Competition in the Movie Industry:

Releasing Dates and Theatre Allocations

as Strategic Variables

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A mi padre, madre, Deborah y Daniel

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Abstract

This thesis focuses on some relevant questions regarding strategic behaviour and performance in the Motion Picture industry using an Empirical Industrial Organization approach. In particular, we analyses several issues related to competition, such as the effects of competition on films' revenues, differences in performance and the strategic decisions of film distributors in a short life-cycle industry. The film distribution market can also be defined as a differentiated product oligopoly, and highly product differentiated industry where firms mainly compete in non-price product attributes. Given the characteristics of this market, temporal decisions play a crucial role. Thus, we aim to extend understanding of the movie market with three essays focused on two of the most important decisions taken by film distributors in the short run: the choice of the movie release date, and the allocation of the number of theatres on the opening and successive weeks.

The first essay analyses the effects of temporal competition on films' box-office revenues. Using information on films released in United States and the four largest European motion pictures markets (the United Kingdom, France, Germany and Spain), we examine in detail the competition effect of past, present and future rival films. We find that these rivals have asymmetric effects on the total box-office revenues of a particular film. Additionally, we find different temporal patterns for these effects depending on the type of film considered. Our analysis may provide guidance to film studios and distributors on how to improve their release timing decisions.

Given the relevance of the release date as a strategic competition variable, as shown in the first essay, film distributors are likely to be interested in coordinating their release schedules with other companies in order to avoid the negative effects of competition. In light of this, the aim of the second essay is to evaluate the presence of anti-competitive practices through the study of the distributors' decisions regarding their film release schedules in the Spanish motion picture market. The empirical evidence shows that Major Distributors have been able to better mitigate temporal competition than other distributors, reducing the clustering of their film releases. These results provide some indirect evidence on the presence of either collusive behaviour among the Major Distributors, which have a dominant market share in the main international movie markets, or other anti-competitive practices that cause market power to be less evenly distributed in the market.

Major Distributors are likely take advantage of their market power to condition the subsequent theatre allocation process. With this in mind, the third essay focuses on theatre allocation as a strategic decision variable. Taking into account the structure of the distribution market, we explore whether the different types of distributors have different impacts on theatre allocation - both in opening and subsequent weeks - in terms of distribution intensity. We use weekly box-office revenue in the United States motion picture market. We find that the theatre elasticities of box-office revenues for all the Major Distributors are significantly lower than those corresponding to non-Majors, throughout the entire movie run. These results are consistent with a greater market power of the Majors that could be used to push exhibitors to allocate a large number of theatres to theirs films.

While the three essays that comprise this thesis use standard econometric models to analyse competition and firms' performance in the motion picture market, it should be emphasised that all of them contain specific methodological contributions. Taken as a whole, the essays contribute to a better understanding of the motion picture market through the analysis of the distributors' decisions on two key strategic variables - the release date and the allocation of theatres - and provide valuable insights into how Major Distributors are using their market power in the movie industry.

Resumen

Esta tesis se centra en el análisis de algunas preguntas relevantes sobre el comportamiento en la industria cinematográfica, desde el punto de vista de la Organización Industrial. Concretamente estudia varios temas de competencia, tales como sus efectos sobre la recaudación de las películas, las diferencias en performances y las decisiones estratégicas de los distribuidores de cine en una industria con producto de ciclo de vida corto. El mercado de distribución de cine también puede ser definido como un oligopolio de producto diferenciado, donde las empresas compiten principalmente en atributos del producto distintos del precio. Dadas las características de este mercado, las decisiones temporales juegan un rol crucial. Se pretende ampliar el conocimiento del mercado cinematográfico con tres ensayos que se centran en dos de las decisiones más importantes de los distribuidores en el corto plazo: la elección de la fecha de estreno y la asignación de teatros en la semana de estreno y en las siguientes.

El primer ensayo analiza los efectos de la competencia temporal sobre la recaudación por taquilla de las películas. Utilizando información de las películas estrenadas en los Estados Unidos y en cuatro de los mercados cinematográficos europeos más importantes (Reino Unido, Francia, Alemania y España), examinamos en detalle los efectos de la competencia de las películas rivales presentes, pasadas y futuras. Encontramos que estos competidores presentan efectos asimétricos sobre la recaudación por taquilla de una película determinada. Además, nuestros resultados muestran que los efectos de la competencia presentan diferentes patrones temporales para distintos tipos de películas. Este análisis puede proporcionar una guía a los *estudios cinematográficos y a los distribuidores para mejorar sus decisiones respecto a los calendarios de estrenos.*

El primer ensayo muestra la relevancia de la fecha de estreno como una variable de competencia estratégica. En consecuencia, los distribuidores de cine podrían estar interesados en coordinar sus calendarios de estreno con otras compañías para evitar los efectos negativos de la competencia. Entonces, el objetivo del segundo ensayo es evaluar la presencia de prácticas restrictivas de la competencia, a través del estudio de las decisiones de los distribuidores respecto a los calendarios de estreno de sus películas, en el mercado cinematográfico español. La evidencia empírica muestra que las Grandes Distribuidoras han sido capaces de mitigar la competencia temporal mejor que otras distribuidoras, separando el estreno de sus películas. Estos resultados proporcionan evidencia indirecta ya sea de la presencia de conductas colusorias entre los Grandes Distribuidores, que tienen una cuota de mercado dominante en los principales mercado cinematográficos internacionales, o de la presencia de otras prácticas anticompetitivas que causan que el poder de mercado esté menos distribuido en el mercado.

Las Grandes Distribuidoras probablemente aprovechen su poder de mercado para condicionar el posterior proceso de asignación de teatros. Así, el tercer ensayo se centra en el estudio de la asignación de teatros como variable de decisión estratégica. Considerando la estructura del mercado de distribución, evaluamos si los distintos tipos de distribuidores tienen efectos diferentes en la asignación de los teatros, tanto en la semana de estreno como en las siguientes, en cuanto a intensidad de distribución. Para *ello utilizamos datos de la recaudación por taquilla semanal de los Estados Unidos. Encontramos que las elasticidades teatro de la recaudación para todos los distribuidores son significativamente menores que las del resto de distribuidores, a lo largo de toda la vida de la películas. Estos resultados son consistentes con el gran poder de mercado de las Grandes Distribuidoras, que puede ser usado para hacer que los exhibidores asignen un gran número de teatros a sus películas.*

Los tres ensayos que componen esta tesis utilizan modelos econométricos estándar para analizar la competencia y la performance de las empresas en el mercado cinematográfico, pero todos ellos con aportaciones metodológicas específicas. Resumiendo, estos ensayos contribuyen a mejorar la comprensión del mercado cinematográfico a través del análisis de las decisiones de los distribuidores en dos variables estratégicas claves: las fechas de estreno y la asignación de los teatros. Especialmente ofrecen una precepción de cómo las Grandes Distribuidoras podrían estar utilizando su poder de mercado en la industria del cine.

Chapter 1: Introduction

This thesis analyses several issues related to competition in the motion picture industry, a highly product-differentiated industry where firms mainly compete in non-price product attributes. The special characteristics of this industry make it a particularly interesting topic of study within the literature on Empirical Industrial Organization. Moreover, this thesis should prove relevant for market competition analyses in other entertainment industries where content, time considerations and other non-monetary product features are also important.

The economic agents in the motion picture industry can be classified into three groups: producers, distributors and exhibitors. They each have different objectives that in turn may lead to several “conflict of interests”. In the Golden Age of the studio system, prior to the Hollywood Antitrust Case of 1948, incentives were aligned due to the vertical integration of the main firms in the sector, which distributed and exhibited their own productions. While exhibition has been mostly independent of production and distribution activities since then, the latter activities are, in many cases, connected under the same or related firms. Within this sector, we mainly focus our research on the competitive behaviour and the strategic decisions of distributors.

Several features of the distribution market are worth mentioning. First, the distribution market can be viewed in the United States and Europe as an oligopoly where a small group of distributors, which are linked to the Major Hollywood film studios, have a large market share. Second, as all films are different by nature, product differentiation in this market is extremely high. Third, motion pictures have an extremely short life-cycle (Zufryden 1996 and 2000) that, in addition, differs from the life-cycle of a typical consumer product insofar as they are intended for immediate consumption. In general, film life-cycles on the big screen are characterized by an initial spike in revenues after opening followed by a rapid decay as new films enter the exhibition market and the value of the film declines. Thus, there are many new movies released in a relatively short time period (De Vany and Walls 1997). In fact, in recent times there has been a trend towards shorter runs and a higher concentration of box office revenues around the opening weekend (Kanzler 2011). Fourth, once films are released, there is usually a lack of subsequent competition in prices. That is, movies do not generally compete on prices because there are no price differences among films exhibited in a cinema theatre at a given time. Moreover, ticket prices are very similar within each local market (see Orbach and Einav 2007, Chisholm and Norman 2012). Finally, there is high seasonality in cinema demand throughout the year, with periods of high demand during holidays (Moul and Shugan 2005, Vogel 2005 and Einav 2007).

Given the above features, the most important decisions in the film distribution market are the choice of proper dates of release, the allocation of the number of theatres during the opening week and the following weeks, and the determination of the advertising budget and strategy. Other film attributes (e.g., the characteristics and quality of the film) are also important, but they cannot be easily changed in the short run. If timing is badly selected and the potential audience is poorly targeted by the advertising campaign, it will be too late to redesign the movie run due to the short life cycle of movies. Thus, in the motion picture industry temporal decisions play a crucial role.

Within this context, the purpose of this thesis is to examine firms' strategic behaviour and a series of issues related to competition in the distribution market, where the variety and duration of exhibited films rely on the conditions negotiated between distributors and exhibitors. First of all, in order to assess the importance of the release dates as a strategic variable of competition, we analyse the role of temporal competition and how rivals' release decisions impact on box-office revenues. Then, we investigate the presence of anti-competitive practices through the study of the distributors' decisions regarding their films' release schedules. Finally, we analyse the link between the distributors' market shares and the allocation of theatres. From these results, we expect to identify relevant aspects of distributors' strategic behaviour and uncover evidence on the existence of bargaining power.

The thesis comprises three essays which we now briefly describe. The first essay analyses the effects of temporal competition on films' box-office revenues. The available literature confirms the importance of considering competition as a key factor in determining box-office revenues (Elberse and Eliashberg 2003, Ainslie et al. 2005, Basuroy et al. 2006, Calantone et al. 2010). However, little attention has been given to the asymmetric competition of past, present and future rival films. We fill this gap using an empirical model that explicitly distinguishes between the effects of past, present and future releases on the total box-office revenues of a particular film. Such an analysis is appealing in terms of its policy implications and may provide guidance to distributors on how to improve their release timing decisions. The proposed empirical strategy can also be easily implemented in other industries, especially in entertainment, where timing decisions are also critical for the profitability of new (short life-cycle) products.

In this first essay, we propose estimating a reduced-form model where total box-office revenues are explained by a set of control variables approximating some quality characteristics of the film, the competitive environment and the seasonality in underlying demand. We estimate this model using information on the films released in the United States and the four largest European motion pictures markets (the United Kingdom, France, Germany and Spain) between 2000 and 2009. Thus, we have a panel data set where the time dimension has been substituted by a country dimension. The panel structure of our data allows using econometric techniques to deal with one of the major difficulties when carrying out empirical analyses in the movie market, namely the presence of highly differentiated products. In particular, we take advantage of the geographical dimension of our data to control for unobserved heterogeneity among released films. As much of films' differences are not observed by the researcher, this approach is quite appealing as it permits a consistent estimation of the effect of rival movies on revenues.

The purpose of the second essay is to analyse differences in performance among distributors when deciding the date of release of their films, which is a non-price attribute of distributors' films. Using a sample of movies released in Spain between 2002 and 2009, this essay attempts to provide some evidence on the presence of collusive behaviour in release dates, which was one of the arguments used by the Spanish Competition Authority to fine the five Spanish distributors linked to the Major studios in Hollywood in 2006 for anticompetitive practices.

Majors and their affiliated local distribution companies have a dominant market share in the main international movie markets and their competitive behaviour has come under suspicion in some countries, including Spain. Although the market dominance of these distributors might suggest that they are engaging in anticompetitive practices, there is little evidence on collusion in this industry. A notable exception is Moul (2008), who examined collusion in rental rates. Whereas the first essay shows that the release date of a movie is a critical competition variable and implies that distributors might be interested in coordinating release schedules with other companies to avoid such competition, there has been little attention given in the literature to the question of collusion in release dates. To examine this issue, we adapt one of the most popular methods for detecting price-based collusive practices (for a survey, see Harrington 2008) to the analysis of films' release dates.

In particular, in this second essay we test whether Majors have been able to alternate and/or separate their releases more than other distributors. Although this result might also be caused by other factors (e.g. abuse of dominant position or first-mover advantages) that somehow give them extra market power, we take it as an indirect evidence of collusive behaviour. In doing so, we bring together two different frameworks, namely the aforementioned literature on detecting collusive practices and the empirical studies on spatial or temporal product differentiation analysis (Borenstein and Netz 1999, Corts 2001, Netz and Taylor 2002, Osashi 2005).

Following the latter literature, we estimate a reduced-form model to examine the determinants of distributors' release schedules. More specifically, following Corts (2001) the target variable to be modelled here is the temporal distance between the releases of two films. However, we adapt and extend this framework in two ways. First, we apply a flexible statistical procedure to identify relevant "demand windows", i.e., temporal market segments. Second, we define a relative measure of the temporal distance between the releases of any two films that takes the optimal equilibrium of Hotelling's (1929) spatial competition model as its benchmark. We do so separately for suspected cartel members and competitive firms in order to test whether Majors behave in a manner that differs from the competitive sector of the distribution market.

