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AWP-04-2011

Date: November 2011

How do your rivals' releasing dates affect your box office?

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Abstract

In this paper, we study to what extent a movie's box office receipts are affected by the temporal distribution of rival films. We propose a theoretical model that analyses the effects of past, present and future releases on a film's results. Using this model we can analyse how rivals' release dates impact on others' box office revenues. This theoretical model also allows us to carry out some comparative statics by changing some relevant parameters such as time depreciation, film quality or the timeline of exhibition. We have tested the empirical implications of this model using information on the films released in five countries: the USA, the United Kingdom, Germany, France and Spain. In order to maintain a degree of homogeneity, we have constructed an unbalanced panel consisting of films that were released in at least three of these countries. The geographical dimension of our data set allows us to use panel data techniques to control for unobserved heterogeneity among the films released. This allows us to control for one of the most relevant features of the movie market, namely the presence of highly differentiated products.

Keywords temporal competition, movie exhibition, film industry, panel data, unobserved heterogeneity, differentiated products

Classification JEL: Z10

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1. Introduction

The motion pictures industry has received increasing attention from academics in recent years due to several features which make it a particularly interesting topic of study. First, the motion picture industry can be defined as a differentiated product oligopoly. All movies are different by definition and the distribution market is also controlled by a small group of companies: the major film studios. Second, due to this heterogeneity and the fact that products in this industry are for immediate consumption, the life cycle for movies differs significantly from that of typical consumer products, being characterized by a box-office peak in the first week of release that is followed by an exponential decay pattern over time as new films enter the exhibition market and the value of the film declines. In general, between 60% and 70% of film revenues at the box-office are collected in the first three weeks,[1] so that motion pictures exhibition is a short life-cycle industry. Third, cinema demand is characterized by large fluctuations along the year, with high peaks in certain weeks. In this context, when distributors believe that a film may be a blockbuster they will try to release it in high-demand periods as they know that one month's revenues during these periods can produce box office sales equivalent to several months in low-demand phases.[2] However, when studios try to maximize box-office revenues they face an interesting strategic problem, namely the trade-off between trying to capture as much of the revenues as possible during the peak demand period while avoiding head-to-head competition for the same audience. This head-to-head competition is especially critical in the first few weeks of running a film as the whole commercial life of a film depends on the performance during the first weeks.[3] Moreover, this head-to-head competition cannot be alleviated by reducing prices as ticket prices are very similar within each local market (Orbach & Einav, 2007) and there are no price differences among films exhibited in a cinema theatre at a given moment.[4]

[1] See Krider & Weinberg (1998) and Krider, Li, Liu, & Weinberg (2005).

[2] See Moul & Shugan (2005), Vogel (2007) and Radas & Shugan (1998).

[3] For instance, a good performance during the first weekend might create a positive word-of-mouth effect capturing the attention of the public, media and exhibitors (De Vany, 2004).

[4] We can observe some price discrimination but this is in terms of days, seasons or consumer groups, not among movies. The exception is the case of 3-D movies but these can be considered as a different commodity.

Considering all these features that lead to a rapid and frequent release of new movies, the release date in the motion picture industry is an essential variable in distributors' strategies. The commercial success of a film depends crucially on the release date, partly because a movie's opening weekend is usually the most profitable but also because movies that are released close together are likely to impose negative effects on each other's revenues (Corts, 2001).

In this framework, this paper analyses the role of temporal competition inside the movie distribution market and its effect on box office receipts. The economic performance of movies is an increasing research field in Economics but most of the literature is focused on how box office revenues are determined by a series of explanatory variables related to the movie's classification (sequel, rating, and genre), production features (budget, star and director power), quality (critics' reviews, award nominations and academy awards), and distribution characteristics (advertising, marketing expenditure and opening screens).[5] Previous papers have generally used multivariate linear regression to predict film performance measured by two different dependent variables: cumulative domestic rentals and the total length of run of each film. Thus, Sochay (1994) found that competition, measured by a concentration ratio for a specific film, has a significant effect on box-office performance. Jedidi et al. (1998) analysed competitive intensity during a movie's opening weekend and over its run and identified four different types of movies. Elberse and Eliashberg (2003) analysed competition for screens (i.e., screens allocated by exhibitors) and for revenues (i.e., attention from audiences) using weekly data from the US, France, Germany, Spain and the UK. They distinguished between new releases and on-going movies and found that competition is stronger among movies with similar characteristics and that the longer the movies are on release, the lesser the competition effect. Moreover, they observe that competition for revenue is a strong predictor of revenues throughout a movie's run. Movie performance is also hurt by simultaneous releases of the same genre and rating (Ainslie, Dreze, & Zufryden, 2005) and by the release of other films with a similar target audience (Basuroy, Desai, & Talukdar, 2006).[6] More recently, Calantone et al. (2010) have estimated a model using weekly data that accounts directly and

[5] See Hadida (2009) and McKenzie (2010) for a summary of this literature.

[6] However, Basuroy et al. (2006) have found that on-going films' competition for screens has a positive effect on weekly box office receipts and screen coverage.

indirectly (through the numbers of theatres) for competitive effects on the performance of a movie. They conclude that on-going (i.e. incumbent) movies have a higher negative effect than new releases.

We develop a theoretical framework to examine in detail the competition effect, i.e., the effect of other film releases on the *total* box-office revenues of a particular film. This model allows us to test to what extent the temporal competition has asymmetric effects, i.e. whether past, present and future rival releases have similar or different effects on a particular film's outcome. Our theoretical model also shows that modelling the competition effect on total box-office revenues is an empirical issue and cannot be easily inferred from the (estimated) effects on weekly box-office revenues. Indeed, we show that the competition effect on total box-office revenues depends on several key characteristics of the film market such as the relative quality of the movies, the number of weeks films are on screens (i.e. the decay rate), and the underlying seasonal pattern.

