominant U.S. release date, to test our empirical model. We also only consider the strategic interaction between the top three Hollywood movies in each season. Our results suggest three things. First, less competition, through an imposition of an import quota, would only slightly decrease the release gap (approximately 1%), but would more significantly increase the box office revenue of movies that obtain the quota (6.7%). Second, word-of-mouth has a positive impact on the length of the release gap. In particular, we conduct a counterfactual in which a movie would receive no effects from word-of-mouth. Our counterfactual results suggest the release gap and box office revenue would indeed decrease by 3.6% and 4.6% on average across the 18 countries. Third, the release gap effect has a negative impact on the length of the release gap. When the release gap effect disappears, the average release gap and box office revenue across 18 countries would increase by 18.3% and 60.9%.

The remaining sections of our paper are organized as follows: Section 2 reviews the extensive and growing literature on box office revenues, piracy, and international trade in movies. Section 3 briefly discusses the movie industry in general and in the context of movie piracy and release gap trends. Section 4 describes our model of the release gap decision. Section 5 describes our data set we use in our analysis, while sections 6 and 7 present our estimates and counterfactuals. Section 8 concludes.

2 Literature Review

There is a large literature on the determinants of box office revenues. Einav (2007) uses a long panel of movies' weekly box office revenue to separately identify the effect of seasonality, movie decay pattern, and movies' quality on movies' box office revenue. Dellarocas, Zhang, and Awad (2007), Duan, Gu, and Whinston (2008), and Moul (2007) evaluate the effects of user reviews and word-of-mouth on box office revenues. Lastly, a few papers have analyzed other factors affecting box office revenues, such as a movie's script (Eliashberg, Hui, and Zhang (2007)), advertising (Rennhoff and Wilbur (2011)), and the presence of big stars (Elberse (2007)).

On top of these factors, there is a growing literature that attempts to evaluate the impact of piracy on box office revenues. Rob and Waldfogel (2007) collects survey data from 500 students from the University of Pennsylvania and finds the displacement effect to be approximately 0.2. Zentner (2010) uses a panel of country-level data on movie consumption and broadband penetration to evaluate the effect of P2P file sharing on retail purchases as well as on box office revenue. He finds P2P file sharing has a large and negative impact on retail purchases but no statistically significant impact on box office revenue. DeVany and Walls (2007) finds a single widely-released movie lost $40 million in revenue due to pre-release and contemporaneous Internet downloads of the movie. Ma, Montgomery, Singh, and Smith (2013) uses U.S. box office data together with unique Internet file-sharing data and finds pre-release piracy can lead to a 20% decrease in box office revenue compared to piracy that occurs post-release. Danaher and Waldfogel (2012) makes use of the variation in international release gaps and box office performances in 17 countries, together with time breaks for the adoption of BitTorrent, to identify the effect of release gaps on box office performances. Their results indicate international box office returns were at least 7% lower than they would have been in the absence of pre-release piracy. Danaher, Smith, and Telang (2014) provides a review of the recent literature.

Our paper contributes to the literature by extending Einav (2007)'s framework to structurally analyze the determinants (seasonality, movie decay pattern, and movie quality) of box office revenues in the U.S. and 18 foreign countries. Also, we extend the framework to analyze two additional determinants–piracy and word-of-mouth.

A few papers also attempt to analyze the release timing decision of movies. Several papers focus on the U.S. market. Krider and Weinberg (1998) characterizes the equilibrium of a model in which two movies compete by choosing the release dates. They test the predictions of the model using the data from the 1990 summer season in the U.S.. Einav (2010) builds on Einav (2007) to structurally estimate a release date timing game in the U.S. market. He finds that release dates of movies are too clustered on holiday weekends and distributors could increase box office revenues by shifting holiday release by one or two weeks. Several papers focus on the release gap decision in the international market. McCalman (2005) builds a model and predicts that release gaps and piracy have a U-shape relationship. Song and Shankar (2014) estimates a simultaneous system of equations and shows that release gaps increase with word-of-mouth and decrease with piracy in 62 countries during 2007-08. Belleflamme and Paolini (2015) shows that, both theoretically and empirically, higher budgets allow movie distributors to release their movies closer to peak seasons. Our paper contributes to the literature by assembling a long panel of box office and release gaps in 18 countries. Ours is also the first to structurally estimate the release gap decision in the international market, taking into account the seasonality, movie decay pattern, competition among movies, piracy, and word-of-mouth.

Our study also fits into the international trade literature motivated by the availability of rich micro-level data sets. Most existing work, however, studies trade flows in manufacturing goods, as services data is often difficult to obtain. A recent exception has been the literature on international trade in movies. Marvasti and Canterbery (2005) determines cultural distance by applying a gravity-iceberg model to U.S. movie exports. Using a gravity framework as well, Hanson and Xiang (2008) finds market size, language, and trade costs are all important determinants of U.S. movie exports. Hanson and Xiang (2011) applies versions of the model in Melitz (2003) to trade in movies, finding the data reject the bilateral fixed export cost model in favor of the model with a global fixed export cost. Hanson and Xiang (2011) shows countries import the same number of U.S. movies but differ in their box office sales of these movies. This variation across the intensive margin, not the extensive margin, differs from trade in manufacturing, since most studies find the extensive margin plays an important role in trade in manufacturing.[4] Bridgman (2012) finds results consistent with Hanson and Xiang (2011) but for the case of a particular company, United Artists, during the period 1935 to 1949, thus,

[4]See, for example, Hummels and Klenow (2005) and Kehoe and Ruhl (2013)

providing a look at the historical data on trade in services. Ferreira, Petrin, and Waldfogel (2012) employs a structural econometric model of the global movie industry to quantify the gains from trade from importing U.S. movies. Half of these gains from trade result from access to higher quality movies.

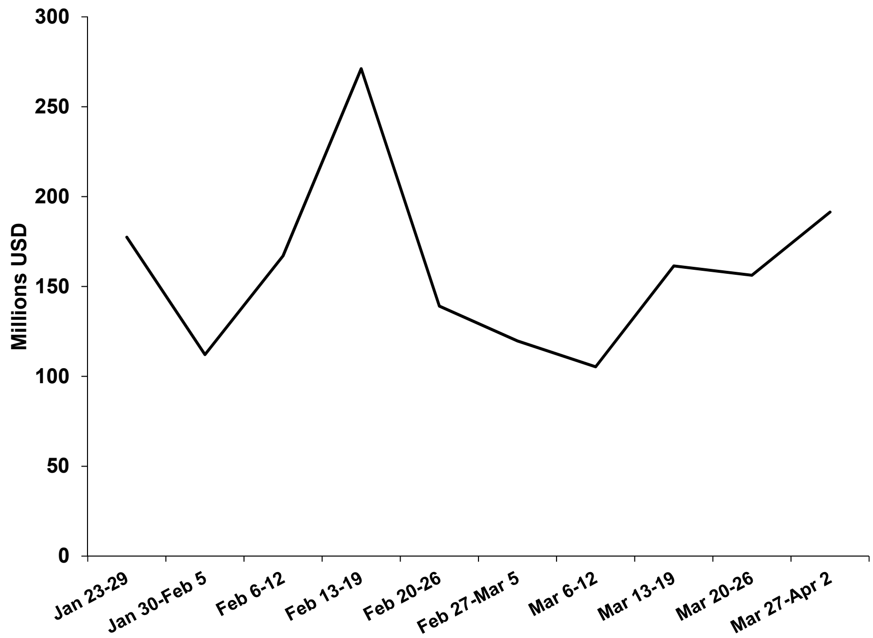
3 Strategic Choice of Release Dates

3.1 Seasonality, Movie Decay, and Competition in the Local (U.S.) Market

Competition through prices and quantities is common in many industries. However, prices play a smaller role in some industries. A prime example is the movie industry in which the movie ticket price is fixed for various reasons. Movie distributors, therefore, compete along other dimensions, one of which is the timing of the release of the movie.