The third essay is focused on a different key strategic decision variable, namely theatre allocation. This variable could potentially be used as a flexible instrument that can be fine-tuned over the movie run to adjust supply and demand. However, for the release weekend, theatre allocation has to be decided in advance i.e., without knowing the actual performance of the film. Distributor's market power together with the production budget and advertisement could be the main factors underlying the number of screens on release. Therefore, taking into account the structure of the distribution market we explore whether the different types of distributors have a differing influences on the theatre allocation process. Distributors with larger market shares (Major studios) are likely have greater bargaining power and thus may be able to impose their clauses of the exhibition contracts. Hence, in order to maximize their revenues per film, distributors may try to force theatre owners to allocate more screens than the optimal from the exhibitors' point of view. There is a lack of data on exhibition contracts (see McKenzie 2012) that may be due to the fact that they might provide invaluable information in antitrust cases which have been pursued in various countries. Therefore, we cannot have direct evidence on the general clauses that each distributor offers in their exhibition contracts. However, from the observed differences between theatre elasticity of box-office revenues among distributors, we can establish some conjectures on the distributors' strategies regarding theatre allocation.

The empirical exercise involves estimating the weekly box-office revenue in the United States motion picture market between 2000 and 2009. Although many researchers have developed models of weekly box office revenues including theatres as an endogenous variable (Elberse and Eliashberg 2003, Basuroy et al. 2006), no studies have considered the estimated elasticities as a proxy of the Majors' market power. In terms of the traditional "structure-conduct-performance" paradigm of industrial organization, we investigate whether (and how) a film's box-office performance is affected by the market structure through the (unobserved) conduct of the distributors regarding theatre allocation. The panel nature of the data set allows us to control for unobserved heterogeneity among the films released. In particular, we use the Hausman and Taylor (1981) estimator that proposes a random effects model to deal with the endogeneity problems that some of the explanatory variables may cause.

In summary, this thesis comprises a systematic analysis of the distributors' decisions on two key strategic variables: the release date and the allocation of theatres. The empirical estimations have identified different behaviours according to the distributors' market share which, in turn, may be interpreted as indirect proof of the Majors' higher bargaining power. Alternative non-collusive explanations are possible but we believe that they are less plausible. Finally, some relevant policy implications can be derived from the three papers included in this dissertation.

It should be noted that the three essays in the following chapters have been submitted to international journals or have been written with that purpose. The first essay is an article that has being accepted for publication in the Journal of Cultural Economics. Both the first and the second essays are co-authored by Juan Prieto-Rodriguez and my co-directors Victor Fernandez-Blanco and Luis Orea. The third essay is co-authored by Juan Prieto-Rodriguez and Victoria Ateca-Amestoy.

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Chapter 2: How do your Rivals' Releasing Dates affect your Box Office?

2.1. Introduction

The motion picture 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, so that motion pictures exhibition is a short life-cycle industry. These characteristics are observed both in the US and the European market. Moreover, Kanzler (2011) pointed out that there is a trend towards shorter runs and increased concentration of box office around opening weekend, particularly for wide releases.

Finally, cinema demand is characterized by fluctuations along the year, with high peaks in certain weeks. In this context, when distributors believe that a film may be a blockbuster they may try to release it in high-demand periods as they know that one month's revenue during these periods could produce box office sales equivalent to several months in low-demand phases. 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 periods and avoiding head-to-head competition for the same audience. This head-to-head competition is 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. Moreover, this head-to-head competition has not been alleviated by reducing prices as ticket prices are very similar within each local market (see Orbach and Einav 2007, Chisholm and Norman 2012) and there are no price differences among films exhibited in a cinema theatre at a given moment.

In light of the aforementioned features, 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 generate negative effects on each other's revenues (Corts 2001).

In this framework, this Chapter 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 expanding research field in Economics. There is an extensive literature that analyses 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). Previous Chapters 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 and Zufryden 2005) and by the release of other films with a similar target audience (Basuroy, Desai and Talukdar 2006). More recently, Calantone et al. (2010) have estimated a model using weekly data that accounts directly and 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.

This literature confirms the importance of considering competition as a key factor in determining box-office revenues. Our paper, on the other hand, deals explicitly with the effects of competing films released in past, present and future weeks on the total box-office revenues of a particular film. We use panel data techniques and thus we control for the specific effects of each film. In doing so we will take into account that *Little Miss Sunshine* is not *Avatar*.

Although other sources of revenues might be more important, theatres are a relevant market not only in terms of revenue figures but also as a predictor of the revenues of a film in other markets. For instance, McKenzie (2010) concluded for the Australian market that success at the box office is an extremely important determinant of the demand for DVDs. Additionally, Lang et al. (2011) pointed out that previous box office success has strong positive effects on DVD sales. The past box office performance of a movie appears to be the single most important determinant of DVD sales.

Consequently, our empirical model uses aggregate movie theatre revenues (for each film in each country) and hence it can be viewed as a “reduced form” of more complex models based on weekly data. Our empirical strategy allows us to measure the effects of competition on total box office revenue in a direct manner, without the need to deal with econometric issues that appear with dynamic models. For instance, the word-of-mouth effect not only requires the use of weekly data but also the estimation of dynamic models with different sources of endogeneity, and autoregressive errors. This dynamic framework makes it difficult to control for unobservable film effects that are likely correlated with some of our explanatory variables (see Verbeek 2008). However, if unobserved heterogeneity is not addressed we will have biased estimators. Since unobserved heterogeneity is expected to be important in our application, a dynamic model may therefore not be the most appropriate. Furthermore, although the weekly-based models can be used to measure the competition effect on total revenues, this would require computing a set of derivatives and obtaining confidence intervals for the estimated effects is not straightforward in a dynamic setting. By estimating a reduced-form model, however, we can measure the effects of competition on total box office revenue in a direct way, giving practitioners a simple management tool. Moreover, a reduced-form model allows us to control for the individual effects specific to each film and the endogeneity problems.

Our reduced-form specification provides a simple econometric specification designed specifically to measure and test competition effects on total box office revenues of films released close each other. Correct inference about these effects can be carried out in a standard regression framework using the well-known fixed effects estimator. As the coefficients of our model have simple interpretations, the model is a useful policy tool which can be used to provide guidance to distributors to decide the release of their firms.

Moreover, our empirical model allows us to both measure and test to what extent past, present and future rival releases have asymmetric effects on the total box-office revenues of a particular film. This information is 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 empirical results could help them to use their release dates as a strategic variable to keep or capture market share from their rivals. With this information the distributors could 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.

The Chapter is organized as follows. In the next section we describe the data base used and in Section 2.3 the empirical model to be estimated is outlined. In Section 2.4 the principal results are presented. The final section concludes.

2.2. 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 and the four largest European motion pictures markets (United Kingdom, France, Germany and Spain). From this information, we have selected those movies released in at least three of these countries. Our final database comprises 2,811 movies and 11,908 valid observations. This database has a panel data structure where the time dimension has been substituted by a spatial (country) dimension. In order to arrive at this structure we first had 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 the Internet Movie Database web site (www.imdb.com).

For each movie and country, our dataset includes the following information: the corresponding titles, the official release dates, total box-office revenues, number of theatres on the release date, maximum number of theatres 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.

2.3. Empirical Model

According to previous literature, the box office revenues of a film depend on the characteristics that determine the quality of the film, the competitive environment and the seasonality in underlying demand.[1] Considering all these determinants, we propose estimating the following empirical model:

$$MarketShare_{ic} = \alpha_i + \gamma_f \, OwnThts_{ic} + \gamma_{ff} \, OwnThts_{ic}{}^2 + \sum_{r=-3}^{3} \lambda_r \, RivThts(r)_{ic} + \lambda_{rr} \, RivThts(r)_{ic}{}^2 + \sum_{w=2}^{52} \theta_w \, D(w)_{ic} + \varepsilon_{ic} \qquad (2.1)$$

where subscript *c* stands for country, subscript *w* identifies film *i*'s opening week, and ε_{ic} is the error term. The film-specific constant term α_i captures observed and unobserved film characteristics. Some characteristics such as genre, awards, stars, distributor, etc. might be available but can not be included in a fixed effects panel data model. There are many characteristic that are unobservable and these may be important because the motion picture industry is one of the most highly product-differentiated markets, as each movie is unique by nature. This is confirmed by Einav

[1] For more details see the theoretical model developed in Gutierrez-Navratil et al. (2011).

(2007, p. 138), who found that “observable variables (...) explain only a small fraction of the variation in quality”. As some of these unobserved characteristics are likely to be correlated with our explanatory variables (e.g. theatres numbers) our parameter estimates will be biased. This problem appears if we estimate the model by ordinary least squares whatever we have cross sectional or panel data. However, if we have a panel data set (as is the case in our application where the time dimension has been substituted by a country dimension), we can deal with this problem using a fixed effects estimator that controls for film characteristics that can be considered invariant across countries.

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.[2]

Following the previous literature, as explanatory variables we include the opening-week theatres of the movie *i*, $OwnThts_{ic}$, to proxy the potential attractiveness of the film i.e. its ex-ante competitive intensity or power (see Hadida 2009). Since the relevant geographical market in the movie theatre industry is local in nature (Davis 2006 and Sunada 2012), the variable $OwnThts_{ic}$ may also be viewed as an “inverse”

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

measure of customer transaction costs. For both reasons we expect a positive coefficient for this variable.

Neelamegham and Chintagunta (1999) pointed out that the number of screens might be considered endogenous because the evolution of the number of theatres over time will partially depend on the performance of the movie. Hence, as our dependent variable aggregates all weekly revenues, any measure of the number of screens allocated to a movie beyond the opening week is likely an endogenous variable (see Elberse and Eliashberg, 2003 for more details about this interdependence or simultaneity). However, exhibitors allocate screens to a movie in its opening week based on their expectations regarding potential demand, which does not depend, by definition, on previous revenues. Instead, the expected opening week revenues depend on the characteristics of the films. As the full set of characteristics of films is being controlled by our movie-specific effects, our estimator solves this source of endogeneity regarding opening-week theatres.

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, $r=0$), up to three weeks before ($-3 \leq r < 0$) and three weeks after[3] ($0 < r \leq 3$) 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

[3] We focus our analysis on the most potentially harmful rival films, those released during the period from three weeks before to three weeks after movie i's release.

normalized by subtracting their means, so the first-order coefficients can be interpreted as derivatives evaluated at the sample arithmetic mean. Since previous literature has found that competition effects may depend on film *i*'s characteristics we split the sample using the MPAA rating and estimate equation (2.1) for three different groups of films: general, teenager and restricted audiences.[4]

Table 2.1. Summary statistics of data

Data	Units	Mean	Min	Max	Std. Dev.
Market Share	Percentage	0.003673	1.75E-08	0.113305	0.007205
OwnThts	Thousands	0.422	0.001	4.366	0.803
RivThts 0	Thousands	1.816	0.000	15.387	2.426
RivThts 1	Thousands	2.034	0.000	15.388	2.599
RivThts 2	Thousands	2.045	0.000	15.388	2.600
RivThts 3	Thousands	2.032	0.000	15.388	2.566
RivThts-1	Thousands	2.061	0.000	15.388	2.611
RivThts-2	Thousands	2.036	0.000	15.388	2.551
RivThts-3	Thousands	2.047	0.000	15.388	2.597

Note, in addition, that we also include squared values of both $OwnThts_{ic}$ and $RivThts(r)_{ic}$ to capture non-linear size and competition effects respectively. Finally, following the same strategy as Einav (2007) to estimate seasonality in underlying demand we include a set of weekly dummy variables (the first week is set as the base). A summary of the descriptive statistics for the above variables is shown in Table 2.1.

[4] We just used three categories since we had to harmonize rating scales that differ across countries. The general audience group includes films suitable for all age groups and for children over 6 years (G and PG rating). The restricted audience group includes films more suitable for ages over 17 years (R rating) and the teenager audiences group includes films suitable for teenagers (PG-13).

2.4. Estimation and Results

Equation (2.1) 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.[5] Table 2.2 displays the results of both fixed effects and random effects estimations. We provide cluster-robust standard errors, where clustering by film permits correlation of the errors within films but constrains errors to be independent across films. On the basis of the robust Hausman test,[6] we reject the null hypothesis that the individual effect (α_i) and regressors are uncorrelated.[7] Thus, the fixed effects model is our preferred model as it allows us to explain market shares controlling for unobserved differences across movies.

The results in Table 2.2 show that the FE model explains nearly 29% 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 opening-week theatres where the film was exhibited ($OwnThts_{ic}$) 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 $OwnThts_{ic}$ as the estimated second-order coefficient of this variable is negative and statistically

[5] We use an F test to test whether the film-specific constant terms (α_i) are all equal. We obtain a value of 5.23, which far exceeds any critical value of an F (2810, 9030). Therefore, we reject the null hypothesis in favor of the individual effects model.

[6] We follow Cameron and Trivedi (2009), who use the method of Wooldridge (2002).

[7] The value for the F(16, 2810) statistic is 115.64, above any critical value, so we strongly reject the null hypothesis that the individual effects and explanatory variables are uncorrelated.

significant. Hence, increasing the number of theatres is found to raise the box office performance but not indefinitely.[8]

Table 2.2. Fixed effects and random effects model

	ln (*MarketShare*)					
	Fixed effects model			Random effects model		
Variable	Coefficient		*robust-t*	Coefficient		*robust-t*
OwnThts	2.7530	***	*40.52*	3.6606	***	*60.17*
RivThts 0	-0.1010	***	*-4.62*	-0.2005	***	*-8.52*
RivThts 1	-0.0750	***	*-3.40*	-0.1002	***	*-4.27*
RivThts 2	-0.0709	***	*-3.17*	-0.0956	***	*-4.05*
RivThts 3	-0.0298		*-1.27*	-0.0444	*	*-1.82*
RivThts-1	-0.0734	***	*-3.11*	-0.0822	***	*-3.32*
RivThts-2	-0.0473	**	*-2.06*	-0.0332		*-1.39*
RivThts-3	-0.0099		*-0.42*	-0.0066		*-0.27*
$(OwnThts)^2$	-0.0007	***	*-29.87*	-0.0010	***	*-38.57*
$(RivThts\ 0)^2$	1.1E-05	***	*3.88*	2.2E-05	***	*7.53*
$(RivThts\ 1)^2$	3.0E-06		*1.21*	6.0E-06	**	*2.32*
$(RivThts\ 2)^2$	7.6E-06	***	*3.12*	1.0E-05	***	*3.96*
$(RivThts\ 3)^2$	2.2E-06		*0.78*	3.0E-06		*1.03*
$(RivThts\text{-}1)^2$	4.7E-06	*	*1.80*	5.7E-06	**	*2.08*
$(RivThts\text{-}2)^2$	6.3E-06	**	*2.45*	4.8E-06	*	*1.78*
$(RivThts\text{-}3)^2$	4.5E-07		*0.18*	-4.5E-08		*-0.02*
Weekly Dummies	yes			yes		
Constant	-6.8914	***	*-66.18*	-6.9967	***	*-66.96*
N	11908			11908		
R^2	0.2848					
F(67,2810)	36.470					
Hausman test	F(16, 2810) = 115.64 Prob > F = 0.0000					

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

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

[8] An in-depth analysis of this effect can be found on Chapter 4 of this thesis.