The above issues are of crucial relevance to film studios and distributors because they often carry out intense market research before releasing their movies in order to discover audience's preferences and anticipate market responses. Our theoretical model could help them to improve release timing decisions through knowledge of the payoff matrix of the release game, comparing the gains of avoiding competition by opening before a rival or by delaying the release and opening later. Unlike previous papers, our empirical analysis uses cumulative data rather than weekly figures because distributors are more interested in total revenues.[7] Another distinctive characteristic of our paper is the longitudinal nature of our analysis. We have collected data on movies released between 2000 and 2009 in five countries, namely the United States and the four largest European motion pictures markets (United Kingdom, France, Germany and Spain). The geographical dimension allows us to use panel data techniques to control for the heterogeneous nature of movies. Hence, our paper contributes to two research fields in motion picture economic literature: international comparisons among exhibition

[7] We focus on box office revenues as distribution and marketing costs at this time are sunk costs. Additionally, it is known that nontheatrical revenues depend on movie's box office revenues and the importance of nontheatrical revenues is growing, especially for DVD, PPV and TV (Ginsburgh & Weyers, 1999; Hennig-Thurau, Houston, & Walsh, 2006).

markets and the control of unobserved heterogeneity by application of panel data techniques[8].

The paper is organized as follows. In the next section, we lay out the theoretical model. In section 3 we describe the data base used and in section 4 the empirical model to be estimated is outlined. In Section 5 the principal results are presented. The final section concludes.

2. The benchmark model

In this section we propose a demand model to assess the competition effect of other films on total box-office revenues, where these revenues for a particular movie depend on primary demand, the number of other films and (own and rival) movie characteristics. Our model benefits especially from Krider and Weinberg (1998). These authors model competition between two films using a share attraction framework and conduct an equilibrium analysis of the release date timing game.[9] Although temporal decisions are strategic choices in movie industry, it should be noted that our model does not explain how the actual release date is determined. We simply try to provide a theoretical framework that shows that: *i)* modelling the competition effect of other films on total box-office revenues is not obvious and cannot be easily inferred from (estimated) effects on weekly box-office revenues; and *ii)* the final effect of competing films is an empirical issue because it depends on several key characteristics of the film market such as the relative quality of the movies, the number of weeks films on exhibition (i.e. the decay rate), and the underlying seasonal pattern.[10] In particular, following Einav (2007), Krider & Weinberg (1998) and Moul (2007), we assume that the revenues of a particular movie i at time t , $R_i(t)$, can be written using a *logit* function as:

[8]The great majority of the studies reviewed use cross-sectional data from a single country and they try to use as many covariates as possible to control for heterogeneity across movies. However, they cannot control for unobserved heterogeneity. One exception is Craig et al. (2005), which follows a panel data approach.

[9] They also concluded that a primary concern in timing releases is to stay away from movies that have the same target audience.

[10] Modelling release decisions is a difficult task due to two important characteristics of the film market that should be properly addressed: (1) releasing decisions are discrete and (2) film heterogeneity imposes large asymmetries among agents. Corts (2001) tried to deal with these problems by analysing the time gap among movies released in the same period and estimating a reduced form model. More recently, Einav (2010) explains the observed release date decisions as the equilibrium outcome of a sequential-move game model with private information.

$$R_i(t) = D(t)S_i(t) = D(t)\frac{A_i(t)}{\sum_j A_j(t)+A_i(t)} \quad (1)$$

where t stands for time (week); j stands for all the movies on screen at time t except movie i; $D(t)$ is the primary demand at week t and captures the underlying seasonality of total demand throughout the year; $S_i(t)$ is the share of movie i , which in turn depends on its perceived quality or attraction, $A_i(t)$, and the attraction of competing films, $A_j(t)$. As shown by Moul & Shugan (2005) and Einav (2007), the logit demand function for cinema can be obtained from a utility maximization problem where it is assumed, following the literature on discrete choice models of demand, that consumers choose the movie that yields the highest utility.[11] It should be noted that in order to keep the theoretical model as simple as possible we do not allow for market expansion effects due to more or better movies (see Einav, 2007). Therefore, we must interpret our model as a reduced form expression of demand where the expansion market effects have been "solved out"[12] and the estimated impact of variables on demand should then be interpreted as equilibrium effects.[13]

According to (1), total box office of movie i can be written as follow:

$$R_i = \sum_{t=c_i}^{T_i} R_i(t) = \sum_{t=c_i}^{T_i} D(t)S_i(t) \quad (2)$$

where c_i and T_i are the opening week and the last week of exhibition of movie i. The attraction of this movie is zero before opening at $t<c_i$ and after leaving the screen at $t>T_i$. As is customary in the literature, we next assume that its attraction decreases exponentially over time, where $c_i \leq t \leq T_i$. Therefore, the attraction function $A_i(t)$ can be written as:

$$A_i(t) = \begin{cases} 0, & t < c_i \\ e^{\alpha_i - \beta_i(t-c_i)}, & c_i \leq t \leq T_i \\ 0, & t > T_i \end{cases} \quad (3)$$

[11] Einav (2007) also includes a term that captures seasonal changes in demand but, unlike in equation (1), this term is not separable from movies' shares as they are defined with respect an "extended" market that includes an *outside good*. We follow, however, the same strategy as Einav (2007) to estimate seasonal changes in demand, i.e. by using a set of weekly dummy variables under the assumption that the demand seasonality is stable over time.

[12] Note, however, that our model is equivalent to Einav's (2007) model when either the expansion effect is maximum or the substitution between movies and other goods is large (i.e. his parameter σ is zero).