The timing of the movie release is important for several reasons. Let us consider one holiday window in the U.S. to illustrate the point, February 2015 (Presidents' Day), for example. There were four movies that can be considered a success: *Fifty Shades of Grey* (with a total box office of $166 million), *The SpongeBob Movie: Sponge Out of Water* (with a total box office of $163 million), *Kingsman: The Secret Service* (with a total box office of $128 million), and *Jupiter Ascending* (with a total box office of $47 million). All four movies were released in the week of February 6th (*The SpongeBob Movie: Sponge Out of Water* and *Jupiter Ascending*) or in the week of February 13th (*Fifty Shades of Grey* and *Kingsman: The Secret Service*). These movies were released either in the week of February 13th or the week before mainly because Presidents' Day, which is an anchor for one of the big holiday movie seasons in the U.S., is in the week of February 15. As Figure 1 shows, from the end of January to the end of March, the sum of the box office of the top 12 movies were the highest in the week of Presidents' Day. In other words, the demand for movies is the highest in the week of February 13th. If a movie's box office run over the weeks were steady, movie distributors would not necessarily need to release their movies in peak season. However, it is common knowledge in the industry that a movie's box office revenue decays quickly. As Figure 2 shows, the box office revenue for the four movies

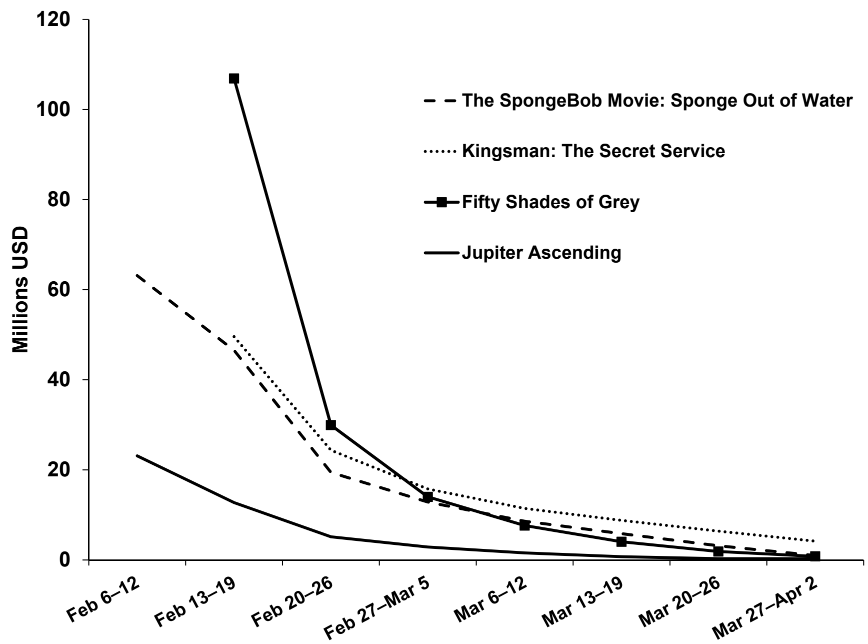
Figure 1: Top 12 Gross Box Office (Jan - Mar 2015)



in our example decays very fast after the opening week. For three of the four movies, the box office revenues in the second week of release decayed more than 50% compared to their opening weeks. The box office of the most popular movie in the period, *Fifty Shades of Grey*, even declined by 70% in its second week of release. The fast decay of box office revenue makes the timing of the movie's release even more important. While the seasonality and fast decay of box office revenue make the decision regarding the release date important, movie distributors still might not want to release their movies during peak season in order to avoid competition. As Ed Arentz of Music Box Films, the distributor for the movie *Meru*, told a New York Times reporter, "It's kind of like landing an airplane. There's only so many runways. If you try to land too many planes at the same time, some are going to crash."[5] Joe Roth, chairman of Walt Disney Studios said similar things back in 1996: "If you only think about your own business, you think, 'I've got a good story department, we're going to go out and do this.' And you don't

[5]Buckley, Cara 2015. "Why This Movie Now? Planning Release Dates, From 'Straight Outta Compton' to 'Meru'." August 11. `http://www.nytimes.com/2015/08/12/movies/why-this-movie-now-planning-release-dates-from-straight-outta-compton-to-meru.html`

Figure 2: Box Office Run for Four Movies (Feb 2015)



think that everybody else is thinking the same way. In a given weekend in a year you'll have five movies open, and there's certainly not enough people to go around."[6] Einav (2010) documents that distributors change the release dates of movies in the U.S. market for strategic reasons. In particular, movies with lower box office quality (as estimated in Einav (2007)) are significantly more likely to change release dates to avoid the movies with higher box office quality.

3.2 Word-of-Mouth and Piracy in the International Market

Table 1: Domestic Share of Box Office Revenue for All Time Highest Grossing Movies

Decade	Domestic Share
1980s	61%
1990s	44%
2000s	45%
2010s	38%

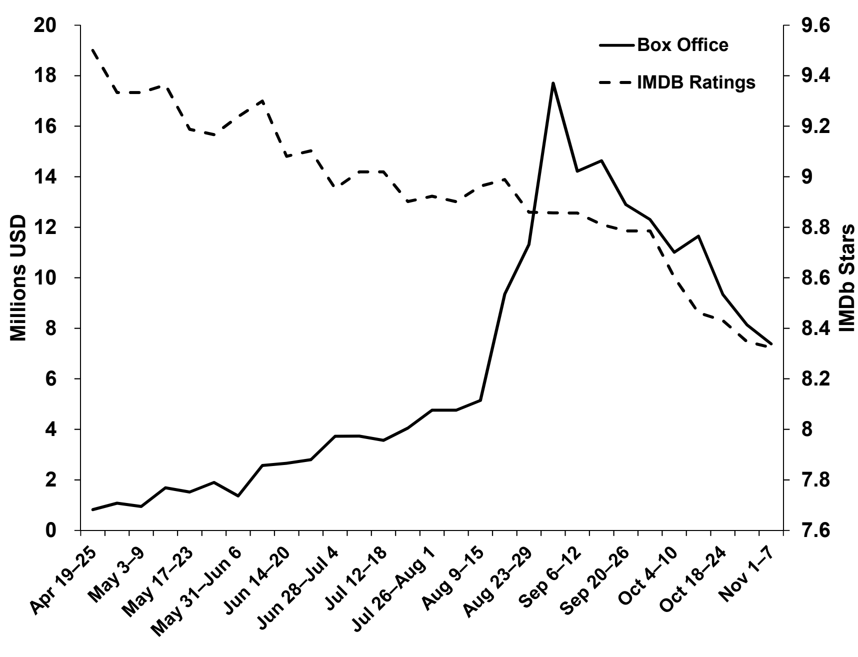
Source: www.the-numbers.com

[6] Los Angeles Times, December 31, 1996.