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 2.2 show evidence of an 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.

We have recovered all of the estimated movie fixed effects to check the robustness of our analysis. We obtained a left-skewed distribution with a relatively large variance. According to these results, if a movie is a real fiasco there seems to be no limit to its failure. On the other hand we have found that *Amelie*, *American Beauty*, *Avatar*, *Billy Elliot*, *Brokeback Mountain*, *Chicago*, *Chocolat*, *Crouching Tiger Hidden Dragon*, *The Dark Knight*, *Finding Nemo*, *Gran Torino*, *Harry Potter I*, *II*, *III* and *IV*, *Ice Age III*, *The Incredibles*, *Lost in Translation*, *Million Dollar Baby*, *My Big Fat Greek Wedding*, *Pirates of Caribbean II* and *III*, *Ratatouille*, *Shrek 2*, *Slumdog Millionaire* and *Toy Story II* are the films located above the 99th percentile value in the fixed effect distribution.

Previous literature suggests that the competition effect strongly depends on movies' characteristics, including their rating. As films with different ratings are aimed at different target audiences, one would expect a substantial difference in the way the temporal competition affects total box-office revenues of films with different ratings. To examine this issue we have estimated our model for three groups of movies:

general, restricted and teenager audience. For each rating type we consider all rival movies regardless of their rating. The estimated parameters are shown in Table 2.3.

Table 2.3. Fixed effects model with movies for general, restricted audience and teenagers

	ln (*MarketShare*)								
	FE (general audience)			FE (restricted)			FE (teenagers)		
Variable	Coefficient		*robust-t*	Coefficient		*robust-t*	Coefficient		*robust-t*
OwnThts	2.8366	***	*17.70*	2.3132	***	*12.88*	2.6076	***	*25.34*
RivThts 0	-0.1937	***	*-4.24*	-0.1750	***	*-3.54*	-0.0596	*	*-1.76*
RivThts 1	-0.1089	***	*-2.61*	-0.0910		*-1.42*	-0.0858	**	*-2.43*
RivThts 2	-0.0154		*-0.32*	0.0186		*0.28*	-0.0788	**	*-2.27*
RivThts 3	-0.0555		*-1.22*	-0.1277	**	*-1.96*	-0.0184		*-0.48*
RivThts-1	-0.0599		*-1.23*	-0.1310	**	*-2.11*	-0.0368		*-0.99*
RivThts-2	-0.0204		*-0.45*	-0.0001		*0.00*	-0.0606		*-1.61*
RivThts-3	-0.0333		*-0.68*	0.1141	*	*1.95*	-0.0306		*-0.85*
$(OwnThts)^2$	-0.0007	***	*-16.18*	-0.0007	***	*-10.09*	-0.0007	***	*-18.48*
$(RivThts\ 0)^2$	2.4E-05	***	*3.88*	1.6E-05	***	*2.78*	4.0E-06		*0.93*
$(RivThts\ 1)^2$	6.5E-06		*1.36*	7.4E-06		*0.97*	5.9E-07		*0.16*
$(RivThts\ 2)^2$	2.3E-06		*0.40*	2.6E-06		*0.37*	8.1E-06	**	*2.21*
$(RivThts\ 3)^2$	1.4E-05	**	*2.48*	1.7E-05	***	*2.62*	-4.8E-07		*-0.10*
$(RivThts\text{-}1)^2$	5.9E-06		*0.99*	6.4E-06		*0.96*	-5.2E-07		*-0.12*
$(RivThts\text{-}2)^2$	6.6E-06		*1.22*	-9.0E-07		*-0.14*	7.6E-06	*	*1.81*
$(RivThts\text{-}3)^2$	8.5E-06	*	*1.70*	-1.3E-05	**	*-2.12*	1.6E-07		*0.04*
Weekly Dummies	yes			yes			yes		
Constant	-7.26028	***	*-29.45*	-7.09645	***	*-30.95*	-6.87982	***	*-38.84*
N	4307			2193			5412		
R^2	0.2759			0.3620			0.3041		
F	F(67, 2150) = 7.99			F(67, 1400) = 5.22			F(67, 2362) = 15.05		
Hausman test	F(16, 2150) = 38.76 Prob > F = 0.0000			F(16, 1400) = 12.15 Prob > F = 0.0000			F(16, 2362) = 47.55 Prob > F = 0.0000		

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

The three models estimated have similar goodness of fit, with the general audience model explaining 28% of the market share variance, the model for the restricted audience explaining 36% while the figure is 30% for the teenager audience model. As with the overall-sample model in Table 2.2, 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 opening-week theatres where a movie was exhibited ($OwnThts_{ic}$) 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 2.2 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 most important rivals are those released the previous week. In the case of teenager audience 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 squared effects (see Table 2.4). 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 $OwnThts_{ic}$ as a benchmark to discuss the competition effects. In all models, the estimated elasticities relative to the opening-week theatres 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.

Table 2.4. Elasticities evaluated at mean

	∂(lnShareRev)/∂(lnX)												
Variable	η (all)		ratio	η (general audience)		ratio	η (restricted)		ratio	η (teenagers)		ratio
OwnThts	1.1480	***		1.0623	***		1.1174	***		1.0917	***	
RivThts 0	-0.1804	***	-0.1571	-0.2593	***	-0.2440	-0.4073	***	-0.3645	-0.1063	*	-0.0974
RivThts 1	-0.1514	***	-0.1319	-0.1533	***	-0.1443	-0.2340		-0.2094	-0.1783	**	-0.1633
RivThts 2	-0.1413	***	-0.1231	-0.0241		-0.0227	0.0912		0.0816	-0.1574	**	-0.1442
RivThts 3	-0.0595		-0.0519	-0.0944		-0.0889	-0.2569	**	-0.2299	-0.0380		-0.0348
RivThts-1	-0.1492	***	-0.1300	-0.0893		-0.0840	-0.3890	**	-0.3481	-0.0764		-0.0700
RivThts-2	-0.0932	**	-0.0812	-0.0373		-0.0351	-0.0096		-0.0086	-0.1199		-0.1099
RivThts-3	-0.0201		-0.0175	-0.0575		-0.0541	0.2611	*	0.2337	-0.0641		-0.0587

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

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 theatres reduces box-office share by 0.18%. 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 *OwnThts*$_{ic}$ as a benchmark, we conclude that the contemporaneous competition effect represents, in absolute terms, less than a fifth of the own-effect of theatres for the overall model. This effect goes up to one third for restricted audience films, and decreases markedly for films not restricted to teenagers.

In the case of the model that considers all movies, where the effects of both past and future rivals are significant and negative, we get a decreasing impact as we move away over time, i.e. the closer the release, the higher the negative impact. It is also worth mentioning that the estimated elasticities in Table 2.4 show the existence of asymmetric effects of past and future film releases. In this model we can see that future rivals always have a higher effect than past rivals. Indeed, the effect of past rivals decreases more rapidly as the release is farther away.

Comparing the estimations of the different rating movie groups, different patterns with respect to the impact of previous or subsequent releases are detected. 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 rivals in the case of restricted films.

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

2.5. Conclusion and Managerial Implications

In this Chapter we show the role of temporal competition in the movie exhibition market and its effect on market share. We take into account the possible differences between present, past and future film releases to test the extent to which temporal competition has asymmetric effects. Information about the existence and the details of these asymmetries are of relevance for managerial decision making. They can use this information to manage their release dates to defend or capture market share from their rivals.

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: 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 by splitting the sample of films according to their ratings to check for differential effects by type of film.

In the main model, which considers all movies, we found that the effect of contemporary rivals is always larger than that of previous-released or future rivals. In general, we find a decreasing impact of other film releases as their launch dates move away in time from the release week of the reference film. Regarding the temporal pattern of competition effects we observe that future rivals always have a higher effect than past rivals. In fact, the effect of past rivals decreases more rapidly as the distance between releases grows. This result shows evidence of a clear asymmetry between the effect of past and future film releases. Such asymmetry should be considered by managers when making decisions about the choice of release dates. In general, it seems more important to avoid competition from future releases than from movies already on screen. Thus, if there is a potential blockbuster to be released, it would be preferable to release our film later rather than sooner.

In any case it is necessary to consider the type of audience aimed at when taking these decisions. When we compare the three additional models according to movies ratings, we found substantial differences among them and different patterns with respect to the impact of previous or subsequent releases. According to the above, the releasing policy should be different for the different types of films.

Regarding the general audience movies, these are more affected by rival movies released the same week, and other important rivals are those released the following week. The audience of movies for the general public is more interested in novelty. An expected blockbuster will lead general audience films to be postponed. However, the restricted movies are more affected by rivals that were released the same week or the week before. Consequently, the restricted movies audience may be more sensitive to a word-of-mouth effect related to previously-released pictures. If there is an important rival, restricted movies should therefore anticipate rivals` release and be launched before them.

The teenager audience movies are more affected by rivals released in the following two weeks than by those rivals released the same week. This audience also seems to be more interested in novelty, as with general public films. It is therefore better to avoid competition by delaying the release and opening later than other blockbusters.

These results should provide some guidance to distributors to improve their release timing decisions, using the release date as a strategic variable to maximize total box office revenues. Since the choice of release date is sensitive to the kind of product, it is recommended that distributors diversify their portfolios of movies.

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Chapter 3: Do Movie Majors Really Collude? Indirect Evidence from Release Schedules

3.1. Introduction

Most empirical industry studies focused on market competition examine firms' price and quantity decisions, taking other product characteristics as given. However, competition in many other industries is conducted through other product attributes. This is the case of the film market where the film's release date is a critical variable of competition among distributors. Similar timing considerations are also important in other entertainment industries such as the release decisions of books, compact disks, video games, and other new products. As pointed out by Einav (2010), the lack of subsequent competition in prices and the recurrent timing decisions associated with different films makes the motion picture industry quite attractive for empirical analysis on market competition in non-price attributes, especially those that can be altered in the short run.

The release date of a film is a particularly important variable for its distributor to maximize the film's box office revenues, as we have seen in the previous Chapter. Indeed, cinema demand is highly variable throughout the year with large peaks at holidays (see Einav 2007). In this sense, blockbusters tend to have their releases concentrated in high-demand periods as distributors know that one month's revenues during high-demand periods can produce box office sales that are equal to several months' revenues in low-demand periods (see Radas and Shugan 1998, Moul and Shugan 2005, Vogel 2007). On the other hand, the weekly revenue of a film decreases exponentially over time as new films enter the exhibition market and the value of the film declines. As films typically collect between 60% and 70% of its total revenue during its first three weeks (see Krider and Weinberg 1998, Krider et al. 2005), the overlapping timing of release may have important negative effects on revenues (see De Vany and Walls 1997, Elberse and Eliashberg 2003, Gutierrez-Navratil et al. 2013). In particular, distributors should avoid competition with close substitutes in the first weekend because the entire commercial life of a film depends on its performance in its first weekend.[9]

For all these reasons, understanding competition among distributors in the film market requires a model that endogenizes release timing decisions. This is a challenging issue because release decisions are discrete and films are not homogeneous. Probably, this is the main reason why the use of structural models is quite limited in the literature. A remarkable exception is Einav (2010), who advocates using a (non-cooperative) sequential timing game to endogenize release timing decisions among asymmetric agents. Using this framework, he finds that distributors could increase theatrical revenues by shifting release dates by 1 or 2 weeks. As the proposed model is based on a non-cooperative game, no evidence of collusion in release dates is provided.

One of the most salient features of the Spanish film market is the great power that is yielded by the local distributors that are linked to the Hollywood Major film studios (Major Distributors).[10] Since the 1990s, these Major Distributors have dominated the Spanish theatrical motion picture market, and they have shifted among

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[9] For instance, a good performance during the first weekend might create a positive word-of-mouth effect and capture the attention of the public, the media and exhibitors (De Vany and Walls, 1999).

[10] By the "Major Distributors", we refer to the following companies: Disney, Fox, Sony, Warner Bros and UIP/Paramount/Universal.

the leading positions during this time.[11] On average, these firms have represented more than two-thirds of box office revenues and have distributed most of the international blockbusters; in recent years, they have also distributed most of the Spanish blockbusters. Their market dominance might indicate that they are engaging in anticompetitive practices to the detriment of other distributors.

Although antitrust issues are fairly prominent in the film industry's history (see De Vany and Eckert 1991, Gil 2010), there is not much evidence on collusion in this industry. One exception is Moul (2008), who examined collusion in rental rates (i.e. the percentage of exhibitor box-office revenues that will be returned to the distributor) and found that the hypothesis of some collusion among distributors matches the data fairly well. Despite a film's release date is a critical variable of competition and distributors might be interested in coordinating release schedules to maximize films' box office revenues, there is a lack of attention to the question of collusion in release dates, a non-price attribute of distributors' films.