[13] This strategy has been followed by Moul (2007) and Einav (2007) to address the potential endogeneity problem regarding the number of screens and advertising.

Following Krider and Weinberg (1998), the attraction depends on (i) the initial quality or marketability, α_i, which is the capacity of the movie to capture the audience's interest before the release based on factors such as advertisingt, cast, script, genre, special effects, etc.; and (ii) the depreciation rate or playability, β_i, which is the ability to keep the audience after its release and which depends on several factors including the word of mouth effect.[14] For notational ease, hereafter we normalize all weeks with respect to the week of release of movie *i*. That is, *t*=0 when the film *i* is released, and hence c_i=0. We also assume that rivals' movies (*j*) have the same depreciation rate β_j and quality α_j. We finally assume that all movies are T_j weeks on screen (i.e. movies released T_j weeks before or after also compete with the movie *i*, affecting its revenues).

We focus our analysis on the most potentially harmful films, those released during the period from two weeks before to two weeks after movie *i*'s release. In order to keep the model as simple as possible, we assume that the pool of competitors released in $t<-2$ (and $t>2$) is the same every week and equal to *n*. Let us rewrite the attraction of movie *i*'s competing films in its opening week as follows:

$$\sum_j A_j(0) = \sum_{j|t<-2} e^{\alpha_j+t\beta_j} + \sum_{j|t=-2} e^{\alpha_j-2\beta_j} + \sum_{j|t=-1} e^{\alpha_j-\beta_j} + \sum_{j|t=0} e^{\alpha_j} \qquad (4)$$

This expression can be approximated as follows:

$$\sum_j A_j(0) = \left[ne^{\alpha_j-T_j\beta_j} + \cdots + ne^{\alpha_j-3\beta_j}\right] + \sum_{-2}^{0} n_h e^{\alpha_j+h\beta_j} \qquad (5)$$

where n_h represents the number of releases in the week *h*. It is worth nothing that the term in brackets is actually ne^{α_j} times the sum of terms of a geometric progression of ratio $e^{-\beta_j}$. Hence, the attraction of competing films in (5) is equivalent to:

$$\sum_j A_j(0) = ne^{\alpha_j}\frac{\left(e^{-2\beta_j}-e^{-T_j\beta_j}\right)}{\left(e^{\beta_j}-1\right)} + \sum_{-2}^{0} n_h e^{\alpha_j+h\beta_j} \qquad (6)$$

Inserting (6) into (1), we can write the revenues of movie *i* in its opening week as:

[14] The term $(t\text{-}c_i)$ captures two effects (see, for instance, Einav, 2007). First, most people watch a movie only once, and the potential market shrinks over time. Second, most people prefer watching a movie earlier in its release. As Moul (2005) pointed out, this term can be viewed as a way to capture a saturation effect and consumer preferences for "fresh" products, which are standard in the marketing literature.

$$R_i(0) = D(0)\frac{e^{\alpha_i}}{ne^{\alpha_j}\frac{\left(e^{-2\beta_j}-e^{-T_j\beta_j}\right)}{\left(e^{\beta_j}-1\right)}+\sum_{-2}^{0} n_h e^{\alpha_j+h\beta_j}+e^{\alpha_i}} \qquad (7)$$

Let us move on to revenues in the following weeks. The revenues of the movie *i* in the week following the release are:

$$R_i(1) = D(1)\frac{e^{\alpha_i-\beta_i}}{ne^{\alpha_j}\frac{\left(e^{-3\beta_j}-e^{-T_j\beta_j}\right)}{\left(e^{\beta_j}-1\right)}+\sum_{-2}^{1} n_h e^{\alpha_j+(h-1)\beta_j}+e^{\alpha_i-\beta_i}} \qquad (8)$$

Regarding the transition from (7) to (8), three comments are in order. First, the attractiveness of movie *i* is depreciated one period, i.e. $A_i(1) = e^{\alpha_i-\beta_i}$. Second, n_1 movies released one week after movie *i* are added to the set of competing movies. And third, the competitors released in T_j. disappear from the pool of less harmful movies, i.e. only the competitors released in (or later than) T_j-1 remain on screen. The above *rotation* process, where new movies are added while other movies as dropped from the set of competing movies, is included in the model in order to imitate the dynamic pattern in a real-world cinema market and is taken into account to examine the following week's revenues. Following the same strategy, the revenues in the second and third weeks can be written respectively as:

$$R_i(2) = D(2)\frac{e^{\alpha_i-2\beta_i}}{ne^{\alpha_j}\frac{\left(e^{-4\beta_j}-e^{-T_j\beta_j}\right)}{\left(e^{\beta_j}-1\right)}+\sum_{-2}^{2} n_h e^{\alpha_j+(h-2)\beta_j}+e^{\alpha_i-2\beta_i}} \qquad (9)$$

and

$$R_i(3) = D(3)\frac{e^{\alpha_i-3\beta_i}}{ne^{\alpha_j}\frac{\left(e^{-5\beta_j}-e^{-T_j\beta_j}\right)}{\left(e^{\beta_j}-1\right)}+\sum_{-2}^{2} n_h e^{\alpha_j+(h-3)\beta_j}+e^{\alpha_i-3\beta_i}+ne^{\alpha_j}} \qquad (10)$$