Over the years, the international market has become more and more important for the movie industry. As Table 1 shows, the domestic share of box office revenue for the all time highest grossing movies has been declining over the years.[7] In the 1980s, more than 60% of the total box office came from the domestic (U.S.) market, but this domestic share has dropped significantly to less than 40% this decade.

The release date decision in the international market has become more critical in determining the overall success of a movie. In addition to the forces at play in the local market (seasonality, fast decay of box office revenue, and competition), there are two additional determinants of the release date decision in a foreign country: word-of-mouth and piracy.

Figure 3: IMDb Rating and U.S. Box Office (*My Big Fat Greek Wedding*)



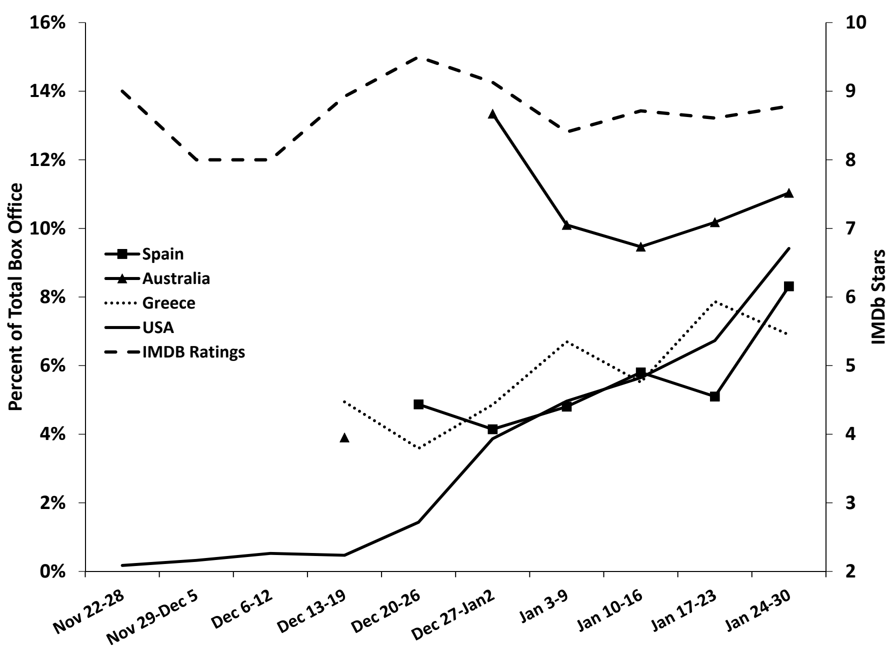
The industry has long known the importance of word-of-mouth. In the local (U.S.) market, a low budget movie which has limited initial release but good reviews will have the chance to be released nationwide later. The movie *My Big Fat Greek Wedding* was a prime example (Figure

[7]The all time highest grossing movies are defined using the total box office information in `www.the-numbers.com`.

3). It was first released in April 2002 on a limited scale. The initial average rating of the movie was above 9 on IMDb. The box office gradually increased and the movie was eventually released nationwide in August 2002. A sequel was released in 2016.

In the international market, if a movie gets positive reviews in its early theatrical run in the U.S., it could generate positive effects on the box office runs in foreign countries. *The King's Speech* is one such example (Figure 4). The movie was first released in late November in the U.S.. The movie did not do very well in the box office in the first four weeks, but it had very good ratings on IMDb (approximately 9). Gradually, the box office in the U.S. picked up. Also, the box office in foreign markets, such as Australia, Japan, and Greece, were better than that from the initial U.S. release.

Figure 4: IMDb Rating and International Box Office (*The King's Speech*)



Another determinant of the release date decision in international markets is movie piracy. According to the MPAA, movie piracy is a threat to movie revenue. In countries with high movie piracy, such as China, Russia, and Thailand, the MPAA estimates that the percent of potential market lost to piracy can be more than 80%.

An Indian martial arts movie, *Brother*, was released on the same day, August 14, 2015, everywhere in the world. Rohit Sharma, who is responsible for international distribution of the movie, said his company had no choice but to release the movie on the same day because of the holiday season (it was the Indian Independence Day) and the threat of piracy. He said that "if the film did not open in other countries at the same time, especially in the United States, soaring online piracy would erode its worldwide earnings."[8] The threat of piracy might shorten the release gap between the U.S. and foreign releases. Blockbusters in the past had long release gaps between the U.S. and foreign release. For instance, *Star Wars: Episode IV* was released on May 25, 1977 in the U.S. but was not released in Hong Kong until January 26, 1978. However, the release gap has been much shorter these days. Many movie distributors decide to release their movies on the same day worldwide. Some even release their movies earlier in foreign countries. For instance, the movie *Iron Man 3* was released a week earlier in Hong Kong than in the U.S..

4 Model of Strategic Choice of Release Gap

4.1 Discrete Choice Demand Model for Movies

We follow Einav (2007) to build a discrete choice model of demand for movies in country k. For notational simplicity, we suppress the country subscript in the exposition of the demand model. We assume the utility of consumer i from going to movie j in week t is

$$u_{ijt} = \theta_j - \lambda(t - r_j) + \tau_t + \xi_{jt} + \zeta_{it} + (1-\sigma)\varepsilon_{ijt}, \tag{1}$$

where θ_j is a movie j fixed effect, r_j is the release week of movie j, λ is the movie decay parameter, $\tau_t = \hat{\tau}_t + \varphi_t$ is the sum of the week fixed effect ($\hat{\tau}_t$) and holiday fixed effect (φ_t) capturing seasonality, ξ_{jt} is an unobserved preference shock (assumed the same for every consumer) for movie j in week t, and $\zeta_{it} + (1-\sigma)\varepsilon_{ijt}$ is an individual error term, the distribution for which we describe momentarily.

[8]Buckley, Cara 2015. "Why This Movie Now? Planning Release Dates, From 'Straight Outta Compton' to 'Meru'." August 11. `http://www.nytimes.com/2015/08/12/movies/why-this-movie-now-planning-release-dates-from-straight-outta-compton-to-meru.html`

Consumer i can also choose not to go to a movie in week t and, instead, derive utility from an outside good (good 0). Utility from the outside good is

$$u_{i0t} = \zeta'_{it} + (1-\sigma)\varepsilon_{i0t}.$$

We follow Berry (1994) in the nested logit demand setting by assuming ε_{ijt} (and ε_{i0t}) is distributed i.i.d. extreme value and ζ_{it} (and ζ'_{it}) has a distribution that depends on $\sigma \in [0,1]$. The sum $\zeta_{it} + (1-\sigma)\varepsilon_{ijt}$ (and $\zeta'_{it} + (1-\sigma)\varepsilon_{i0t}$) is also distributed extreme value.

The parameter σ captures the market-expansion effect. It captures whether a new movie draws consumers from other movies or from people who would otherwise not go to movies at all. When σ approaches one, there is no substitution between the outside good and inside goods, and hence no market-expansion effect. When σ approaches zero, the model boils down to a simple logit model in which more observed seasonality can be attributed to variation in the number and quality of movies across the year.