In this sense, it is worth mentioning that the Spanish Competition Authority (SCA) resolved in May 2006 to fine five Hollywood major studios 2.4 million euros for standardizing the exhibition conditions of their films, which results in both horizontal and vertical restrictions on competition.[12] The SCA resolution is clear that "from dates [...] previous [...] to 1998, the implicated distribution companies have been using similar conditions in their contracts with exhibitors to show their films. They always

[11] For instance, in 2009 the market share of these Major Distributors was 73%.

[12]This sentence has been confirmed by the Spanish National Court in 2013, although some fines were adjusted.

make temporary rental contracts and set identical or similar conditions in such important aspects as payment systems, pricing, billing, revenue control, film advertising, theatre selection (number of screens), exhibition time and delivery, and return of copies" (see #5 in the Proven Facts Section of the Resolution of the Spanish Competition Authority, 2006). The SCA also fined the Spanish Film Distributors Federation (FEDICINE) because it was accustomed to exchanging strategic data relevant to the competition and facilitating the coordination between distributors.

It is notable that all the distributors charged in this resolution established the same rental price for their blockbuster movies. The SCA attributed this similarity to the absence of competition between distributors when films' release dates are chosen.[13] In particular, the SCA stated that if distributors had competed against one another, the possibility of two releases from Major Distributors coinciding on the same day would have led them to negotiate lower prices with exhibitors to achieve greater distribution in theatres. However, this reduction in price can hardly occur if the distributors coordinate with their competitors by alternating and/or separating the releases of their films.[14] Accordingly, because coordinating release schedules weakens the negotiating position of exhibitors,[15] the ability of exhibitors to provide better services

[13] In addition, and according to the SCA, the determination of the same rental price cannot be caused by common cost structures because films' production and advertising costs vary considerably because motion pictures are highly differentiated products. Furthermore, distributors do not have identical operating costs, and the box office revenues of each of their films cannot be predicted with certainty.

[14]This fact was recognized by the distributors that were fined by the SCA. For example, Fox noted that one criterion for choosing the release date is that no similar film will be released on the same date. UIP claimed that competition among Major Distributors is particularly focused on obtaining the best theaters on the release dates of their films (see the Resolution of the SCA, 2006, p. 13).

[15] Indeed, the film market in Spain is characterized by asymmetry in negotiation between the exhibitors and Major Distributors. Whereas exhibitors are mainly local, the Major Distributors are integrated with

and prices to customers is clearly limited and customers' alternatives are reduced. Moreover, release-coordinating agreements might also hinder market access for other distributors.

Moul (2008) did not examine the link between collusion in rental rates (a price product attribute) and collusion in films' release dates (a non-price product attribute). We do not either examine this very interesting issue, but we will try to shed light on one of the main arguments used by the SCA to fine the Major Distributors, namely the allegedly coordination in films' release dates. In particular, using data for the 2002-2009 period, we test whether these Major Distributors have been more able to alternate and/or separate their releases than other distributors.[16] We will take this result as an indirect evidence of a possible collusive behaviour. We are aware that our results might also be caused by other factors (e.g. abuse of dominant position or first-mover advantages) that somehow give Hollywood Majors extra market power. However, these practices could be also considered as anticompetitive practices as market power is less evenly distributed in the market.

As there is a lack of attention to the question of collusion in non-price attributes in the empirical literature on detecting cartels (see, for instance, Harrington 2008, Davis and Garces 2010), we had to adapt one of the available (price-based) approaches to identify differences in release decisions between Major Distributors and

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the U.S. distributors that own the most popular films and commercially exploit these films nationally and globally. Because of this asymmetry, Spanish distributors can operate profitably without a particular exhibitor or exhibitors in Spain, whereas exhibitors can hardly stay in business without the Major Distributors.

[16] The implications of contracts between distributors and exhibitors in the Spanish film market have been addressed by Gil (2009, 2013).

those that were not fined. To the best of our knowledge, our study is one of the first papers that use a reduced-type model to examine collusion in non-price attributes in a highly differentiated product market.

Instead of estimating a traditional reduced-form price equation, we examine the determinants of the temporal distance between the releases of any two films that have been released in a certain temporal segment or "theatre demand window". This empirical strategy, which is based on temporal windows, was first used by Corts (2001) in his study on the effects of a vertical market structure on competition in the U.S. film industry. Here, we adapt this framework to our dataset and extend it in two ways: we use a statistical and flexible procedure to define market segments (whereas Corts, 2001, uses ad hoc criteria to define temporal windows), and we define a relative measure of the temporal distance between the releases of any two films that takes the optimal equilibrium of the spatial competition model of Hotelling (1929) as its benchmark.

In the next section, we describe our procedure to detect collusion, analyze the role of release dates as a strategic variable and explain the methodology that was applied to identify the demand windows. In Section 3.3, we describe the steps we followed to build the sample and define the empirical specifications of the model. In Section 3.4, we describe the method of estimation and present the most relevant results. The final section concludes.

3.2. A Reduced-form Model of Distributors' Release Schedules

Economic analyses of prices, market shares, and other economic data have often been used to uncover prosecutable cases of collusion. One of the most popular methods of detecting collusion involves asking the following question: "Does the behaviour of suspected colluding firms differ from that of competitive firms?" (Harrington 2008, p. 222). This method involves comparing the behaviour of suspected colluders with a competitive benchmark that is defined by non-colluding firms. A common implementation of this approach is to estimate *reduced-form price equations* by regressing the price on the demand and cost factors. These price equations are estimated separately for suspected cartel members and competitive firms to test whether they differ on a statistical basis; if they are shown to differ, then colluding firms might be acting in a manner consistent with a collusive model. For instance, this approach was used by Porter and Zona (1993, 1999) to detect collusive behaviour in highway construction contracts and school milk procurement, respectively.

Because the SCA only fined five of the distributors in Spain, differences in performance should be expected between both sets of distributors, i.e., penalized and not penalized distributors. Thus, the degree of competition in the Spanish film market can be tested by estimating reduced-form models. An alternative approach to identifying collusion is to search for a structural break in firms' behaviour. Such a break could be associated with the formation of a cartel, but also with a cartel's death. In both cases, there should be a discrete change in the behaviour of a group of firms, but this was not the case in the Spanish movie market from 2002 to 2009.

However, unlike most papers on detecting collusion, our dependent variable is not the rental price determined by distributors, but a proper measure of the release date of a film, which is our strategic variable. We initially follow the approach proposed by Corts (2001) in his study of the U.S. film industry and, instead of specific dates, we use a measure of the temporal distance between any two films released in a specific time period (a "window") as the dependent variable. Therefore, our empirical research focuses on pairs of films.[17] As our dependent variable can be interpreted as a measure of product differentiation, our empirical strategy not only is inspired by the studies on detecting collusive practices, but also it is connected to the empirical literature that uses reduced-form models to analyze spatial or temporal competition.[18] The combination of both literatures is thus one of the contributions of the Chapter.

The model to be estimated can be written as follows:

$$GAP_{i,w} = \alpha + \beta x_i + \alpha_w + \epsilon_{i,w} \tag{3.1}$$

where the subscript *i* represents a pair of films that have been released in theatre demand window *w*, GAP_i is a relative measure of the temporal distance that separates the release of the two films,[19] and $\varepsilon_{i,w}$ is the error term. The window-specific effects α_w capture the unobserved window-specific heterogeneities, such as the presence of

[17] Using the same empirical strategy, Osashi (2005) analyzes the temporal distance between two launches in the U.S. video game industry.

[18] For instance, Borenstein and Netz (1999) examine the scheduling of flight departure times in the airline industry in an attempt to provide insight into the incentives that encourage companies to minimize or maximize differentiation and to either "steal" customers from competitors or reduce price competition, respectively. Salvanes et. al. (2005) use a similar approach to empirically test the degree of departure-time differentiation in the Norwegian airline industry, and Netzand and Taylor (2002) empirically test the locations of petrol stations in the Los Angeles Basin with the same approach.

[19] Our GAP variable can be interpreted as a measure of product differentiation, as in Borenstein and Netz (1999) and Netz and Taylor (2002).

holidays or the seasonality of overall demand (see Einav 2007). Thus, equation (3.1) can be estimated using panel data techniques.

The set of explanatory variables x_i includes characteristics of both films (e.g., their genres, nationalities, age ratings, awards, or the presence of national or foreign stars) that might influence distributors' release-date decisions. Once we have controlled for these characteristics, the coefficient α will give the average distance between the release dates of any two films. Because α is a conditional average, unobserved differences in distributors' performance should be captured by the coefficient. Additionally, by determining whether the genre, the rating or any other relevant movie feature is significant, we will be able to examine whether a criterion for choosing release dates involves ensuring that no similar film will be released on the same date, as Fox indicated to the SCA.

However, the most important hypothesis from the point of view of competition involves evaluating the differences in distributor performances. Although it is legitimate (and feasible) for a particular distributor to space its releases to minimize the possibility that a film steals revenues from other films that belong to the same distributor, this process is illegal when it is undertaken by coordinating their release dates with competing distributors. Verifying whether the estimated α_s differ between suspected cartel members and non-colluding firms allows us to provide additional evidence to corroborate or refute the arguments used by the SCA to fine the Major Distributors for anti-competitive practices. More specifically, we will test whether these distributors have been able to better avoid the negative effects of competition among their films by increasing the temporal distances that separate their releases. If this distance increases considerably for pairs of films that belongs to the alleged cartel (relative to the remaining pairs of films), then it might be argued that these distributors have arranged the release dates to maximize their box office revenues.

To estimate equation (3.1), we must define the relevant temporal market, i.e., the set of films that will be combined in pairs. One option is to match all the films that are released throughout the entire period analyzed in our study. However, not all of the possible combinations are equally relevant. Because most of a film's revenues are generated during its first three weeks on the market, closer release dates have greater negative effects on the box office revenues of each pair of films (see Gutierrez-Navratil et al. 2013). Furthermore, if we combine all of the films, we will be implicitly assuming that each film is a potential competitor of every other film, regardless of the distance between their releases. To avoid this assumption, we follow the approach of "theatre demand windows" proposed by Corts (2001) and divide the analyzed period into different subperiods or "demand windows". We only take into account those pairs of films that actually compete with one another, i.e., movies that are released in the same demand window.

To build the demand windows, we account for the seasonality of demand in the motion picture industry. First, we identify the peaks and valleys of average weekly box office revenues from 2002 to 2009, and we assume that surrounding a high demand peak, each window begins in one valley and ends in another valley and that the pattern does not change over time. When a distributor fixes the release date of a film, the effect that this film might have on the seasonality of movie demand is unknown. Therefore, the release-date decision must be made on the basis of structural and temporal market segmentation, which is well known by all Spanish distributors. We use an annual average of weekly box office revenues as a proxy for this traditional segmentation and the Moving Average Convergence Divergence (MACD) statistical indicator to detect significant peaks and valleys; the MACD is commonly used to interpret stock market trends and generate buying and selling alert signals (see Fernandez-Blanco et al. 2008).

The above-mentioned statistical indicator predicts changes within a trend and generates signals where significant valleys and peaks begin.[20] The proposed methodology allows us to obtain demand windows of different sizes that depend on the observed seasonality of average demand in the sector. Moreover, our empirical strategy to identify demand windows is related to the first of the two methods proposed by Corts (2001). However, we use statistical techniques to identify relevant subperiods or windows, whereas the demand windows devised by Corts (2001) were selected based on external information and an *ad hoc* criterion. The second approach proposed by Corts (2001) identified windows by selecting several key dates (such as Christmas Day, the return of the summer holidays, the Oscars, and the beginning of

[20]A significant peak is identified when the MACD line intersects its moving average line (signal) in ascending order. On the contrary, signals that identify a valley occur when the MACD line intersects its moving average (signal) in descending order. The MACD line is formed by subtracting the short moving average from the long moving average; we calculate it as MACD = $EMA_8 - EMA_4$. Here, EMA_8 is the exponential moving average box office revenues of the last eight weeks and EMA_4corresponds to the last four weeks. A signal line is formed by smoothing the MACD line using an exponential moving average of the MACD for two weeks. The three tuning (weak) parameters that are used here to calculate the exponential moving averages have been selected by the calibration of the model.

Easter) and constructing five-week-long windows that were centred on these important dates that did not take any other weeks into account. The application of that method to our dataset would result in a significant reduction of the number of windows because there are many consecutive holidays and long periods with no holiday; it would also force us to remove most of the films that were released throughout a given year from our sample. In addition, our statistical approach allows us to check whether the constant-window-size assumption made by Corts (2001) is validated in our dataset.