While equation (9) is just equation (8) moved one week, in equation (10) we have treated the number of competitors released in *t>2* (see the last term of the denominator) separately because they are less harmful than previous movies released closer to movie *i*. Now, and as we did with movies released in *t<-2*, we assume for simplicity that the pool of competitors released in *t>2* is the same every week and equal to *n*. Consequently, the revenues after four weeks can be written as:

$$R_i(4) = D(4)\frac{e^{\alpha_i - 4\beta_i}}{ne^{\alpha_j}\frac{\left(e^{-6\beta_j} - e^{-k\beta_j}\right)}{\left(e^{\beta_j} - 1\right)} + \sum_{-2}^{2} n_h e^{\alpha_j + (h-4)\beta_j} + e^{\alpha_i - 4\beta_i} + \left[ne^{\alpha_j - \beta_j} + ne^{\alpha_j}\right]} \quad (11)$$

and so on. Summing up weekly revenues, total revenue for movie *i* can be expressed as follows:

$$R_i = \sum_{l=0}^{2} \frac{D(l)e^{\alpha_i - l\beta_i}}{ne^{\alpha_j}\frac{\left(e^{-(l+2)\beta_j} - e^{-T_i\beta_j}\right)}{\left(e^{\beta_j} - 1\right)} + \sum_{-2}^{l} n_h e^{\alpha_j + (h-l)\beta_j} + e^{\alpha_i - l\beta_i}} +$$
$$\sum_{l=3}^{T_i - 2} \frac{D(l)e^{\alpha_i - l\beta_i}}{ne^{\alpha_j}\frac{\left(e^{-(l+2)\beta_j} - e^{-T_i\beta_j}\right)}{\left(e^{\beta_j} - 1\right)} + \sum_{-2}^{2} n_h e^{\alpha_j + (h-l)\beta_j} + e^{\alpha_i - l\beta_i} + ne^{\alpha_j}\frac{e^{\beta_j} - e^{-(l-3)\beta_j}}{\left(e^{\beta_j} - 1\right)}} + \quad (12)$$
$$\sum_{l=T_i - 1}^{T_i} \frac{D(l)e^{\alpha_i - l\beta_i}}{\sum_{l-T_i}^{2} n_h e^{\alpha_j + (h-l)\beta_j} + e^{\alpha_i - l\beta_i} + ne^{\alpha_j}\frac{e^{\beta_j} - e^{-(l-3)\beta_j}}{\left(e^{\beta_j} - 1\right)}}$$

This equation indicates that the success of a particular movie *i* can be written as a function of the decay-adjusted quality of movie *i*; the number and quality of competing movies that were released before, simultaneously with or after movie *i*; and the seasonality of overall demand for cinema over time. If D_i stands for the average demand level during movie *i*'s time exhibition, movie *i*'s cumulative box office revenues can be written as:

$$R_i = f(\alpha_i, \beta_i, D_i, \alpha_j, \beta_j, n_0, n_{-1}, n_{-2}, \ldots, n_1, n_2, \ldots) \quad (13)$$

In the next section we show that the *relative* effect on movie *i*'s revenues of competing films released, say, one week before or one week after movie *i*'s release is ambiguous. Moreover, the sign of the gap between both effects might change notably from one observation to the next as it depends on the quality of the movies, decay rates, and the underlying seasonal pattern.

Competition Effects

In this section we use the model developed in the previous section to carry out some comparative statics that, by changing some relevant parameters such as time depreciation, film quality or timeline of exhibition, allow us to analyse the effect on total revenues of contemporaneous, past and future extra movies. We first compute the effect on movie *i*'s total revenues of an extra movie released in t=0, i.e. the same week as movie *i*. This effect can be computed by taking the derivative of weekly revenues with respect to n_0. Regarding the revenues in the opening week, the derivative with respect to n_0 is:

$$\frac{\partial[R_i(0)]}{\partial n_0} = -D(0)\frac{e^{\alpha_i}}{C(\mathrm{t})}\cdot\frac{e^{\alpha_j}}{C(\mathrm{t})} = -D(0)S_i(0)S_j(0) \tag{14}$$

where $C(t)$ stands for the sum of attractions of all movies on screen during week t, i.e. the denominator in equation (1). Regarding the following weeks, the derivative with respect to n_0 is:

$$\frac{\partial R_i(t)}{\partial n_0} = -D(t)\frac{e^{\alpha_i - t\beta_i}}{C(\mathrm{t})}\cdot\frac{e^{\alpha_j - t\beta_j}}{C(\mathrm{t})} = -D(t)S_i(t)S_j(t) \tag{15}$$

By adding the derivatives for all weeks that the movie remains on screen we obtain the effect on total revenues:

$$\frac{\partial R_i}{\partial n_0} = \frac{\partial \sum_0^{T_i} R_i(t)}{\partial n_0} = -\sum_0^{T_i} D(t)S_i(t)S_j(t) \tag{16}$$

If an extra movie is released one week before movie *i*'s release, i.e. in t=-1, the effect on total revenues is:[15]

$$\frac{\partial R_i}{\partial n_{-1}} = \frac{\partial \sum_0^{T_i} R_i(t)}{\partial n_{-1}} = -\sum_0^{T_i} D(t)S_i(t)S_j(t+1) = -\boldsymbol{e}^{-\boldsymbol{\beta}_j}\sum_0^{T_i} D(t)S_i(t)S_j^*(t) \tag{17}$$

where S_j^* is the hypothetical share of movie *j* if it were released at the same time as movie *i* and the competing movies in week *t* did not change. If an extra movie is released one week earlier, in t=-2, the effect on total revenues is:

$$\frac{\partial R_i}{\partial n_{-2}} = \frac{\partial \sum_0^{T_i} R_i(t)}{\partial n_{-2}} = -\sum_0^{T_i} D(t)S_i(t)S_j(t+2) = -\boldsymbol{e}^{-\boldsymbol{2\beta}_j}\sum_0^{T_i} D(t)S_i(t)\,S_j^*(t) \tag{18}$$

When a competing movie is released one week after the release of movie *i*, the opening week's revenues are not affected by this new movie. It might, however, have a

[15] For notational ease, we assume hereafter that any movie released before movie *i* affects the whole of movie *i*'s running period. The results are loosely the same because the effect on later revenues tends to zero if T_i is long enough.