The market share for movie j in week t is

$$s_{jt} = \frac{\exp\left(\frac{\theta_j - \lambda(t-r_j)+\tau_t+\xi_{jt}}{1-\sigma}\right)}{D_t^{\sigma} + D_t}, \tag{2}$$

where

$$D_t = \sum_{j' \in J_t} \exp\left(\frac{\theta_{j'} - \lambda(t-r_{j'}) + \tau_t + \xi_{j't}}{1-\sigma}\right) \tag{3}$$

and J_t is the set of all movies shown in theaters in week t. Rearranging equation (2) gives us

$$\log(s_{jt}) - \log(s_{0t}) = \theta_j - \lambda(t-r_j) + \tau_t + \sigma \log\left(\frac{s_{jt}}{1-s_{0t}}\right) + \xi_{jt}. \tag{4}$$

The identification of the parameters $(\theta_j, \lambda, \tau_t, \sigma)$ is similar to Einav (2007). Given the movie decay pattern (λ), we observe movies throughout their entire run, during which they experience different seasonality and competitors. A high-quality movie may be released in a week with high demand, but it still runs in subsequent weeks in which seasonality and the level of competition are different. Other low-quality movies, released at different weeks, might be observed at the same time as the high-quality one. A comparison of their market shares identifies their relative qualities, thus, movie fixed effects. Seasonality is then identified through observing different choice sets over different weeks across the years.

The identification of the market-expansion effect, σ, requires multiple observations of the same weeks in different years. We assume the seasonality across years is stable so that comparing the same week in different years can identify market expansion. For example, suppose better (or more) movies are released on Thanksgiving 2008 compared with those released on Thanksgiving 2009. Conditional on movies' quality and seasonality, higher Thanksgiving 2008 revenue can be attributed to a strong market-expansion effect (low σ), while lower Thanksgiving 2008 revenue can be attributed to weak market-expansion effect (high σ). This guides the choice of instrument for the within-industry market share, $\frac{s_{jt}}{1-s_{0t}}$, which is endogenous. Because the number of movies is positively related to the level of competition, it is also negatively related to the within-industry share. The key assumption is that the instrument (number of movies in the week) is not correlated with the error term, ξ_{jt}.

We separately estimate the relevant parameters, $\theta_j, \lambda, \tau_t$, and σ, for each country. We then take λ and τ_t as exogenous and re-estimate θ_j in the release gap decision game, which we describe in more detail in the next section.

4.2 Release Gap Decision Game

We extend the demand model in the previous section and model the release gap decision game as a private information sequential game similar to that in Einav (2010).

As in equation (1), the utility of consumer i going to movie j in week t depends on the movie's quality (θ_j), the age of the movie ($t - r_j$), seasonality in week t (τ_t) and demand shocks ($\xi_{jt}+\zeta_{it}+(1-\sigma)\varepsilon_{ijt}$). In the previous section, we assume all the release dates of all movies (r) are exogenous. Here, we allow the release dates of up to three Hollywood movies to be endogenously chosen, while the other local movies' release dates are still assumed to be exogenous. To simplify the analysis, we assume the unobserved preference shock for movie j to be zero, i.e. $\xi_{jt} = 0$. Therefore, the utility for a local movie j whose release date is still exogenous is

$$u_{ijt} = \theta_j - \lambda(t - r_j) + \tau_t + \zeta_{it} + (1 - \sigma)\varepsilon_{ijt}. \tag{5}$$

The utility for a Hollywood movie j whose release date is endogenously chosen becomes

$$u_{ijt} = \hat{\theta}_j(r_j) - \lambda(t - r_j) + \tau_t + \zeta_{it} + (1 - \sigma)\varepsilon_{ijt}, \tag{6}$$

where the movie's quality, $\hat{\theta}_j(r_j)$, is a function of the release date, r_j. We modify the movie fixed effect, θ_j, with $\hat{\theta}_j(r_j)$ to capture two effects: i) the negative effect of the release gap between the U.S. and local release and ii) the positive effect of the word-of-mouth on the box office revenue of movie j in the U.S. market.

To capture the negative effect of the release gap, we would have to model that the movie fixed effect, $\hat{\theta}_j(r_j)$, decreases with the release gap. We assume the effect of release gap depends on the movie decay pattern in the country (λ). This is motivated by the result that movies decay faster in countries with higher piracy. In particular, we assume that if the distributor of movie j chooses a release date such that the release gap increases (decreases) by one week compared to the release gap observed in the data, movie j's fixed effect would decrease (increase) by $\lambda \times \alpha$. To differentiate the differences between the release gap effects between the countries with high and low piracy, we create a dummy for the estimate of α.[9] In particular,

$$\alpha = \begin{cases} \hat{\alpha} & \text{if the country is in the low piracy region;} \\ \hat{\alpha} + \phi & \text{if the country is in the high piracy region.} \end{cases} \tag{7}$$

To capture the word-of-mouth effect, we model that the movie fixed effect, $\hat{\theta}_j(r_j)$, is a function of two types of word-of-mouth (good and bad). In particular, we use the number of good and bad IMDb reviews as proxies for these two types of word-of-mouth (more on this in Section 5).[10] Define κ^g_{jt} and κ^b_{jt} as the number of good and bad reviews for movie j in week t. We then assume the movie fixed effect changes with the cumulative number of good and bad reviews for

[9] We acknowledge that the release gap effect might also capture the effect of factors other than piracy, such as the cultural distance between the U.S. and foreign countries. However, empirical results in other studies suggest the effects of these other factors are relatively small compared to piracy and word-of-mouth. For instance, the empirical results in Song and Shankar (2014) suggest that the effect of a one standard deviation change in cultural distance on the release gap is only 10% of the effect of a one standard deviation change in word-of-mouth and 1% of the effect of a one standard deviation change in piracy.

[10] Another proxy for word-of-mouth is to calculate expected U.S. market share of movie j using the movie demand estimates in the U.S. market. The estimated effects of word-of-mouth on release gaps and box office revenues using expected U.S. market share are similar to those using IMDb reviews. But, we cannot distinguish the effects of good and bad word-of-mouth using this proxy.

movie j in week t, or, $\sum_{s=r_j^{US}}^{t} \kappa_{js}^{g}$ and $\sum_{s=r_j^{US}}^{t} \kappa_{js}^{b}$, where r_j^{US} is the release date of movie j in the U.S. market.

The movie fixed effect is, thus,

$$\hat{\theta}_j(r_j) = \theta_j - \lambda\alpha(\max\{r_j; r_j^{US}\} - \max\{r_j^{local}; r_j^{US}\}) + \lambda\beta^g \left(\sum_{s=r_j^{US}}^{r_j} \kappa_{js}^{g} - \sum_{s=r_j^{US}}^{r_j^{local}} \kappa_{js}^{g} \right) + \lambda\beta^b \left(\sum_{s=r_j^{US}}^{r_j} \kappa_{js}^{b} - \sum_{s=r_j^{US}}^{r_j^{local}} \kappa_{js}^{b} \right), \tag{8}$$

where θ_j is the estimate of movie j's fixed effect from the estimation of the discrete choice demand model and r_j^{local} is the actual release date of movie j in country k. The second part of equation (8) captures the effect of the release gap on the movie's fixed effect. Note that by construction we assume that if the release date chosen (r_j) is earlier than the release date in the U.S. market (r_j^{US}), the release gap is zero instead of negative. We expect a longer release gap would reduce consumers' interest in the movie because of reasons such as piracy, and, thus, we expect $\alpha > 0$. Also, we would expect the effect of the release gap on the fixed effect to be stronger in the high piracy region; thus, we expect $\phi > 0$ as well. The last two parts of equation (8) capture the word-of-mouth effect of good and bad reviews on IMDb. The more good (bad) reviews a movie receives, the more (less) consumers would be interested in the movie in country k. We, thus, expect $\beta^g > 0$ and $\beta^b < 0$.