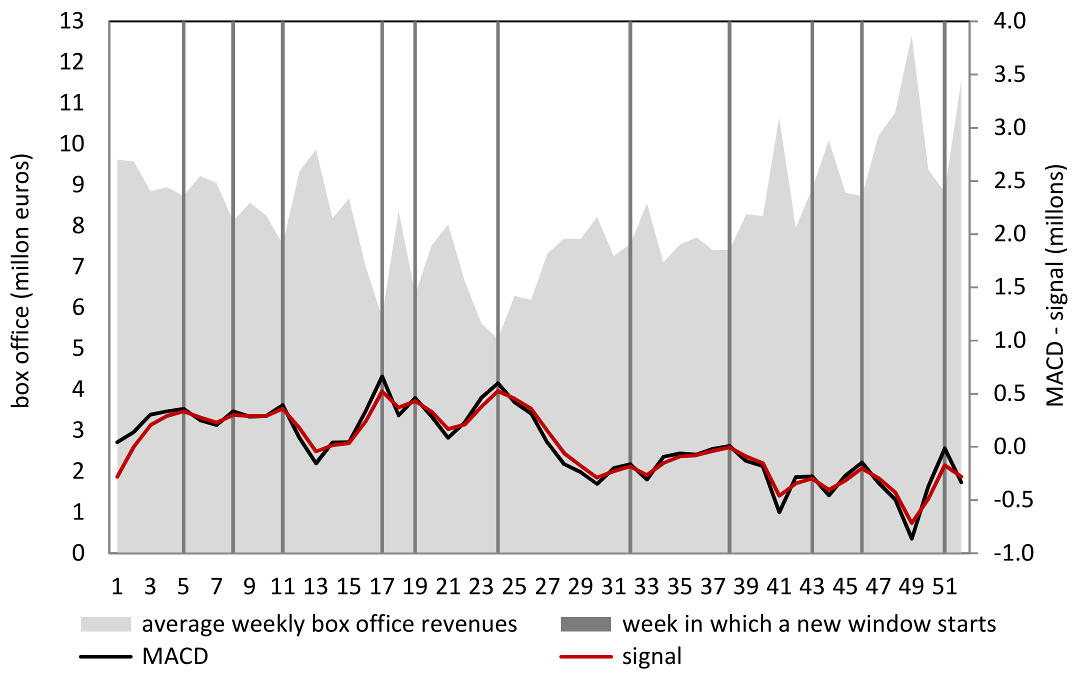
3.3. Sample, Variables and Empirical Model

The data related to the official release dates of each movie in Spain and the rest of the considered countries[21] are provided by A. C. Nielsen EDI, in addition to the distributors, genres, weekly and total revenues and age ratings. Additional information about the characteristics of the films (such as their nationalities, whether they have national and international stars, and whether they have received national and international awards) were obtained from the official data of the Spanish Institute of Cinema and Audiovisual Arts (ICAA) and other sources, such as the Internet Movie Database website (www.imdb.com) and web pages of the films. Our database includes all of the films that were released during the 2002-2009 period. To build our windows, (as discussed above), we applied the MACD approach. In particular, using the average weekly box office revenues in the 2002-2009 period as the target variable, we

[21] In some cases, we will compare the release dates in Spain and other countries.

identified 89 windows, as depicted graphically in Figure 3.1. The sizes of the windows (measured in weeks) are not constant; therefore, assuming a uniform window size is not justified. In addition, we observed that the major peaks for the average weekly box office revenues coincide with all the nationwide celebrations. For instance, the peaks at the beginning and end of the year match New Year's Day and Christmas. We observed a significant peak on Easter and on the National Day of Spain; the maximum peak was reached on Spanish Constitution Day.

Figure 3.1. Average weekly box office revenues, Moving Average Convergence Divergence (MACD) and signal, for the 2002-2009 period.



By combining only those films that were released in each particular window, we arrived at 71,188 pairs of films, which is therefore the number of observations in our sample. Because the main purpose of this Chapter is to discover whether there is different behaviour between the Major Distributors and other distributors, we split the sample into the following five groups: *SDM*, *SDNM*, *D5, DDMNM*, and *DDNMNM*. The *SDM* group gathers all of the observations in which both films of the pair were distributed by the same Major Distributor; the *SDNM* group includes the observations in which the two films were from the same non-major distributor; *D5* includes all of the pairs of films that were distributed by different Major Distributors; *DDMNM* gathers the pairs in which both films were distributed by different distributors and only one of them was a Major Distributor; and the *DDNMNM* group encompasses those pairs of films that were distributed by different distributors, where neither was a Major Distributor. A summary of the descriptive statistics of the data by windows is presented in Table 3.1. From the total of 71,188 pairs of films, 1,406 are pairs that were released by the same non-major distributor (*SDNM*). The films released by the same Major Distributor (*SDM*) constitute 1,756 pairs. Furthermore, 7,300 pairs were released by different Major Distributors. The remaining pairs of films were released by different distributors: of these, 28,091 are pairs in which neither was distributed by a Major Distributor (*DDNMNM*), and 32,635 are pairs in which one was distributed by a Major Distributor and the other one was not (*DDMNM*).

Once-we have identified all possible combinations of films in a window, the dependent variable (*GAP*) is set as a relative measure of the temporal distance that separates the release dates of two films. This variable was defined as the number of days between the two releases divided by the average gap value that would result if the films of the distributors that participate in each pair had been released such that they were equally temporally spaced along each window. We normalize the dependent variable in this way to account for the fact that distributors that distribute a large number of films cannot temporally separate their own films to the same extent as smaller distributors. This empirical strategy follows Borestein and Netz (1999) in their study of the airline industry, in which they normalized the average distance in the departure times of flights by the maximum possible differentiation that each airline could have achieved by separating its flights on a given day.

We compute this average gap and employ the scenario in which films are released equidistantly within a window as our benchmark[22]. The average distance under this assumption is as follows:

$$\bar{d}(n,m) = \left(\frac{\sum_{i=1}^{n-1} i - \frac{1}{n}\sum_{i=1}^{n-1} i^2}{\sum_{i=1}^{n-1} i}\right)m = \left(\frac{n+1}{3n}\right)m \qquad (3.2)$$

where *m* is the window length (measured in numbers of days), and *n* is the number of films released in each window by the distributors that were involved in the release of the two films in each observation. This measure, which is denoted $\bar{d}$, is the average distance that would result if the films were released uniformly along the window, which would result from efforts to capture as much demand as possible and limit competition. Therefore, this measure will capture the expected benchmark for movies released by the same distributor, which will naturally try not to cannibalize itself regardless of whether it is a Major Distributor. Moreover, this normalization allows us to compare the gap across groups with different numbers of films released in each

[22] We used a constant distance between films and a distance to the ends of the windows that is equal to one half of the distance between films, as proposed by Hotelling (1929).

window and to control for the window-size effects because the distance between releases varies significantly and depends on the different sizes of the windows.

Additionally, we have constructed a set of control variables that are intended to capture certain movie characteristics that are relevant for a movie's commercial success[23]. Because two movies that share the same characteristics are more substitutive than two movies that differ greatly, two films that share many of these features may be considered close competitors. Thus, it would be expected that such variables would have a positive effect on the distance between two releases if the distributors tried to mitigate competition by separating their releases. *SG* is a dummy variable that identifies observations in which both of the films in a pair are of the same genre.[24] Similarly, *GR* and *RR* are dummies that were created to identify observations in which both films have the same age rating. In the *GR* variable, we have grouped the categories "general audiences" and "suitable for audiences age seven and older". Similarly, in the *RR* variable we have grouped the categories "suitable for audiences age 13 and older" and "restricted audiences". Therefore, our reference category is that the two films in a pair are aimed at two different age groups. Other dummy variables related to nationality were also created, including *FO* if both films are foreign and *SP* if both are Spanish.

[23] See De Vany and Walls (2004), McKenzie and Walls (2013), McKenzie (2009), Nelson et al. (2001), Deuchert et al. (2005), and Ravid and Basuroy (2004). Furthermore, for a brief outline of those papers that analyzed the effects of these characteristics, see Hadida (2009).

[24] This variable was created by grouping the films in eight groups according to the following classification of genres from Nielsen: Action/Adventure, Animation, Black Comedy/Comedy/Romantic Comedy, Documentary, Drama, Fantasy/Science Fiction, Horror/Suspense, Musical/Special Events/Unknown/Western.

The presence of stars or the fact that films may have received awards is other key factor in selecting release dates. When a movie has stars or has received an important award, it is perceived as a higher-quality film; therefore, we expect that distributors will be more interested in separating the releases of two such films to avoid the negative effects of competition. Thus, we have included a set of dummy variables whose expected coefficients are positive. The *INST_1* and *INST_2* variables stand respectively for cases in which one or both of the films in a pair have an international star. *NAST_1* and *NAST_2* variables are defined equally but with national stars. Finally, the *NAST_INST* dummy variable identifies cases in which one film of a pair has a national star and the other film has an international star.[25] Similarly, to account for received awards, *NAAW_2* and *INAW_2* variables respectively identify pairs of films in which both have received national or international awards, and *NAAW_1* and *INAW_1* pairs of films in which only one film in a pair has won a national or an international award. Finally, the *NAAW_INAW* variable indicates cases in which one film has won a national award and the other has won an international award.[26]

To perform our analysis, it is important to consider that in Spain – as in other major film markets – the "biggest" box-office hits mostly correspond to a few international blockbusters from the Major Distributors (see the European Audiovisual Observatory 2006, De Vany and Walls 1996, Walls 2005). These films, which typically have substantial budgets, take advantage of expensive release campaigns with

[25] In general, by international and national stars we refer to actors or directors who have won an Oscar or a Goya (a Spanish award), respectively, with certain exceptions.

[26] We have considered the Oscar and Goya awards in their main categories and the principal award in Festivals (Berlin, Cannes, San Sebastian and Venice).

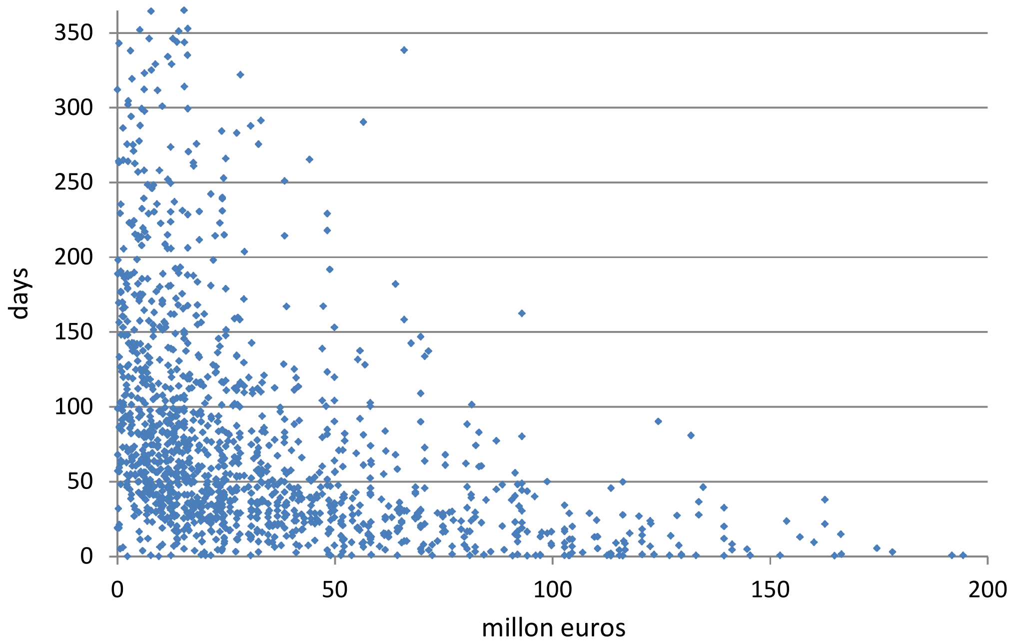
significant investments in advertising, marketing, merchandising, tours, etc., and which are designed at the supranational level by the structural matrices of major U.S. distributors and film studios.[27] Such campaigns, which often represent a worldwide release, significantly determine the launching of the films and leave little leeway for affiliates to choose the release dates in their own countries. Thus, it is crucial to consider the degree (or absence) of discretion enjoyed by a Spanish distributor to choose the release dates of such movies.

One way to control for the degree of discretion is to measure the temporal distance between the releases of a particular film in Spain compared to other countries. Figure 3.2 shows the average distance between the release date in Spain and in four other important film markets (the USA, the UK, France and Germany) for a set of 1,418 films that were released over the 2002-2009 period. This figure shows that the larger the budget, the smaller the distance in the release dates among countries.[28] These data support the notion that subsidiary distributors are less able to choose the release date for films with large budgets, which are almost always associated with supranational release campaigns.

[27] In 2005, the average cost of a movie from the Major Hollywood studios rose to 96.2 million dollars, of which 37.6% (36.2 million dollars) corresponded to promotion and marketing costs (European Audiovisual Observatory, 2006). By contrast, in 2008, the average cost of a Spanish production was 2.62 million euro, of which only 16.2% were operating costs, including copies and advertising (Ministerio de Cultura, 2009).

[28] It should be noted that the budget variable is not available for all the movies in our database; for this reason, it is not included as a control variable.

Figure 3.2. Average distance between the release dates in Spain and the UK, Germany, France and USA, by budget, for the 2002-2009 period.



Note: displays up to 365 days and 200 million euro budget.

This limitation indicates that release-date decisions are made at two different levels. First, international hits are managed at the supranational level by distributors that compete in the European or global market. Second, national and low-budget foreign films are managed at the national level by distributors that may or may not be linked to the Major Distributors. Only at this level can Spanish distributors unilaterally coordinate their release strategies (i.e., without heed to the decisions of parent companies or controlling partners).

In summary, foreign blockbusters' releases may be conditioned by launch campaigns designed at the supranational level that leave national distributors without any decisional power. Because these movies are expected to attract a substantial share of the demand of moviegoers worldwide, we expect that these blockbusters will be released to avoid as much competition as possible from other popular movies; furthermore, smaller films will also be released with as much distance from blockbusters as possible. To test this hypothesis, we created the dummy variable *NO_FLEX* for cases in which the releases of one or both films of the pair are designed at the supranational level and the Spanish distributor does not have the ability to decide the release date. This variable takes the value of one when one or both films of the pair were released with a distance less than or equal to two days in at least four of the five markets for which we have full information (the USA, the UK, France, Germany and Spain). We leave two days as a margin to account for the fact that opening days may not usually fall on a Friday in each country and for the existence of any holiday that might change the opening day in a specific country.

To maximize profits, a single distributor will tend to separate its own films from one another more than from those of its rivals; if two of a distributor's films were released in a short timeframe, the result would be lost revenue for both. However, this problem might be different if rival distributors are coordinating their decisions because they might behave as a single company in deciding on release dates of the combined group's films; they would not be acting as independent distributors who are competing and autonomously selecting their release dates. Therefore, one way to detect collusion in this industry is to examine whether the release-date scheduling applied to films distributed by the same firm (*SDM* and *SDNM*) is similar to the observed release-date scheduling that is applied to pairs of films released by different distributors (*D5*, *DDMNM* and *DDNMNM*). Moreover, if Major Distributors are coordinating their policies, we would expect the *D5* group to have a different performance record than those of the *DDMNM* and *DDNMNM* groups.