strong effect on revenues in the following weeks. If an extra movie is released in *t*=1, the effect on total revenues is:

$$\frac{\partial R_i}{\partial n_1} = \frac{\partial \sum_1^{T_i} R_i(t)}{\partial n_1} = -\sum_1^{T_i} D(t) S_i(t) S_j(t-1) = -\, \boldsymbol{e^{\beta_j}} \sum_1^{T_i} D(t) S_i(t) S_j^*(t) \tag{19}$$

And if it is released two weeks later:

$$\frac{\partial R_i}{\partial n_2} = \frac{\partial \sum_2^{T_i} R_i(t)}{\partial n_2} = -\sum_2^{T_i} D(t) S_i(t) S_j(t-2) = -\boldsymbol{e^{2\beta_j}} \sum_2^{T_i} D(t) S_i(t) S_j^*(t) \tag{20}$$

The equations above suggest, as expected, that the effect of an additional competitor on total revenues of a movie depends on its date of release. However, if we move the date of release of our competitor, the evolution of the competition might be intuitive or counterintuitive. For instance, equations (16) and (17) suggest that if a competing movie is released the same week its effect is *always* higher than if it is released one or more weeks earlier.[16] However, comparing equations (16) and (19) we cannot affirm that the effect of a movie released a week later is *always* less than if it is release the same week. This only can be asserted when the underlying demand is not increasing.[17]

Similar comments arise if we compare the effects of a particular film released just one week earlier or one week later. The effect on the revenues of movie *i* when a rival movie *j* is released one week before or one week after is not symmetric. Indeed, when a competing movie is released earlier, it competes against movie *i* from the beginning. If it were released one week later, the opening week's revenues are not affected by this new movie, though it might have stronger effect on revenues in the following weeks. Computing the difference between both effects we get:

[16] Note that this result does not fit with the results obtained by Calantone et al (2010).

[17] It is straightforward to show this result if we assume that T_i is long enough, so that the difference between (16) and (19) is approximated by:

$$\frac{\partial R_i}{\partial n_0} - \frac{\partial R_i}{\partial n_1} \cong -\sum_0^{T_i-1} [D(t) S_i(t) - D(t+1) S_i(t+1)]\, S_j(t)$$

The sign of this difference is ambiguous when primary demand is increasing because movie shares always decrease as time increases.

$$\frac{\partial R_i}{\partial n_1} - \frac{\partial R_i}{\partial n_{-1}} = \left[\frac{\partial R_i(0)}{\partial n_1} - \frac{\partial R_i(0)}{\partial n_{-1}}\right] + \sum_1^{T_i}\left[\frac{\partial R_i(t)}{\partial n_1} - \frac{\partial R_i(0)}{\partial n_{-1}}\right] \tag{21}$$

or more specifically:

$$\frac{\partial R_i}{\partial n_1} - \frac{\partial R_i}{\partial n_{-1}} = D(0)S_i(0)S_j^*(0)\boldsymbol{e^{-\beta_j}} - \sum_1^{T_i} D(t)S_i(t)S_j^*(t)\left[\boldsymbol{e^{\beta_j} - e^{-\beta_j}}\right] \tag{22}$$

We arrive at an expression in which the first term is positive and the second negative. For this reason, we cannot affirm anything about which one is higher. Moreover, using some simulation results it is easy to show that net value varies a lot depending on the magnitude of several key characteristics of the film market, such us the relative quality of the movies, the number of weeks films are on screens(i.e. the decay rate), and the underlying seasonal pattern.

3. Sample and data base

This section summarizes the data we used to perform our empirical analysis. The sample consists of box office revenues for movies released in five countries from January 1st, 2000 to December 31st, 2009. We have collected the information provided by A. C. Nielsen EDI on movies released in the United States, the United Kingdom, Spain, France and Germany. From this original information, we have selected those movies released in at least three of these countries. Our eventual database incorporates 2,811 movies and 11,908 valid observations. This database has a panel data structure where the common time dimension has been substituted by a country (spatial) dimension. In order to arrive at this structure we first needed to match the movies across countries because many movies were released with different titles in each country. This was done by using the information provided by Internet Movie Database web site (www.imdb.com).

For each movie and country, our dataset includes the following information: corresponding title in each country, the official release dates, total box-office revenues, number of theaters on the release date, maximum number of theaters counted for a film over the course of its run, the distributors, and the MPAA rating. In the case of France we have total attendance instead of total box-office revenues.

4. The Empirical Model

According to equation (13) above, the box office performance of a particular movie *i* can be written as a function of the film's own characteristics film (i.e. α_i, β_i), as well as the number (n_0, n_{-1}, n_{-2} ...) and characteristics (α_j, β_j) of competing movies that were released before, simultaneously with or after movie *i*, and the seasonality of overall demand (D_i). Considering all these determinants, the empirical counterpart of equation (13) can be written as:

$$MarketShare_{ic} = \alpha_i + \gamma_f\, MaxThts_{ic} + \gamma_{ff}\, MaxThts_{ic}{}^2 + \sum_{r=-3}^{3} \lambda_r\, RivThts(r)_{ic} + \lambda_{rr}\, RivThts(r)_{ic}{}^2 + \sum_{w=2}^{52} \theta_w\, D(w)_{ic} + \varepsilon_{ic} \qquad (23)$$

where subscript *c* stands for country, subscript *w* identifies film *i*'s opening week, and ε_{ic} is the error term. The movie-specific constant term α_i captures unobserved film-specific heterogeneity, such as its budget, marketing costs, genre, star, critic reviews, and distributor, as well as its intrinsic quality. This heterogeneity cannot be modeled with cross-section data. However, it can be analyzed under the structure of panel data, and this is one of the main contributions of our paper. In accordance with the main features of our dataset, we have constructed a panel data model where the time dimension has been substituted by a country dimension.