We construct the payoff for each Hollywood movie as follows. In each week t in country k, there are J_t movies competing in the market. The set of movies in J_t includes Hollywood exports which decide on their release gaps and local movies whose release dates are assumed to be exogenous. We assume a Hollywood movie j, which was released on r_j, will run in the theater for H weeks.[11] If the movie is still on its theatrical run in week t, movie j's payoff is its market share, which is a function of the movie decay pattern (λ), seasonality (τ_t), the market expansion effect (σ), and the release dates of movie j (r_j) and of other movies $-j$ (r_{-j}):

$$\hat{s}_{jt}(r_j, r_{-j}; \lambda, \sigma) = \frac{\exp((\hat{\theta}_j(r_j) - \lambda(t - r_j) + \tau_t)/(1 - \sigma))}{\hat{D}_t^{\sigma} + \hat{D}_t},$$

[11] The choice of H is guided by computational constraints. In our estimation, we assume $H = 2$. In the countries in our sample, the box office revenue of the first two weeks accounts for almost 60% of the total box office revenue of a movie on average.

where

$$\hat{D}_t = \sum_{l \in J_t(r_j, r_{-j})} \exp\left(\frac{\hat{\theta}_l(r_l) - \lambda(t - r_l) + \tau_t}{1 - \sigma}\right). \tag{9}$$

We assume the payoff for player j in week t whose movie was released in r_j is the sum of the market share of movie j in week t and an error term:

$$\begin{aligned} \pi_{jt}(r_j, r_{-j}; \lambda, \sigma) &= \sum_{t=r_j}^{r_j+H} \hat{s}_{jt}(r_j, r_{-j}; \lambda, \sigma) + \epsilon^j_{r_j} \\ &= \hat{\pi}_j(r_j, r_{-j}; \lambda, \sigma) + \epsilon^j_{r_j}. \end{aligned} \tag{10}$$

The profit shock, $\epsilon^j_{r_j}$, is assumed to be an i.i.d. draw from a type I extreme value distribution and is assumed to be private information of distributor j.

Let us define R_j as the set of weeks in which distributor j can choose to release the movie. Conditional on other distributors' release choices, r_{-j}, distributor j chooses to release the movie on r_j with the following probability:

$$\Pr(r_j | r_{-j}) = \frac{\exp(\hat{\pi}_j(r_j, r_{-j}; \lambda, \sigma))}{\sum_{r'_j \in R_j} \exp(\hat{\pi}_j(r'_j, r_{-j}; \lambda, \sigma))}. \tag{11}$$

As in Einav (2010), this game is played sequentially with each player moving according to a pre-specified order. Because the payoffs of distributor j only depend on the actions of other players, but not on their profit shocks, $\epsilon^{-j}_{r_{-j}}$, each distributor's strategy would only depend on the actions chosen by distributors who moved previously.

We use pseudo-backward induction to solve the equilibrium. Let N be the total number of players, and the order of play specified as a permutation $o \in \mathcal{P}_N$, such that $o(m) = j$ implies that the mth player to move in the game is distributor j. Let $\text{prev}(j) = \{k : o^{-1}(k) < o^{-1}(j)\}$ be the set of distributors who decide their release dates before j. We solve the game backwards by solving the release date problem of the last distributor, $o(N)$, conditional on the other distributors' decisions. Using equation (11), distributor $o(N)$ chooses to release on $r_{o(N)}$ with probability

$$\Pr(r_{o(N)} | r_{-o(N)}) = \frac{\exp(\hat{\pi}_j(r_{o(N)}, r_{-o(N)}; \lambda, \sigma))}{\sum_{r'_{o(N)} \in R_{o(N)}} \exp(\hat{\pi}_j(r'_{o(N)}, r_{-o(N)}; \lambda, \sigma))}. \tag{12}$$

We then make use of equation (12) to update the continuation values for other players. In particular,

$$\hat{\pi}_j^{N-1}(r_{-o(N)};\lambda,\sigma) = \sum_{r_{o(N)}\in R_{o(N)}} \Pr(r_{o(N)}|r_{-o(N)})\hat{\pi}_j(r_{o(N)},r_{-o(N)};\lambda,\sigma)\ \forall j \in \text{prev}(o(N)) \quad (13)$$

and

$$\pi_j^{N-1}(r_{-o(N)};\lambda,\sigma) = \hat{\pi}_j^{N-1}(r_{-o(N)};\lambda,\sigma) + \epsilon_{r_j}^j\ \forall j \in \text{prev}(o(N)). \quad (14)$$

The conditional release choice probability can then be updated using the continuation values specified in equation (13):

$$\Pr(r_j|r_{\text{prev}(j)}) = \frac{\exp(\hat{\pi}_j^{o^{-1}(j)}(r_j|r_{\text{prev}(j)}))}{\sum_{r'_j\in R_j}\exp(\hat{\pi}_j^{o^{-1}(j)}(r'_j|r_{\text{prev}(j)}))}. \quad (15)$$

This procedure enables us to obtain an equilibrium with a positive probability over each possible outcome of the game. Given a pre-specified order o, the likelihood of a particular outcome r is

$$\Pr(r|o) = \prod_{j=1}^{N}\Pr(r_j|r_{\text{prev}(j),o}). \quad (16)$$

To take the empirical model to the data, we need to reduce the computational burden by restricting the number of players (N) and the number of weeks in which a distributor j can choose to release its movie (R_j) in each season.

We restrict the number of players in each season window to be 3 by choosing the top three U.S. movies in terms of their movie fixed effects (θ_j) in the U.S. market. In some cases, not all three movies were released in a foreign country. The game would then be boiled down to a release gap decision of only one or two players in the season.

As in Einav (2010), we choose four annual release seasons, all around a dominant U.S. release date, to test our empirical model. The four seasons are Presidents' Day, Memorial Day, Fourth of July, and Thanksgiving. Each season includes the holiday week, 2 weeks before, and 4 weeks after, adding up to 7 weeks in total, i.e. the number of weeks in R_j is always 7. We, thus, have a total of 28 seasons (from our 7 years of data, 2008-2014) of observation for each of the 18 countries on which the estimates are based.

5 Data

Our data sample consists of all movie titles showing in theaters in a given country in each weekend over the period 2008 to 2014. Naturally, for any given country and week, the total list of movies contains U.S. and non-U.S. titles. For each movie title in a given country and weekend, the data include the movie's weekend box office revenue, box office revenue to date, release date in the U.S., box office revenue in the U.S., and other summary details. The sample contains movie data for 18 different countries, a list of which appears below in Table 2. The countries were chosen to create the largest possible set of countries with data available on a weekly basis for all years 2008 to 2014. Data on movies from publicly funded sources are limited and of low quality. Instead, we build our movie sample by collecting data from the private industry source Boxofficemojo.com.

We then supplement the movie data with data from other sources. Data on average movie ticket prices across countries come from two sources. The first, for the years between 2008 to 2012, is UNESCO. The second is Numbeo.com, a cost of living database, which we use to collect the movie ticket price in the year 2014. Interpolation between the UNESCO movie ticket prices and the price from Numbeo.com constructs the remaining prices in 2013 and 2014. Each country's population is taken from the World Bank's World Development Indicators.