To test for this possibility, we estimate the following specification of the reduced-form model of distributors' release schedules:

$$\begin{aligned} GAP_{i,w} = \; & \alpha + \beta_{SG}SG_i + \beta_{NAAW\_1}NAAW\_1_i + \beta_{NAAW\_2}NAAW\_2_i + \\ & \beta_{INAW\_1}INAW\_1_i + \beta_{INAW\_2}INAW\_2_i + \beta_{NAAW\_INAW}NAAW\_INAW_i + \\ & \beta_{NAST\_1}NAST\_1_i + \beta_{NAST\_2}NAST\_2_i + \beta_{INST\_1}INST\_1_i + \\ & \beta_{INST\_2}INST\_2_i + \beta_{NAST\_INST}NAST\_INST_i + \beta_{SP}SP_i + \beta_{FO}FO_i + \\ & \beta_{GR}GR_i + \beta_{RR}RR_i + \beta_{F}NO\_FLEX_i + \alpha_w + \epsilon_{i,w} \end{aligned} \tag{3.3}$$

The model includes dummy variables that control for similarities in the characteristics of films, the presence of stars and the awards received. The summary statistics of all of the variables are presented in Table 3.1.

Equation (3.3) will be estimated separately for each of the distributor groups defined above: *SDM*, *SDNM*, *D5*, *DDMNM*, and *DDNMNM*. For each equation, the constant term α will capture the average relative distance between two films that are distributed by the group of distributors that are included in that particular estimation after controlling for the films' characteristics and unobserved demand window heterogeneity. Therefore, comparing α across equations will allow us to capture differences in distributor groups' performances. For instance, by comparing the two intercepts of the *SDM* and *D5* samples, we will be able to examine whether the Major Distributors jointly behave as if they were a single distributor in selecting the release dates of their films by separating their releases to avoid competition among them.

Table 3.1. Summary statistics of average data by windows

By windows:					
	mean	std. dev.	min.	max.	total
GAP	0.763	0.115	0.394	0.998	-
Weeks	4.7	1.7	2	8	419
Films	37.69	14.74	12	75	3,266
Pairs	799.9	581.6	66	2,775	
Pairs of:					
SDM	19.7	15.4	1	75	1,756
SDNM	15.8	16.0	0	83	1,406
D5	82.0	56.9	5	276	7,300
DDMNM	366.7	255.0	35	1,166	32,635
DDNMNM	315.6	272.7	17	1,373	28,091
SG	196.0	146.3	13	742	17,443
NAAW_1	40.8	44.6	0	172	3,630
NAAW_2	0.7	1.5	0	6	65
INAW_1	165.9	130.1	0	610	14,767
INAW_2	11.9	13.3	0	66	1,055
NAAW_INAW	5.9	7.7	0	37	521
NAST_1	52.4	48.7	0	222	4,664
NAST_2	2.0	3.3	0	15	178
INST_1	293.0	198.3	28	846	26,081
INST_2	61.0	46.0	3	210	5,425
NAST_INST	21.2	19.0	0	75	1,886
SP	42.6	38.2	0	231	3,788
FO	473.3	380.4	28	1,770	42,125
GR	104.9	98.8	3	465	9,338
RR	333.0	263.3	21	1,225	29,640
NO_FLEX	8.8	15.5	0	63	781

3.4. Results

We conducted several tests to select the best empirical strategy for our estimations. The values of these tests are shown in Table 3.2. The F tests examine whether the window-specific effects are statistically significant. For pairs of films that are distributed by the same company, which are modelled by *SDM* and *SDNM*, we cannot reject the null hypothesis that they are not statistically significant, and therefore, we estimate these two models using ordinary least square. The window-specific effects are statistically significant in the other three models, i.e., those models that were estimated for the *D5*, *DDMNM*, and *DDNMNM* groups; thus, the fixed effects or random effects estimators fit our data better than an ordinary least square estimator would. Because the performed Hausman tests suggest that the window-specific effects and regressors are correlated, we display the parameter estimates for the last three models using only the fixed effects estimator. We have used White's method to obtain robustness tests in the presence of heteroskedasticity, where clustering by windows permits correlation of the errors within them but forces errors to be independent across distinct windows.

Table 3.2. Estimated models

	SDM			*SDNM*			*D5*			*DDMNM*			*DDNMNM*		
Variable	Coeff.		*robust-t*	Coeff.		*robust-t*	Coeff.		*robust-t*	Coeff.		*robust-t*	Coeff.		*robust-t*
SG	-0.0176		*-0.52*	-0.0234		*-0.71*	0.0020		*0.09*	-0.0088		*-0.98*	-0.0141		*-1.43*
NAAW_1	0.0723		*0.98*	0.0264		*0.36*	-0.0268		*-0.57*	-0.0005		*-0.02*	-0.0102		*-0.36*
NAAW_2	0.3528	**	*2.46*	-			-0.1558		*-1.20*	-0.0138		*-0.16*	-0.0243		*-0.20*
INAW_1	0.0181		*0.50*	0.0565		*1.64*	-0.0031		*-0.09*	0.0277	*	*1.88*	0.0381	**	*2.61*
INAW_2	0.3130	**	*2.27*	0.0399		*0.51*	-0.1310	**	*-2.22*	0.0542		*1.54*	0.0892	***	*3.25*
NAAW_INAW	0.2310		*1.18*	0.0225		*0.19*	0.0263		*0.24*	-0.0216		*-0.54*	0.0177		*0.39*
NAST_1	-0.1459	**	*-2.05*	0.1138	**	*2.53*	0.0469		*1.08*	0.0376		*1.57*	0.0599	**	*2.21*
NAST_2	-0.1839		*-1.04*	-0.0058		*-0.04*	0.1912	*	*1.93*	0.0246		*0.41*	0.1738	***	*2.68*
INST_1	-0.0442		*-1.43*	-0.0020		*-0.06*	0.0438	**	*2.01*	0.0172		*1.31*	0.0249		*1.55*
INST_2	0.0245		*0.63*	0.0773		*1.27*	0.0705	**	*2.02*	0.0367	*	*1.79*	0.0368		*1.49*
NAST_INST	-0.0277		*-0.51*	0.0826		*0.59*	0.0158		*0.35*	0.0224		*0.89*	0.0044		*0.14*
SP	0.0679		*0.61*	-0.0060		*-0.12*	0.0731		*1.59*	0.0241		*1.13*	-0.0232		*-1.57*
FO	0.0388		*0.85*	0.0462		*1.46*	0.0109		*0.41*	0.0027		*0.26*	0.0110		*1.01*
GR	0.0363		*1.11*	-0.0379		*-0.73*	-0.0234		*-0.94*	-0.0021		*-0.15*	-0.0230		*-1.51*
RR	0.0332		*1.29*	-0.0331		*-1.19*	-0.0080		*-0.36*	-0.0074		*-0.66*	-0.0136		*-1.19*
NO_FLEX	0.0952	*	*1.92*	0.0991		*1.58*	0.0957	*	*1.90*	0.0105		*0.25*	0.2964		*1.31*
CONS	0.8763	***	*16.79*	0.8628	***	*21.63*	0.8650	***	*34.74*	0.8048	***	*77.04*	0.7642	***	*70.82*
N	1756			1406			7300			32635			28091		
F	F(16,88) = 4.22			F(15,86) = 3.07			F(16,88) = 2.42			F(16,88) = 0.89			F(16,88) = 2.43		
F test $H0: a_w = a$, *p/ w=1,…63*	F(88,1651) = 0.81			F(86,1304) = 0.90			F(88,7195) = 2.16			F(88,32530) = 7.35			F(88,27986) = 5.73		
Hausman test	-			-			F(16,88) = 1.88			F(16,88) = 4.90			F(16,88) = 3.85		
estimated by	OLS			OLS			FE			FE			FE		

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

The parameter estimates are shown in Table 3.2. At first sight, we can observe in that both magnitude and statistical significance of the estimated parameters vary across the different groups of firms. Now, we discuss the coefficients associated with movie features. With respect to movies distributed by Major Distributors (*SDM*), these companies try to mitigate the competition between their own movies by separating pairs of films in which both have received either national or international awards. However, they tend to release closer pairs of films that have a national star (*NAST_1*). The strategy of smaller distributors (*SDNM*)[29] is to release their pairs of movies with a larger gap if a movie has a national star. With respect to pairs of movies that are not distributed by the same company, when films are released by two different Major Distributors (*D5*), they tend to be released further apart if at least one film has an international star or when both movies have a national star. In contrast, we observe that Majors tend to release closer pairs of films that have received international awards. This result might indicate that Major Distributors release high-quality films, candidates for an international award or international blockbusters in the same season of the year, e.g., just before the end of the year to be a potential candidate for the Academy Awards or the Golden Globes or during the Academy Award campaign to ensure high demand. For the *DDMNM* group, which corresponds to pairs of films distributed by different distributors where only one film is released by a Major Distributor, the pairs of movies that have an international star have consistently been released with a significantly longer gap. Additionally, films that have received an

[29] In this model, we have removed the variable pertaining to national awards, or *NAAW_2,* because there was only one observation that met this characteristic.

international award tend to be more distanced from the rest of the movies. Finally, in the *DDNMNM* group, which includes all of the pairs of films distributed by different distributors that are not Major Distributors, we observe that the average distance between two film releases is greater when at least one of the films has an international award or a national star.

General speaking, we can conclude that one of the criteria in choosing release dates is avoiding films that share similar characteristics. However, these effects are related to the presence of stars or awards, and no effect was found regarding a movie's genre or rating. Moreover, although these effects are not homogeneous across groups, they are relevant for all of them; thus, the combination of distributors behind a particular pair of movies, awards and the presence of stars will be relevant variables that should be taken into account in choosing when to release these movies.

As discussed above, to account for the fact that foreign blockbusters' release dates might be conditioned on marketing campaigns designed at the supranational level, we have included the dummy variable *NO_FLEX*. We created this variable for cases in which the Spanish distributors do not have any leeway to select the release date of one or both films in a pair of a particular observation. In this sense, it is important to highlight the fact that we have not found many cases in which two global films distributed by either the same Major Distributor or different Major Distributors are released in the same window. Therefore, Major Distributors appear to distribute films whose releases are designed at the supranational level in different windows, which ensures that these films do not compete among themselves. Moreover, by focusing on pairs distributed by the same Major Distributor (*SDM*), when one of a pair of such films is allocated into a particular window, the rest of the films distributed by its company will be released with a larger relative gap to try to avoid close rivalry. This pattern is a clear maximizing strategy that has no moral implications when it is followed by an individual firm, as captured in the *SDM* estimation. However, we observe exactly the same pattern when we compare global releases distributed by a single Major and those releases that were distributed by different Major Distributors (*D5*). This outcome seems to indicate the presence of coordination between Major Distributors. In fact, this result is consistent with our previous result that Major Distributors do not release potential global blockbusters in the same demand window.

Finally, we next discuss our target estimated coefficient, the intercept α. This coefficient has nothing to do with any of the characteristics controlled for the rest of the variables incorporated in the regression (including window unobserved heterogeneity), and hence it can be interpreted as the average (relative) gap between two "homogeneous" films. Because α is a conditional average, unobserved differences in the release performances of distributors' films should be captured by this coefficient. If α is one, then films are distributed uniformly along the window to try to capture as much of the demand as possible by avoiding direct competition, as is proposed in spatial or temporal demand models such as that of Hotelling (1929). Therefore, we expect an intercept close to one when we consider only pairs of films released by the same distributor. The estimated intercepts for *SDM* and *SDNM* are 0.8763 and 0.8628, respectively; these intercepts are not equal to one but are closer to one than the intercepts that were estimated for pairs of movies released by different distributors, except when each is a Major Distributor (*D5*).

The main purpose of this Chapter is to evaluate whether there are differences in the release policies of different types of motion picture distributors and whether there are signs of *between*-firm coordination policies. In that case, we could provide insight into collusive behaviour, which is particularly common among companies with significant market power, i.e., Major Distributors. To test this hypothesis, we have conducted Z-tests to identify significant differences in the intercepts across models. The results are presented in Table 3.3.

Table 3.3. Z- test results

Comparing constant term α_0 between:				
	D5 - SDM	*D5 - SDNM*	*D5 - DDMNM*	*D5 - DDNMNM*
Z test	-0.20	0.05	2.23	3.71
H_0: a_0=a_0	[0.8414]	[0.9680]	[0.0258]	[0.0002]

Note: Probability in brackets.

We are interested in testing whether the Majors are behaving as cartel members when they set the release schedules of their films. For this reason, we compare the intercept of the *D5* group with the intercepts of the other groups. Given our parameter estimates, we can reject the null hypothesis of similar *between*-firm behaviour because the estimated intercept for the three equations with pairs of films distributed by two different firms (the *D5*, *DDMNM* and *DDNMNM* groups) are significantly different. Thus, the average relative distances between the release dates of movies distributed by two Major Distributors are significantly larger than the average temporal distance between movies distributed by different distributors when at least one of them is a non-major distributor. Thus, two Major Distributors are able to distance their releases more than any other combination of two distributors, which supports the idea that Major Distributors are acting in coordination with one another when setting their release schedules. In fact, they behave as if they were a single distributor in setting the release dates of their own films because we cannot reject the null hypothesis that the estimated intercepts for the *SDM*, *SDNM* and *D5* groups are all equal. It appears that Major Distributors jointly set their release schedules in a similar manner as any single distributor selects the release dates of its own films. This result reinforces the previous finding regarding worldwide releases (the *NO_FLEX* variable). It appears that the degree of *within-firm* coordination exhibited by each Major company, which is intended to maximize profits when they fix their own movie release dates, is also achieved *between* Major Distributors. Although it is legitimate for a single distributor to separate its own releases to avoid cannibalizing its own films, this behaviour is censurable when it is the result of a coordinated strategy in a group of firms.