The dependent variable $MarketShare_{ic}$ is the log of film *i*'s total box-office revenues in each country, normalized by the country's annual box-office revenues. This normalization allows us to control for the country-size effects, changes in cinema revenues over time, inflation and changes in the relative prices of movie tickets during the period.[18]

Following the previous literature, as explanatory variables we include the maximum weekly theatres count for a movie *i* over the course of its theatre run, $MaxThts_{ic}$, which provides a proxy for the attractiveness of the film and other qualitative features such as budget, the presence of stars, advertising, and also the distribution strategy and especially its marketing intensity i.e. its ex-ante competitive intensity or power (see Elberse & Eliashberg, 2003 and Hadida; 2009). In addition, since the relevant geographical market in the movie theatre industry is local in nature (Davis,

[18] Due to data limitations, the market share in France has been computed using total attendance instead of total box-office revenues.

2006), it may also be viewed as an "inverse" measure of customer transaction costs. Both reasons imply an expected positive coefficient for this variable.[19]

To examine in detail the competition effect of (past, present and future) rival films on *total* box-office revenues, we include a set of variables, $RivThts(r)_{ic}$, that measures the opening-week theatres of all the rivals of the movie *i* released the same week (in this case, r=0) or up to three weeks before ($-3 \leq r < 0$) or after ($0 < r \leq 3$) the release of movie *i*. This variable takes into account both the number of rivals and their ability to capture attendance. All these independent variables were normalized by subtracting its mean, so the first-order coefficients can be interpreted as derivatives evaluated at the sample arithmetic mean. Our theoretical model suggests a decreasing effect when rival films are moved away from film *i*. Since competition effects may depend on the film *i*'s characteristics we split the sample using the MPAA rating and estimate equation (23) for three different groups: general, restricted audiences and others.[20]

Note, in addition, that we also include squared values of both $MaxThts_{ic}$ and $RivThts(r)_{ic}$ to capture non-linear size and competition effects, respectively. Finally, we include weekly dummy variables (the first week is set as the base) to control for the effects of seasonality. A summary of the descriptive statistics for the above variables is shown in Table 1.

[Insert Table 1 here]

5. Estimation and Results

Equation (23) can be viewed as a panel data model. As is customary, it can be estimated using either a fixed effects or a random effects estimator.[21] Table 2 displays the results of both fixed effects and random effects estimations. We provide cluster-robust standard errors, where clustering by films permits correlation of the errors within

[19] Elberse and Eliashberg (2003) and Calantone et al. (2010) pointed out that the number of screens might be considered endogenous because exhibitors might allocate screens based on their expectations regarding audience demand, and these expectations depend movie's quality. Note, however, that we have included film-specific effects that accounts for this variation, and hence this endogeneity can be addressed using appropriate panel data estimators.

[20] The general audience group includes films suitable for all age groups and for children over 6 years. The restricted audience group includes films suitable only for ages over 17 years and the third group includes the remaining films, mainly those films not restricted to teenagers.

[21] We use an F test to test whether the film-specific constant terms (α_i) are all equal. We obtain a value of 5.61, which far exceeds any critical value of an F[2810, 11178]. Therefore, we reject the null hypothesis in favour of the individual effects model.

films but constrains errors to be independent across films. According to the robust Hausman test,[22] we reject the null hypothesis that the individual effect (α_i) and regressors are uncorrelated.[23] Thus, the fixed effects model is our preferred model as it allows us to explain market shares controlling for unobserved differences across movies.

[Insert Table 2 here]

The results in Table 2 show that the FE model explains nearly 35% of the market share variance. Most of the estimated first-order coefficients have their expected signs at the sample mean. The first-order coefficient of the maximum number of theaters where the film was exhibited ($MaxThts_{ic}$) is positive and statistically significant, as expected. This result is in line with Calantone et al. (2010) and Elberse and Eliashberg (2003), though we provide evidence of a decreasing effect of $MaxThts_{ic}$ as the estimated second-order coefficient of this variable is negative and statistically significant. Hence, increasing the number of theatres could raise the box office performance but not indefinitely.

Generally speaking, the remaining first-order coefficients show that the presence of more (or stronger) past, contemporaneous and future competitors has a statistically significant and negative impact on market share. The positive values of the second-order coefficients indicate, however, that the competition effect is decreasing with the number of rivals. Regarding the temporal pattern of the estimated competition effects, we have found, as expected, that contemporaneous rival movies have a stronger effect than films released in other weeks. This effect increases as rival film releases come closer. The results in Table 2 do not show evidence of a clear asymmetry between the effect of past and future film releases. The temporal pattern of competition effects will be discussed in more detail later in this section.

Our theoretical framework in Section 2 suggests that the competition effect strongly depends on movies' characteristics, including their rating. Because films with different rating are aimed at different target audiences, one would expect a substantial difference in the way in which the temporal competition affects total box-office revenues of films with different ratings. To examine this issue we have estimated our

[22] We follow Cameron & Trivedi (2009), which use the method of Wooldridge (2002).

[23] The value for the F[16, 2810] statistic is 121.78, above any critical value; therefore we strongly rejects the null hypothesis that individual effects and explanatory variables are uncorrelated.

model for three groups of movies: general, restricted audience and others. The parameters estimated are shown in Table 3.