We follow Einav (2007) to restrict our attention to movies which reached a wide release at some point during the whole period that they are on screen. In particular, we only include movies which reached at least 5% of the total number of screens in the country during some week.[12] We also drop observations of limited release and define the actual release date to be the first week in which the number of screens is high enough.[13]

Because the box office data set only has weekend box office revenue and box office revenue to date, we use the following procedures to back out the weekly box office. First, for weeks that a movie appears in consecutive weeks in the data set, we use the difference between the cumulative box office revenue to the current week and the cumulative box office revenue to the

[12]Einav (2007) used a threshold of 600 screens, which is roughly 3-4% of the total number of screens in his data sample period.

[13]Operationally, we define actual release week to be the first week in which the number of screens exceeds the maximum of 5% of total number of screens in the country and 30% of the maximal number of screens showing the movie in its entire run.

previous week as the weekly box office revenue in the current week. Second, because there are some missing weeks in the data set, there are some weeks that we cannot use the difference of box office revenue to date to back out the weekly box office. Instead, we calculate the average ratio of weekend box office revenue and weekly box office revenue for each movie and then use the ratio to extrapolate the weekly box office for the weeks whose previous week's data is missing.

To account for seasonality in each country, we create 52 week dummies for each year in each country. Also, because holiday weekends are an important aspect of the movie industry, and some of the holidays (such as the Lunar New Year in Hong Kong) are not in the same week in each year, we select the five most important holidays in each country and create a holiday dummy to account for this holiday effect on seasonality.

We use the average ticket price, the weekly box office revenue, and the population in a country (which we take as the total market size in the country) to calculate the market share of movies in the country. We interpolate weekly ticket prices and weekly population from the annual ticket price schedule and annual population by assuming prices and population change linearly throughout the year. We then calculate weekly market shares for each movie by dividing weekly box office revenues by weekly ticket price and weekly population size.

Our data on word-of-mouth come from IMDb. For all the movies we use in analyzing the release gap decision game, i.e. the top 3 Hollywood movies in the four U.S. holiday seasons, we collect all of their IMDb ratings submitted by individual reviewers. We then count the number of "bad" ratings, which we define as at or below 5 out of 10 stars, and the number of "good" ratings, which we define as above 5 stars, for each week. We use the ratings as proxies for bad and good word-of-mouth for each movie.

Because we are interested in understanding the relationship between movie piracy and release gap patterns, we also obtain proxies for movie piracy. Because there is no data on movie piracy, we obtain software piracy data from the Business Software Alliance as a proxy to distinguish high and low piracy regions.[14] The data measures the share of unlicensed software installed on computers. We define the high and low piracy regions as having an unlicensed software installation rate of more or less than 50%.

[14]The software piracy data are for the year 2013 and are from a report published in 2014, which currently resides at `www.BSA.org`. The sets of countries in the high and low piracy regions remain unaffected if we use data from different years.

5.1 Summary Statistics

We present three summary statistics from our data in Table 2. The first column of Table 2 shows the release gaps of the top 3 Hollywood movies in the four U.S. holiday seasons mentioned above (Presidents' Day, Memorial Day, Fourth of July, and Thanksgiving). The average release gap is 2.4 weeks. There are slight differences between the high and low piracy region. In particular, the average release gap in the low piracy region is slightly longer than that in the high piracy region (2.559 vs 2.187).

Table 2: Summary Statistics

Country	Release Gap (weeks)	Revenue from First Two Weeks (share of total revenue)	Software Piracy (share of installations)
		Low Piracy Region	
Australia	1.694	0.542	0.21
Austria	2.979	0.483	0.22
Belgium	2.070	0.448	0.24
Germany	2.681	0.466	0.24
Hong Kong	3.158	0.650	0.43
Iceland	2.477	0.522	0.48
Japan	3.118	0.392	0.19
Singapore	2.108	0.661	0.32
Spain	2.750	0.540	0.45
Mean	2.559	0.503	0.31
		High Piracy Region	
Argentina	2.714	0.483	0.69
Bolivia	1.730	0.478	0.79
Brazil	2.143	0.520	0.50
Bulgaria	2.513	0.509	0.63
Mexico	2.020	0.580	0.54
Russia	1.348	0.713	0.62
Thailand	1.382	0.719	0.71
Turkey	2.857	0.493	0.60
Uruguay	2.976	0.424	0.68
Mean	2.187	0.536	0.64
Overall Mean	2.373	0.522	0.47

Source: Boxofficemojo.com and BSA.org

Column 2 of Table 2 reports that more than 50% of box office revenue of a movie comes from the first two weeks of its release on average across the 18 countries in the data. In most countries, the proportion ranges from 50% to 60%. Movies decay fastest in Thailand, a high piracy country, with approximately 72% of a movie's total box office revenue coming from the first two weeks. The movies decay slightly faster in the high piracy region on average (54% of a movie's total box office revenue coming from the first two weeks in this region compared to 50% in the low piracy region).

The third column of Table 2 shows the average software piracy rate across all 18 countries is 47%. The software piracy rate in the low piracy region ranges from 19% in Japan to 48% in Iceland and averages 31%. The software piracy rate in the high piracy region is significantly higher on average at 64% and ranges from 50% in Brazil to 79% in Bolivia.

6 Estimates

6.1 Movie Demand Estimates

Table 3: Movie Demand Estimates

	Movie Decay (λ)		Market Expansion Effect (σ)	
Country	Estimate	Standard Error	Estimate	Standard Error
		Low Piracy Region		
Australia	-0.2354	0.2244	0.4343	0.2244
Austria	-0.2845	0.0339	0.3000	0.0842
Belgium	-0.2035	0.0196	0.4850	0.0507
Germany	-0.3188	0.0444	0.2407	0.1091
Hong Kong	-0.4637	0.0980	0.4544	0.1213
Iceland	-0.3733	0.0452	0.1841	0.1000
Japan	-0.2505	0.0280	0.2963	0.0803
Singapore	-0.7884	0.1251	0.0347	0.1746
Spain	-0.2184	0.0373	0.6516	0.0607
		High Piracy Region		
Argentina	-0.2101	0.1406	0.6166	0.2598
Bolivia	-0.3134	0.0329	0.2228	0.0830
Brazil	-0.1809	0.0264	0.6461	0.0514
Bulgaria	-0.2153	0.0446	0.5470	0.0994
Mexico	-0.1325	0.0302	0.7063	0.0669
Russia	-0.7682	0.2791	0.2018	0.2954
Thailand	-0.7130	0.1757	0.2632	0.1933
Turkey	-0.4434	0.1000	0.1038	0.0099
Uruguay	-0.1563	0.0374	0.5654	0.1074

We first report the estimates from the discrete choice demand model for movies. Table 3 reports the estimates of the movie decay pattern (λ) and market expansion effect (σ).[15] All estimates have the correct sign. The signs of the movie decay pattern, λ, are all negative, while

[15]Estimates of seasonality for each country are not reported here due to space limitations.

the estimates of the market expansion effect, σ, lie between 0 and 1. Almost all of the estimates are statistically significant. We report the estimates based on our division of high and low piracy regions. While there is not much difference in the movie decay parameter λ between the two regions (both are at -0.35 on average), the estimate of the market expansion effect is higher in the high piracy region (0.43 compared to 0.34 on average).