3.5. Conclusion

We have analyzed differences in performance between collusive and competitive firms in a non-price strategic variable in a market where product differentiation is extremely high. To achieve this aim we have adapted one of the most popular (but initially price-based) methods to detect collusive practices in films' release dates, a critical variable of competition among distributors in an industry in which films do not compete on prices. Using a sample of movies released in Spain between 2002 and 2009, our paper attempts to provide some evidence on the presence of collusive behaviour in films' release dates, one of the arguments used by the SCA to fine five Spanish distributors linked to the major studios in Hollywood.

In particular, we advocate estimating a reduced-form model in which our dependent variable is the gap between the release dates of two films. Following Corts (2001), the empirical specification of our model relies on previously defined temporal market segments or theatre-demand windows that, in contrast, were identified using comprehensive statistical techniques. In order to prevent spurious results, we use a relative measure of the temporal gap between two releases that takes the equilibrium of the Hotelling's (1929) spatial competition model as a benchmark.

We have found that distributors try to elude competition between films that share certain characteristics – such as the presence of stars or awards – regardless of the combination of distributors that are releasing a particular pair of movies. It is notable that no effect was found regarding the genre or the rating. Next, we have tested whether Major Distributors have a joint strategy to release their films to avoid overlaps and to separate their release dates. Once we control for the degree of discretion that the Spanish distributors have when choosing the release schedule, our results show that two different Major Distributors are somehow able to better reduce the clustering of their film releases.

Moreover, Major Distributors behave as if they were the same company. Although it is appropriate for a distributor to separate its own releases to avoid cannibalizing its own projects, this behaviour is censurable when it results from synchronization between competing distributors. Under lack of alternative explanations, our results seem to support the arguments used by the Court to fine the Spanish distributors linked to the major studios in Hollywood.

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Chapter 4: Theatre Allocation as a Distributor's Strategic Variable over Movie Runs

4.1. Introduction

The motion picture market is characterized by products with a short life-cycle that compete with many new, unique, and imperfect substitutes in a relatively short time (De Vany and Walls 1997). Typically, the demand for a particular movie first falls and then collapses after a few weeks and, at the same time, there is an abrupt reduction in the number of screens after the first month on exhibit. There are exceptions to this pattern, especially when there is a particularly strong word-of-mouth effect and demand increases, or its fall slows, after the movie's release. Therefore, a high level of uncertainty regarding a movie's commercial success requires an adjustment in supply in terms of theatres over the run. Reducing the number of theatres too early should be avoided in order not to accelerate the fall in demand due to supply constraints, so a degree of flexibility could be important when adjusting the number of theatres.

The number of theatres is one of the main strategic variables[30] that can be decided jointly by the exhibitor and the distributor over a movie's run.[31] Before screening starts, distributors set conditions with exhibitors by means of contracts that establish the number of theatres, profit-sharing rules throughout the run, along with other clauses, such as sliding-scale, best-week, and holdover clauses (De Vany and Walls 1997, Chisholm 2004, Filson 2005, Filson et al. 2005, Gil and Lafontaine 2012, Gil

[30] Advertising is another important strategic variable, especially in the opening week. Several studies have analysed the impact of advertising on box-office revenues, such as Prag and Casavant (1994) and Zufryden (1996). Elberse and Eliashberg (2003) have additionally studied its indirect influence on audiences, through the impact of screens allocated to a movie in its opening-week.

[31] See Basuroy et al. (2006), Elberse and Eliashberg (2003), Fernandez-Blanco et al. (2013), and Hadida (2009).

2013). Whilst being a very interesting research topic for economists, contracts that define the relationship between distributors and exhibitors also constitute an area in which empirical analysis can be especially hard, since contracts are drafted by distributors and accepted by exhibitors on a case-by-case basis, and the terms of contracts are considered insider information, which is of difficult access for researchers, and not made publicly available by distributors.[32]

The main objective of this Chapter is to examine the relationship between the distributors' market share and their influence on the theatre allocation process. Taking into account the structure of this particular market, we explore whether the different types of distributors follow different theatre allocation strategies in terms of distribution intensity. These strategies must have an impact on the clauses that each Major includes in its exhibition contracts. As mentioned before, the case-to-case contract scenario and a lack of information prevent us from obtaining direct evidence on the general clauses that each distributor offers. Therefore, we infer differences in theatre allocation strategies not from contracts, whose details are unavailable, but from differences in theatre elasticity of box-office revenues throughout the whole movies life-cycle for the different distributors. In particular, we expect to find lower elasticities for the distributor with a higher market share. Since they could use their higher bargaining power to force exhibitor to allocate a large number of theatres to theirs films, a situation that in turn tend to yield small theatre elasticities.

[32] As McKenzie (2012) points out, very few researchers have actually had access to exhibition contracts for empirical analysis, Filson et al. (2005) and Gil (2007) being among the exceptions. Furthermore, as explored by Gil (2013), there is plenty of informal contracting and renegotiation.

In our understanding, many researchers have developed models of weekly box-office revenues that include theatres as an endogenous variable, but they rarely consider estimated theatre elasticities and their relation with the distributors' market share.[33] Therefore, our study contributes to the existing literature by providing evidence of the distinct commercial strategies of these six Majors, and of their different strategies with respect to the remaining distributors, the non-Majors.

By using a panel for the 150 top box-office films in the United States for each of the years in the 2002–2009 period, we estimate models that explain the commercial success of films and theatre elasticity. Given the dynamic nature of our data and the possible endogeneity problem of certain explanatory variables, we use the Hausman–Taylor estimator (Hausman and Taylor 1981). By controlling both for the effect on revenues of the characteristics of the movie that capture its quality and for other variables that represent the market characteristics (competition, seasonality, and timing), we estimate the effect of the number of theatres allocated to the film throughout its whole life-cycle. Since the six main movie distributors, i.e. the so-called Majors, have a large market share, we identified this effect by Majors.[34] In this sense, it is worth mentioning that, as there are remarkable differences in market shares among distributors, the estimated models can be viewed as applications of the traditional "structure-conduct-performance" paradigm of industrial organization. We investigate

[33] One exception is Moul (2008). He estimates elasticities to find indirect evidence on horizontal collusion between Majors (distributors) regarding rental-rates and advertising strategies by observing the consequences downstream (i.e. on the exhibitors' behaviour).
[34] Disney, Fox, Paramount, Sony, Universal, and WB. We consider Major studios including all their distribution brands.

whether a film's box-office performance is affected by the market structure through the (unobserved) conduct of the distributors regarding theatre allocation.

Our results seem to confirm our expectations as they reveal a difference between the behaviour of Majors and non-Majors. Among the Majors, we observe differences that are larger when considering longer runs of movies (i.e., more successful movies that survive on the screens for longer). All these findings constitute indirect evidence of the bargaining power of distributors, and of the importance contracting conditions have on the decision-making process of exhibitors and the commercial success of movies.

We present the dataset and variables in Section 4.2. Section 4.3 discusses the empirical specifications and the estimation method. We analyse the results in Section 4.4, and Section 4.5 concludes.

4.2. Data and Variables

The sample we use for our empirical analysis consists of the 150 top box-office films each year released in the United States during the period 2002–2009, and it is built relying on several sources of information. A.C. Nielsen EDI is used for information on titles, distributors, weekly and cumulative revenue, number of theatres, and certain film characteristics (official release date, identification of sequels, age rating). The Internet Movie Database (website www.imdb.com) and the films' web pages are used for information about other aspects of the film (budget, cast, awards, etc). Due to missing information for some variables, our final database comprises 920 movies.[35] Our dependent variable is the weekly box-office revenues, in real terms, obtained for a first-run film in all the theatres in which it is exhibited in the U.S., in log terms (*lnRev*).[36] Revenues will depend on the following explanatory variables.[37]

We identify the information about the distributor with dummy variables for the six Major distributors (*Dis*, *Fox*, *Param*, *Sony*, *Univ*, and *WB*; the non-Majors is the reference category). The number of theatres in which the movie is shown each week (*lnThts*) measures the film's availability. This variable is interacted with a trend variable and its square term to measure the changes in the effect of theatres on box-office revenue throughout the movie run. To further explore the effect that each Major has in terms of distribution intensity and power to negotiate with exhibitors, the Majors' dummies are interacted with the number of theatres variable and the trend variable.

Our empirical specification also includes the MPAA rating as a proxy for the moral characteristics of the film. The reference category is films for 'general audiences', and we include *Rat_pg* (suitable for audiences aged 7 and older), *Rat_pg13* (13 and older), and *Rat_r* ('restricted audiences').[38] In addition, *Star_1* and *Star_2* are

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[35] For the properties of the distribution of motion picture profits and its implications, see De Vany and Walls (2004). Concentrating on the top films in terms of generated revenue is usual in this literature. For instance, Brewer et al. (2009), De Vany and Walls (1997), and Moul (2008) also use samples restricted to high-performing films.
[36] Current prices, as recorded in the original dataset, are deflated using the Consumer Price Index (CPI) for each of those years, published by the U.S. Bureau of Labor Statistics (BLS).
[37] Eliashberg et al. (2006), Hofmann (2013), and McKenzie (2012) provide overviews of models and the previous results.
[38] Rating systems have proven to be a relevant determinant of box-office revenues (see for instance Walls 2005; and Chen et al. 2013).

dummy variables that measure the presence of stars in the cast.[39] Similarly, we control for international awards with three additional dummy variables *InAw_1*, *InAw_2*, and *InAw_3*.[40] The *Seq* dummy variable allows us to control for the film being supported by a previously successful one. Lastly, since movie production budgets relate to various film characteristics, we include them (*lnBud*), measured in (log) real terms.[41]

We also control for the competitive environment faced by films due to new releases – competing movies have a stronger attraction in the opening week – using the *lnComp* variable, which measures the number of theatres allocated to other movies in their opening week, measured in log terms.[42]

Other variables with a significant effect on movie performance are those related to time and seasonality in the underlying demand. We include the *Hol* dummy variable for cases in which the opening day of the film was a festive day. To capture the heavy seasonality of the U.S. motion picture industry, we rely on the approach by Gutierrez-Navratil et al. (2013)[43] based on Moving Average Convergence Divergence analysis (MACD). This statistical indicator allows us to detect significant peaks and

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[39] The reference category is no star in the cast. *Star_1* measures whether the film has an international star who has not won an Oscar and *Star_2* whether it has at least one international star who has won an Oscar.

[40] *InAw_1* identifies films that have obtained the main awards at minor festivals or minor awards at the major festivals (such as an Oscar in minor categories). *InAw_2* indicates films with a major award at an international film festival (e.g., Cannes, San Sebastian, Venice, or Berlin). *InAw_3* is for films with at least one Oscar award in a major category.

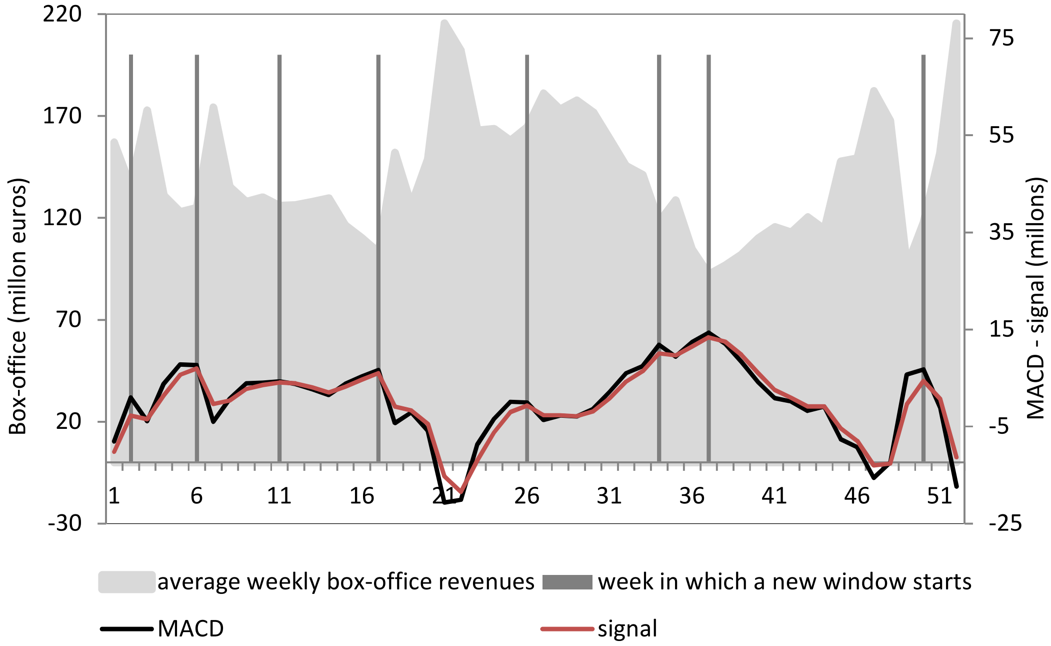
[41] Stars, awards, sequels, and budget are signals (Basuroy et al. 2006, Deuchert et al. 2005, De Vany and Walls 1999, Ginsburgh 2003) and ways of extending established brand names to new products (Ravid 1999).

[42] The timing of entry is among the most important factors of success for short life-cycle products (Calantone et al. 2010, Elberse and Eliashberg 2003, Gutierrez-Navratil et al. 2012). Alternative factors may be the decision between nationwide or platform releases (Chen et al. 2013) or product differentiation across local competitors (Collins et al. 2009).

[43] For more details of this statistical technique see Chapter 3, Section 3.2.

valleys of the average weekly box-office revenues in 2002–2009 period.[44] We assume that each window surround a high demand peak, beginning in one valley and ending in another valley. This method allows us to identify eight demand windows per year. The graphical analysis is displayed in Figure 4.1.