[Insert Table 3 here]

Since our dataset gives us information on this variable, we have decided to replicate our model for three groups of movies (general, restricted audience and others) and analyse whether the competitive effects change significantly between them. The three models estimated have a similar goodness of fit, with the general audience model explaining 33% of the market share variance, the model for restricted audience explaining 41% while the figure is 35% for the other group model. As with the overall-sample model in Table 2, the Hausman test allows us to reject the Random Effects estimator in each model. Again, most of the estimated coefficients retain the expected signs. The maximum number of theaters where a movie was exhibited ($MaxThts_{ic}$) still has a positive and statistically significant effect on the market share in all models. This effect is again significantly decreasing.

Regarding the competition effect, the results are not as clear as those shown in Table 2, because both, the magnitude and statistical significance of the estimated parameters, vary across film groups. In general, the rival films that have a significant impact are only those released close to the film. The rival movies released the same week have a significant, negative and decreasing effect in all cases. In the case of general audience films, other harmful competitors are those that were released one week later. For restricted audience films, the more important rivals are those released the previous week. In the case of other films, rivals released two weeks later have a significant effect.

In order to compare the magnitudes of the different competition effects in a clearer way we have calculated the elasticities of the market shares taking into account the linear and the squared effects (see Table 4). All elasticities are evaluated at the mean of each group of movies. In this table we use the elasticity of the market share with respect to $MaxThts_{ic}$ as a benchmark to discuss the competition effects. In all models, the estimated elasticities relative to the maximum number of theaters are always higher than unity. This indicates that there are economies of scale at the mean, that is, you can take advantage of the size of the releases to some extent but the negative quadratic effects indicate that it will decrease as the film is released in more theatres.

Regarding the competition effects, the most harmful rival films in all models are those films released the same week. However, the elasticity of the market share with respect to contemporaneous rivals is always lower in absolute terms than one. This elasticity for all movies indicates that, at the mean, a 1% increase in contemporaneous rival theaters reduces box-office share by 0.22%. This effect is even more important for restricted audience films where the corresponding elasticity is twice as that found in the overall model (about 0.41). Using the elasticity of the market share with respect to $MaxThts_{ic}$ as a benchmark, we conclude that the contemporaneous competition effect represents, in absolute terms, less than a fifth of the own-effect of theaters for the overall model. This effect goes up to one third for restricted audience films, and decreases markedly for films not restricted to teenagers.

[Insert Table 4 here]

In the case of the model that considers all movies, where the effects of both pre and post-released rivals are significant and negative, we get a decreasing impact as we move over time, i.e. the closer the release the higher the negative impact. It is also worth mentioning that, unlike Table 2, the estimated elasticities in Table 4 suggest the existence of asymmetric effects on past and future film releases.

Comparing the estimations of the different rating movie groups, it the same pattern with respect to the impact of previous or subsequent releases is no longer appreciated. Market share is mainly affected by competitors launched before the own release for restricted films and those launched after for the other two groups of movies. Furthermore, the impacts caused by non-contemporary rivals are only comparable to contemporary films in the case of restricted films.

Summarizing all these findings, it seems that the audience of non-restricted films is more interested in novelty since they are more affected by those films that will be new in the following weeks. However, the restricted movies' audience could be more sensitive to a word-of-mouth effect related to previous released pictures. Following this, it seems that the releasing policy of restricted audience films should pay more attention to films already on exhibition whereas the distribution of other movies has to pay more attention to future rivals.

6. Conclusion

In this paper we show the role of temporal competition in the movie exhibition market and its effect on market share taking into account the possible differences between present, past and future films releases. We develop a theoretical model that allows us to shed light on this issue. The most significant outcome is that a competing movie released in the same week would always have a higher effect than that if it were released in any other week *ceteris paribus*. Moreover, rival films will have different impacts depending on their own characteristics as well as their temporal pattern of release. Therefore we can see that evaluating the final effect of competing films is an empirical issue.

Taking advantage of the results of the theoretical model, we propose an empirical application to examine our main research question. We use the information on the films released in five countries, where the geographical dimension allows us to use panel data techniques to control for the unobserved heterogeneity of the released films and hence capture one of the most relevant features of movie market, that is, the presence of highly differentiated products. We specifically consider the competitors launched in the three week interval around the release date of a particular movie. We also estimate three additional models splitting the films sample according to their ratings to get some distinctive effects by type of film, as suggested by the theoretical model.

In the main model, which considers all the movies, we found that the effect of contemporary rivals is always larger than the previous or future rivals, as suggested by the theoretical model. In general, we find a decreasing impact of other film releases as their launch dates move away from the release week of the reference film, also confirming the findings of our theoretical model.

When we compare the three additional models according to movies ratings, we found a substantial difference between them and different patterns with respect to the impact of previous or subsequent releases. Moreover, audiences of non-restricted films are more affected by movies that will be new in posterior weeks and thus they seem to be more interested in novelty. However, the restricted movies audience may be more sensitive to a word-of-mouth effect related to previously-released pictures. According to the above, the releasing policy should be different for the different types of films. In the case of an expected blockbuster, restricted audience films should anticipate rival releases and try to be launched before them, whereas general audience films and other films should postpone their release since it seems better to be released afterwards.

Acknowledgments

Research for this paper was financed by the Spanish Ministry of Science and Technology Projects #ECO2008-04659 and the Department of Education, Universities and Research of the Basque Government.