Because it is difficult to compare the estimates across countries without taking into account other estimates on seasonality and movie quality, we instead calculate the mean decay elasticities (weighted by box office revenue) implied by the demand estimates for each country. We define decay elasticity as the percentage change of market share when the movie stays in the market for one more week. We then use the estimated decay elasticities to estimate the box office of the first two weeks as a portion of total box office revenue, which can be compared with actual data. Table 4 reports the results.

Table 4: Estimated Decay of Box Office Revenue

Country	Estimated Decay Elasticity	Estimated Revenue from First Two Weeks (share of total revenue)	Actual Revenue from First Two Weeks (share of total revenue)
		Low Piracy Region	
Australia	-0.2389	0.4207	0.5420
Austria	-0.2796	0.4810	0.4829
Belgium	-0.2220	0.3947	0.4476
Germany	-0.2599	0.4521	0.4658
Hong Kong	-0.6456	0.7739	0.6502
Iceland	-0.2951	0.5026	0.5218
Japan	-0.2158	0.3849	0.3922
Singapore	-0.6387	0.7693	0.6606
Spain	-0.3749	0.6091	0.5404
Mean	-0.3182	0.5113	0.5027
		High Piracy Region	
Argentina	-0.3671	0.5988	0.4831
Bolivia	-0.2417	0.4236	0.4777
Brazil	-0.3227	0.5260	0.5196
Bulgaria	-0.2928	0.4997	0.5089
Mexico	-0.2513	0.4391	0.5799
Russia	-0.8221	0.8683	0.7128
Thailand	-0.6677	0.7883	0.7192
Turkey	-0.2469	0.4327	0.4926
Uruguay	-0.2091	0.3744	0.4240
Mean	-0.3570	0.5568	0.5361
Overall Mean	-0.3411	0.5381	0.5224

The first column of Table 4 shows the average decay elasticity across the 18 countries in our sample is -0.34, which means the market shares of a movie would drop almost by half with every additional week in the theater. The decay elasticities vary significantly across countries. There are differences between high and low piracy regions. In particular, the movie decay elasticities are on average lower in the low piracy region than those in the high piracy region.

Because movies decay fairly fast on average, most of the box office revenue of a movie comes from the first two weeks of its release. The second column of Table 4 reports our demand estimates show that 51% (56%) of total box office revenue comes from the first two weeks in the low (high) piracy region. Our estimates are fairly close to the actual movie decays across countries (column 3).

6.2 Release Gap Decision Game Estimates

Table 5 reports the estimates from the release gap decision game. All estimates have the expected sign. The estimate for the release gap effect, α, is positive (0.8887), meaning that a longer release gap would lead to a decrease in the movie fixed effect. The effect is stronger in the high piracy region, as ϕ is also positive. Also, the estimates for the word-of-mouth effect, β^g and β^b, have the expected sign, meaning that more positive (negative) reviews would lead to an increase (a decrease) in the movie fixed effect.

Table 5: Estimates from Release Gap Decision Game

Parameters	Estimates	Standard Error
$\hat{\alpha}$	0.8887	0.3394
ϕ	0.2605	0.1019
β^g	0.0838	0.0525
β^b	-0.0496	0.0386

7 Counterfactuals

We conduct counterfactuals to evaluate i) the competition effect, ii) the word-of-mouth effect and iii) the release gap effect on the release gap decision of movie distributors.

7.1 Competition Effect

We evaluate the importance of competition by restricting the number of Hollywood movies to one per holiday window, which is something similar in our model to the current import quota in China. We assume only the Hollywood movie with the highest fixed effect, θ, would obtain the quota to enter the foreign market.

Table 6: Release Gaps Shortened and Box Office Increases with Import Quota (%)

Country	Release Gaps Shortened	Box Office Increases
	Low Piracy Region	
Australia	1.01	11.73
Austria	0.37	4.06
Belgium	0.50	5.05
Germany	0.57	5.87
Hong Kong	1.29	5.28
Iceland	0.85	7.30
Japan	0.07	0.64
Singapore	1.76	6.77
Spain	0.49	5.91
Mean	0.77	5.85
	High Piracy Region	
Argentina	0.70	7.49
Bolivia	0.71	6.95
Brazil	1.44	10.61
Bulgaria	0.44	3.71
Mexico	1.38	13.85
Russia	3.03	9.56
Thailand	1.79	4.42
Turkey	0.31	5.43
Uruguay	0.63	4.53
Mean	1.16	7.39
Overall Mean	0.97	6.62

Table 6 reports the impact of such an import quota on the release gaps and box office revenue of the Hollywood movies that survive the quota. A priori, it is not clear how the release gap would change when the import quota is imposed. As it turned out, the release gaps in all countries will be shorter when the quota is imposed, but the percentage change is small (only approximately 1%). The reason we see this small effect on the release gaps may be due to the sequential nature of our game. The first mover, which is the best movie, already has a lot of power. So, dropping the lower quality movies may not affect the release gap decision significantly. The impact is slightly larger in the high piracy region than in the low piracy region.

While the release gaps do not change significantly with the import quota, the box office revenues do. Without competition from other Hollywood exports, the box office revenue for the Hollywood movies that survive the quota increases significantly. On average, the box office revenue for these movies increases by 6.6%. The increase in box office revenue is higher in the high piracy region (7.4%) than in the low piracy region (5.9%).

7.2 Word-of-Mouth Effect

Table 7: Release Gap Shortened and Box Office Decreases when Incentives for Word-of-Mouth Disappear (%)

	Release Gap Shortened			Decreases of Box Offices		
Country	Overall	First Mover	Followers	Overall	First Mover	Followers
			Low Piracy Region			
Australia	1.75	0.87	3.34	6.10	4.85	3.79
Austria	1.80	1.53	2.76	4.76	5.45	2.32
Belgium	2.56	2.15	2.43	5.66	5.03	8.02
Germany	2.43	2.08	4.77	5.23	5.69	0.96
Hong Kong	7.44	6.42	20.46	2.81	3.35	3.18
Iceland	2.55	2.32	2.53	6.77	4.38	8.80
Japan	3.11	3.30	1.58	5.86	5.73	7.09
Singapore	9.10	7.55	25.33	3.26	4.25	2.42
Spain	2.16	1.37	4.62	8.27	8.08	3.99
Mean	3.66	3.07	7.54	5.41	5.20	4.51
			High Piracy Region			
Argentina	2.26	0.86	6.16	3.05	6.16	0.76
Bolivia	2.74	1.18	5.43	3.43	5.09	1.53
Brazil	3.27	2.78	2.99	3.37	7.16	1.15
Bulgaria	2.25	1.54	4.39	5.89	4.53	2.77
Mexico	2.08	1.49	2.22	2.78	4.19	1.90
Russia	5.61	4.58	6.34	4.51	4.30	7.74
Thailand	8.92	8.28	18.58	1.96	1.22	5.99
Turkey	1.17	0.79	1.74	5.88	6.83	4.52
Uruguay	2.63	1.99	3.21	3.06	3.03	2.22
Mean	3.43	2.61	5.67	3.77	4.72	3.18
Overall Mean	3.55	3.18	6.61	4.59	4.96	3.85

We next conduct counterfactuals to evaluate the effect of word-of-mouth on the choices of release gap. In particular, we ask the question: how would a distributor's decision about the release gap and its box office revenue be different if the performance in the U.S. market has no word-of-mouth effect on the foreign market? To answer this question, we assume the word-of-mouth effect (β^g and β^b) is zero, meaning that the movie's fixed effect is not a function of the expected box office in the U.S. market. Table 7 shows release gaps would be shorter when the need to accumulate word-of-mouth disappears.