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Table 1. Summary statistics of data

Data	Units	Mean	Min	Max	Std. Dev.
Market Share	percentage	0.003673	1.75E-08	0.113305	0.007205
Max. own theaters	thousands	0.453	0.001	4.393	0.820
Rivals theaters 0	thousands	1.816	0.000	15.387	2.426
Rivals theaters 1	thousands	2.034	0.000	15.388	2.599
Rivals theaters 2	thousands	2.045	0.000	15.388	2.600
Rivals theaters 3	thousands	2.032	0.000	15.388	2.566
Rivals theaters-1	thousands	2.061	0.000	15.388	2.611
Rivals theaters-2	thousands	2.036	0.000	15.388	2.551
Rivals theaters-3	thousands	2.047	0.000	15.388	2.597

Table 2. Fixed effects and Random effects model

	ln (*MarketShare*)					
	Fixed effects model			Random effects model		
Variable	Coefficient		*robust-t*	Coefficient		*robust-t*
MaxThts	3.0843	***	*46.03*	4.1254	***	*68.04*
RivThts 0	-0.1240	***	*-5.97*	-0.2293	***	*-10.39*
RivThts 1	-0.0664	***	*-3.26*	-0.0924	***	*-4.33*
RivThts 2	-0.0718	***	*-3.47*	-0.0950	***	*-4.54*
RivThts 3	-0.0429	**	*-1.97*	-0.0605	***	*-2.83*
RivThts-1	-0.0737	***	*-3.38*	-0.0864	***	*-3.90*
RivThts-2	-0.0625	***	*-2.92*	-0.0542	**	*-2.51*
RivThts-3	-0.0346		*-1.55*	-0.0384	*	*-1.72*
(MaxThts)^2	-0.8130	***	*-32.95*	-1.1000	***	*-39.65*
(RivThts 0)^2	0.0106	***	*4.12*	0.0219	***	*8.32*
(RivThts 1)^2	0.0020		*0.88*	0.0050	**	*2.16*
(RivThts 2)^2	0.0064	***	*2.89*	0.0086	***	*3.89*
(RivThts 3)^2	0.0034		*1.29*	0.0044	*	*1.75*
(RivThts-1)^2	0.0025		*1.07*	0.0032		*1.34*
(RivThts-2)^2	0.0064	***	*2.64*	0.0047	*	*1.94*
(RivThts-3)^2	0.0017		*0.72*	0.0015		*0.64*
Weekly Dummies	yes			yes		
Constant	-6.7885	***	*-67.91*	-6.8456	***	*-64.42*
N	11908			11908		
R^2	0.3491					
F	48.92					
Hausman Test	121.78					

Note: *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Table 3. Fixed effects model with movies for general, restricted audience and others

	ln (*MarketShare*)								
	FE (general audience)			FE (restricted)			FE (others)		
Variable	Coefficient		*robust-t*	Coefficient		*robust-t*	Coefficient		*robust-t*
MaxThts	3.3081	***	21.44	2.5862	***	14.55	2.8611	***	27.35
RivThts 0	-0.2265	***	-5.22	-0.1802	***	-3.80	-0.0828	**	-2.51
RivThts 1	-0.1158	***	-2.82	-0.0566		-0.93	-0.0829	**	-2.36
RivThts 2	-0.0177		-0.40	-0.0254		-0.40	-0.0803	**	-2.32
RivThts 3	-0.0611		-1.36	-0.1245	**	-1.97	-0.0513		-1.35
RivThts-1	-0.0707		-1.53	-0.1370	**	-2.26	-0.0284		-0.79
RivThts-2	-0.0406		-0.93	-0.0323		-0.54	-0.0598		-1.61
RivThts-3	-0.0830	*	-1.80	0.0775		1.39	-0.0441		-1.19
(MaxThts)^2	-0.8440	***	-18.98	-0.7810	***	-11.52	-0.7180	***	-19.55
(RivThts 0)^2	0.0231	***	4.07	0.0173	***	3.23	0.0051		1.26
(RivThts 1)^2	0.0057		1.27	0.0041		0.56	0.0006		0.16
(RivThts 2)^2	0.0034		0.62	0.0074		1.12	0.0075	**	2.00
(RivThts 3)^2	0.0115	**	2.18	0.0172	***	2.68	0.0027		0.58
(RivThts-1)^2	0.0057		1.03	0.0048		0.73	-0.0027		-0.68
(RivThts-2)^2	0.0077		1.45	0.0006		0.10	0.0062		1.49
(RivThts-3)^2	0.0111	**	2.36	-0.0098	*	-1.73	0.0005		0.12
Weekly Dummies	yes			yes			yes		
Constant	-7.20642	***	-30.29	-7.00328	***	-31.84	-6.80926		-39.15
N	4307			2193			5412		
R^2	0.3329			0.4110			0.3528		
F	10.96			6.44			16.93		
Test Hausman	38.02			13.91			47.13		

Note: *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Table 4. Elasticities evaluated at mean

∂(lnShareRev)/∂(lnX)								
Variable	η (all)	ratio	η (general audience)	ratio	η (restricted)	ratio	η (others)	ratio
Max. own theaters	1.3809***		1.3065 ***		1.3916 ***		1.2687 ***	
Rivals theaters 0	-0.2220 ***	-0.1608	-0.2959 ***	-0.2265	-0.4128 ***	-0.2966	-0.1476 **	-0.1164
Rivals theaters 1	-0.1340 ***	-0.0970	-0.1606 ***	-0.1229	-0.1496	-0.1075	-0.1716 **	-0.1353
Rivals theaters 2	-0.1435 ***	-0.1039	-0.0288	-0.0221	-0.0105	-0.0075	-0.1605 **	-0.1265
Rivals theaters 3	-0.0854 **	-0.0619	-0.0986	-0.0755	-0.2486 **	-0.1787	-0.1033	-0.0814
Rivals theaters-1	-0.1505 ***	-0.1090	-0.1031	-0.0789	-0.4267 **	-0.3066	-0.0600	-0.0473
Rivals theaters-2	-0.1239 ***	-0.0897	-0.0657	-0.0503	-0.1043	-0.0749	-0.1188	-0.0937
Rivals theaters-3	-0.0699	-0.0506	-0.1271 *	-0.0973	0.1653	0.1188	-0.0918	-0.0724

Note: *** significant at 1% level; ** significant at 5% level; * significant at 10% level.