Table 8: Release Gap Longer and Box Office Increases when Incentives for Bad Word-of-Mouth Disappear (%)

	Delays of Movie Release			Increases of Box Offices		
Country	Overall	First Mover	Followers	Overall	First Mover	Followers
			Low Piracy Region			
Australia	0.90	0.32	1.27	4.90	2.47	3.88
Austria	0.85	0.56	0.91	4.72	4.08	3.72
Belgium	1.19	0.88	1.13	4.73	3.81	4.05
Germany	1.07	0.73	1.15	4.88	4.52	3.25
Hong Kong	3.30	2.53	3.57	8.44	7.36	5.57
Iceland	1.22	0.79	1.25	5.83	4.47	6.35
Japan	1.07	1.04	1.27	4.21	4.31	3.26
Singapore	4.20	4.41	4.58	7.32	11.33	0.12
Spain	1.03	0.53	1.86	7.52	5.52	6.72
Mean	1.65	1.31	1.89	5.84	5.31	4.10
			High Piracy Region			
Argentina	1.11	0.39	1.76	6.00	6.51	3.95
Bolivia	1.00	0.51	1.72	4.01	4.95	1.97
Brazil	1.47	1.66	0.84	3.70	6.99	0.25
Bulgaria	0.98	0.51	1.42	6.66	2.82	7.21
Mexico	0.80	0.42	0.94	2.94	2.08	2.45
Russia	3.64	1.89	8.66	7.78	2.92	17.88
Thailand	4.09	3.71	3.25	5.23	3.23	5.12
Turkey	0.72	0.32	1.08	6.92	3.89	6.71
Uruguay	1.06	0.56	1.31	3.44	2.19	2.95
Mean	1.65	1.40	2.33	5.19	3.95	5.39
Overall Mean	1.65	1.35	2.11	5.52	4.63	4.75

There are several things to note. First, the word-of-mouth effects are similar between the low and high piracy regions. As Table 7 shows, the change in release gaps and box office revenues are similar between the two regions. Second, the release gaps would be shortened by 3.6% on average in the 18 countries when the word-of-mouth effect disappears (column 1 in Table 7). This word-of-mouth effect on release gaps differs between first movers and followers (columns 2 and 3 in Table 7). In particular, first movers' response in release gaps to the disappearance of word-of-mouth from the U.S. market (a drop of 3.2%) is smaller than the response of the followers (a drop of 6.6%). Third, movies would experience a small drop in box office revenue if the word-of-mouth effect disappears. In particular, box office revenue would drop by 4.6%

on average in the 18 countries (column 4 in Table 7). The word-of-mouth effects on box office revenue do not seem to vary between the first movers and followers (columns 5 and 6 in Table 7).

Table 7 only reports the overall effects of word-of-mouth. We separately show the impact of the negative word-of-mouth in Table 8. When there is only good word-of-mouth (all IMDb ratings are above 5), studios have more incentive to lengthen the release gaps in order to accumulate more word-of-mouth. On average, the release gaps would increase by 1.7% (column 1 in Table 8). There are not many differences between the high and low piracy regions and between the first movers and followers within a country (columns 2 to 3 in Table 8).

When the bad word-of-mouth disappears, the box office revenue will increase by 5.5% on average (column 4 in Table 8). Again, there is not much difference between the high and low piracy regions and between the first movers and followers (columns 5 to 6 in Table 8).

7.3 Release Gap Effect

To evaluate the release gap effect, we assume a longer release gap has no effect on the movie fixed effect, $\hat{\theta}_j(r_j)$, i.e. the second term of equation (8) drops out. We then re-calculate the equilibrium outcomes on release gaps using the new movie fixed effects. Table 9 shows the release gaps would be longer and box office revenues would be higher when a longer release gap has no effect on the movie's fixed effect.

There are several things to note. First, there are significant differences between the low and high piracy region. When the release gap effect disappears, release gaps would increase by 18% on average in the 18 countries in the sample. However, the overall release gaps would increase by 15% in countries in the low piracy region compared to 22% in countries in the high piracy region (column 1 in Table 9). Also, box office revenues would increase significantly when the release gap effect disappears. The box office would increase by 61% on average in the 18 countries (column 4 in Table 9). Again, movies released in the high piracy region would experience a higher increase in box office revenue (71% compared to 51% in the low piracy region).

Second, the release gap effect differs between first movers and followers. Overall, the increase of first movers' release gap would be smaller than that for the followers on average (16% compared to 26%). The pattern holds true in both the low and high piracy region (columns 2 and 3 in

Table 9: Movie Release Delays and Box Office Increases when Release Gap Has No Effect (%)

Country	Delays of Movie Release			Increases of Box Offices		
	Overall	First Mover	Followers	Overall	First Mover	Followers
			Low Piracy Region			
Australia	8.41	6.46	11.25	43.65	51.83	34.98
Austria	9.23	8.73	11.27	50.20	57.83	42.28
Belgium	10.18	9.55	9.44	43.88	44.74	55.79
Germany	9.88	9.53	12.00	45.94	52.10	36.88
Hong Kong	27.43	25.04	44.53	59.43	67.89	45.44
Iceland	11.80	10.75	11.40	51.55	57.56	53.67
Japan	13.45	13.94	9.61	41.79	42.27	37.31
Singapore	32.00	30.32	58.17	54.28	61.41	42.77
Spain	10.80	9.72	13.41	70.28	80.49	64.50
Mean	14.80	13.78	22.95	51.22	57.35	45.96
			High Piracy Region			
Argentina	15.85	10.50	37.36	73.00	107.20	46.82
Bolivia	13.72	10.92	18.42	48.89	65.67	35.53
Brazil	19.46	16.73	23.37	54.42	62.94	46.06
Bulgaria	13.11	11.43	16.16	71.62	82.24	55.48
Mexico	13.39	9.24	20.56	47.26	62.27	37.23
Russia	32.72	30.49	36.66	63.18	63.16	57.50
Thailand	43.48	43.24	64.92	62.00	63.27	55.25
Turkey	8.61	6.97	12.24	78.26	94.04	60.09
Uruguay	15.34	13.98	19.01	49.87	58.63	38.88
Mean	21.86	19.10	27.63	71.26	85.64	54.85
Overall Mean	18.33	16.44	25.82	60.94	73.27	48.09

Table 9). While the release gaps response for first movers is smaller, their box office revenues increase more than followers. On average, first movers' box office revenue would increase by 73%, while followers' box office revenue would increase by 48% (columns 5 and 6 in Table 9). The pattern holds true in both the low and high piracy region.

8 Conclusion

Our paper sheds further light on the decision of Hollywood studios to enter foreign markets, which is a major source of U.S. exports in services. Our structural approach allows us to disentangle the role played by the release gap, word-of-mouth, and competition effects on the release gap decision. Using international box office data from Boxofficemojo.com, we show all three factors are important.

Technological changes in production, distribution, and consumption methods continue to affect the movie industry, a major source of U.S. exports in services. The availability of rich micro-level data sets on international box office performance, such as we use in this paper, provides a means to analyze the continuing changes in this dynamic industry.

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