Figure 4.1. Moving Average Convergence Divergence analysis



We consider seven dummy variables (*Wdw*) to identify each one of the first seven windows of the calendar year (the last window – around Christmas – is taken as the reference category). Last, to control further for the possible decay in revenue as

[44] The major peaks in the average weekly box-office revenues coincide with all the celebrations nationwide, these results are in line with the approach applied by Corts (2001) that identified windows by selecting several key dates. For instance, the maximum peaks in the U.S. are recorded on Memorial Day and at Christmas. We observe other significant peaks on the Birthday of Martin Luther King, Presidents' Day, Independence Day, and Veterans Day. Einav (2009) identifies four windows using a different technique.

movies become less attractive over time, we include a set of dummy variables for each week of the movie run (*Week*).[45] A summary of the descriptive statistics is shown in Table 4.1.

Table 4.1. Summary statistics of the data

		Model 1		Model 2	
Variables	Units	Mean	Std. Dev.	Mean	Std. Dev.
Time variant					
Rev	dollars	6,652,451	13,100,000	6,833,640	15,200,000
Thts	units	1,301	1,193	1,118	1,191
Comp	units	8.1648	2.3277	8.1853	2.3023
Wdw_1	-	0.0839	0.2773	0.0970	0.2961
Wdw_2	-	0.0920	0.2891	0.1081	0.3105
Wdw_3	-	0.1020	0.3026	0.0961	0.2947
Wdw_4	-	0.1639	0.3702	0.1494	0.3565
Wdw_5	-	0.1519	0.3589	0.1756	0.3805
Wdw_6	-	0.0604	0.2383	0.0642	0.2451
Wdw_7	-	0.2573	0.4372	0.2120	0.4088
Wdw_8	-	0.0886	0.2841	0.0976	0.2969
Time invariant					
WB	-	0.1658	0.3721	0.1588	0.3661
Dis	-	0.1373	0.3443	0.2118	0.4092
Fox	-	0.1447	0.3520	0.2559	0.4370
Univ	-	0.1331	0.3398	0.0706	0.2565
Sony	-	0.1510	0.3582	0.0588	0.2356
Param		0.1067	0.3088	0.1059	0.3081
InAw_3	-	0.0190	0.1366	0.0529	0.2242
InAw_2	-	0.0211	0.1439	0.0441	0.2057
InAw_1	-	0.0707	0.2565	0.1353	0.3425
Rat_g	-	0.0348	0.1835	0.0500	0.2183
Rat_pg	-	0.1690	0.3749	0.2353	0.4248
Rat_pg13	-	0.4562	0.4983	0.4441	0.4976
Rat_r	-	0.3400	0.4740	0.2706	0.4449
Bud	dollars	50,800,000	43,500,000	60,000,000	52,900,000
Star_2	-	0.2122	0.4091	0.2294	0.4211
Star_1	-	0.3759	0.4846	0.4176	0.4939
Seq	-	0.1193	0.3243	0.1294	0.3361
Hol	-	0.4720	0.4995	0.5059	0.5007

[45] Einav (2007) identifies two sources of seasonality: seasonality in the underlying demand and seasonality due to the endogenous industry reaction in terms of the timing and quality of releases.

4.3. Empirical Model

Even when considering only those films at the top of the distribution (the year's 150 most successful films), the number of weeks they are screened is relatively low. Then, given the high level of attrition in the sample, we estimate two models considering different time frameworks. The first model includes all movies for the most relevant part of their runs; we set the sample period at 11 weeks in order to limit the attrition bias [46] (9,237 observations corresponding to 947 films). In the second model, we focus on the most successful movies, that is, those films on screen for more than 15 weeks (approximately one third of the total films with the longest runs). We estimate this model to focus our analysis on movies that could have a demand with a different pattern because of a strong word-of-mouth effect. Model 2 is estimated for the first 15 weeks (5,080 observations corresponding to the 340 films that remained on screen for at least 16 weeks).

The appropriateness of this empirical strategy is explained in Table 4.2 in the Appendix, which shows that the withdrawal rate from exhibition reaches its modal value at the tenth and eleventh weeks. Hence, with such withdrawal rates, the attrition bias could be very important if more than 11 weeks are considered when using a general sample of movies. Furthermore, it can be seen that the average revenue drops sharply from the second week onwards. In fact, weekly revenues after week 12 represent, on average, less than two percent of the box-office revenue in the

[46] Attrition bias is a kind of selection bias caused by attrition, i.e. withdrawal of movies over time. Then, limiting the time framework we reduce the attrition.

opening week. Additionally, in Model 2, expanding the temporal dimension of the panel data set beyond the fifteenth week would impose a reduction in the sample of about 10 percent, especially among non-major movies, and we believe that including an additional week is not very relevant in terms of total revenue.

Table 4.2. Withdraw rates, average number of theatres and average revenue by week

Exhibition week	# of films withdrawn	Average number of theatres	Average revenue (in thousands of dollars)
1	5	2391.44	21000
2	3	2443.91	17000
3	3	2196.74	9900
4	17	1737.55	6200
5	33	1286.08	3800
6	48	920.21	2600
7	61	668.25	1700
8	56	501.17	1200
9	50	393.14	825
10	78	311.64	612
11	73	265.31	498
12	64	240.88	435
13	59	220.83	404
14	75	214.90	390
15	48	196.02	363
16	49	187.82	343
17	46	184.63	347
18	43	175.69	334
19	36	170.33	332
20	25	145.60	340
21	32	137.95	295
22	25	132.98	318
23	20	124.44	312
24	17	111.08	289
25	10	96.34	294
Over 25	60	….	…

In accordance with the previous literature, we estimate a weekly box-office revenue equation that includes as independent variables the characteristics that determine the quality of the film, the availability of the film, the competitive environment, and the time and seasonality in the underlying demand. Therefore, we propose estimating the following empirical model:

$$lnRev_{it} = \delta_1 X_{1it} + \delta_2 X_{2it} + \gamma_1 Z_{1i} + \gamma_2 Z_{2i} + \alpha_i + \epsilon_{it} \quad (4.1)$$

where subscript t denotes the exhibition week in which the revenues of the *i*-th film are collected. The film-specific effect α_i captures the unobserved film characteristics assumed to have a zero mean and finite variance $\sigma^2{}_\mu$ and to be independently and identically distributed (i.i.d.) over the panels. Z_{1i} captures the exogenous and time-invariant characteristics of movies that may have an effect on the box-office performance, such as the international awards received, MPAA rating, or distributor. We also include a set of time-invariant variables, Z_{2i}, that can be correlated with the unobserved characteristics captured by the individual effects, α_i. This group of variables includes the budget, the presence of stars, sequel, and holiday. We also include exogenous and time-varying controls in X_{1it} to capture the competition of newly released films, the changes in the underlying demand throughout the year, and the week effects of the movie run. In addition, the number of theatres in which the *i*-th film is exhibited in the *t*-th week, and interaction terms between theatres, distributors, and trend, are time-varying variables included in vector X_{2it} that can be correlated with the individual effects. Finally, ϵ_{it} is the idiosyncratic error that is assumed to have a zero mean and finite variance $\sigma^2{}_\epsilon$ and to be i.i.d. over all the observations in the data.

We estimate this model by using panel data techniques to control for the unobserved heterogeneity among films. There are many characteristic that are unobservable, but they may be important because the motion picture industry is one of the most highly product-differentiated markets, as each movie is unique by nature. Thus, we control for the individual effects of each film. Since some of the explanatory variables may be correlated with these unobserved film-specific effects, the random effects estimator might give inconsistent parameter estimates. The fixed effects estimator would consistently estimate the coefficients of the time-varying variables, but remove all the time-invariant variables.

Therefore, we estimate this panel model using the Hausman and Taylor (1981) estimator, which proposes a random effects model that deals with the potential correlation between certain explanatory variables and the individual effect. This estimator is based upon an instrumental variable estimator that uses both the *between* and the *within* variation of the exogenous variables as instruments. The individual means of the time-varying exogenous variables are used as instrumental variables for the time-invariant variables that are correlated with the individual effects. Accordingly, the order condition for identification requires the number of time-varying exogenous variables (X_{1it}) to be at least as large as the number of time-invariant endogenous variables (Z_{2i}); a condition that requires previously determining which variables are exogenous and which ones are not. The exogeneity hypothesis can be tested using a Hausman test based on the contrast between the fixed effects and the Hausman-Taylor estimators. One of the advantages of the Hausman-Taylor model is that, when it is over-identified (as in this case because there are more time-varying exogenous variables than time-invariant endogenous variables), it is more efficient than fixed-effects [47] (see Hausman and Taylor 1981, Baltagi 2008).

4.4. Results

In order to check whether film distributors follow different strategies regarding theatre allocation, we estimate two models of box-office revenues. Model 1 includes almost all movies for the most relevant part of their runs (up to 11 weeks). Model 2 is focus on the most successful movies, that is, those films on screen for more than 15 weeks.

Both models have been estimated using the fixed effects and the Hausman-Taylor estimators, for robustness grounds. A Hausman test is conducted to test the null hypothesis of no systematic difference in coefficients between δ_{HT} and δ_{FE} (the Hausman-Taylor and the fixed effect estimators, respectively). The null hypothesis is not rejected in both cases. Therefore, the Hausman-Taylor estimator, which is efficient, is also consistent. Since this estimator does not differ from the fixed effects estimator for δ, which is consistent regardless of which components of X_{it} and Z_i are correlated with α_i (see Cameron and Trivedi 2005, p. 762). The results for the two estimated models are shown in Table 4.3.

[47] When the models are just-identified, in the sense that the number of time-varying exogenous variables equals the number of time-invariant endogenous variables, then the coefficients of the time-varying variables estimated by Hausman-Taylor are the same as those estimated by fixed-effects.

Table 4.3. Fixed effect and Hausman-Taylor estimated models

	Model 1						Model 2					
	Fixed Effect			Hausman and Taylor			Fixed Effect			Hausman and Taylor		
Variable	Coeff.		Std. Err.	Coeff.		Std. Err.	Coeff.		Std. Err.	Coeff.		Std. Err.
Dis				0.0434		*0.255*				0.1740		*0.341*
Fox				0.4726	**	*0.202*				0.3949		*0.359*
Param				0.3143		*0.243*				0.8344	**	*0.361*
Sony				0.6364	***	*0.247*				0.8278	*	*0.432*
Univ				-0.0637		*0.230*				0.4542		*0.352*
WB				-0.0137		*0.245*				0.9727	**	*0.393*
lnThts	0.9377	***	*0.008*	0.9375	***	*0.008*	0.9337	***	*0.014*	0.9336	***	*0.014*
*lnThts*Dis*	-0.0417	***	*0.010*	-0.0418	***	*0.010*	0.0068		*0.016*	0.0063		*0.016*
*lnThts*Fox*	-0.0382	***	*0.009*	-0.0382	***	*0.009*	-0.0138		*0.015*	-0.0136		*0.014*
*lnThts*Param*	-0.0483	***	*0.010*	-0.0482	***	*0.010*	-0.0761	***	*0.018*	-0.0759	***	*0.018*
*lnThts*Sony*	-0.0908	***	*0.011*	-0.0907	***	*0.011*	-0.0706	***	*0.023*	-0.0707	***	*0.022*
*lnThts*Univ*	-0.0353	***	*0.012*	-0.0352	***	*0.012*	-0.0230		*0.023*	-0.0233		*0.023*
*lnThts*WB*	-0.0605	***	*0.009*	-0.0604	***	*0.009*	-0.0893	***	*0.016*	-0.0891	***	*0.016*
*lnThts*t*	-0.0035	***	*0.001*	-0.0035	***	*0.001*	0.0132	***	*0.004*	0.0132	***	*0.004*
*lnThts*t*Dis*	-0.0026	***	*0.001*	-0.0026	***	*0.001*	-0.0103	***	*0.003*	-0.0103	***	*0.003*
*lnThts*t*Fox*	-0.0028	***	*0.001*	-0.0028	***	*0.001*	-0.0110	***	*0.003*	-0.0110	***	*0.003*
*lnThts*t*Param*	-0.0067	***	*0.001*	-0.0067	***	*0.001*	-0.0169	***	*0.003*	-0.0169	***	*0.003*
*lnThts*t*Sony*	-0.0066	***	*0.001*	-0.0066	***	*0.001*	-0.0082	**	*0.004*	-0.0081	**	*0.004*
*lnThts*t*Univ*	-0.0043	***	*0.001*	-0.0043	***	*0.001*	-0.0061	*	*0.004*	-0.0061	*	*0.003*
*lnThts*t*WB*	-0.0049	***	*0.001*	-0.0049	***	*0.001*	-0.0104	***	*0.003*	-0.0104	***	*0.003*
*lnThts*t2*							-0.0009	***	*0.000*	-0.0009	***	*0.000*
*lnThts**t^2**Dis*							0.0006	***	*0.000*	0.0006	***	*0.000*
*lnThts**t^2**Fox*							0.0006	***	*0.000*	0.0006	***	*0.000*
*lnThts**t^2**Param*							0.0007	***	*0.000*	0.0007	***	*0.000*
*lnThts**t^2**Sony*							0.0003		*0.000*	0.0003		*0.000*
*lnThts**t^2**Univ*							0.0002		*0.000*	0.0002		*0.000*
*lnThts**t^2**WB*							0.0003	*	*0.000*	0.0003	*	*0.000*
IntAw_3				0.9183	**	*0.389*				0.7400	**	*0.345*
IntAw_2				0.7901	**	*0.378*				0.5919		*0.386*
IntAw_1				0.5206	***	*0.194*				0.4631	***	*0.174*
Rat_r				-0.0983		*0.438*				0.4098		*0.602*
Rat_pg13				-0.5181		*0.420*				0.1890		*0.583*
Rat_pg				-0.0883		*0.287*				0.0559		*0.332*
Star_2				1.8717	**	*0.914*				0.3595		*1.667*
Star_1				1.4769	*	*0.816*				-0.1558		*0.828*
Seq				-0.1722		*0.835*				-0.1793		*0.745*
Hol				0.4884	**	*0.223*				0.3103		*0.353*
lnBud				0.6044	**	*0.260*				0.1736		*0.229*
lnComp	-0.0046	***	*0.001*	-0.0046	***	*0.001*	-0.0135	***	*0.002*	-0.0135	***	*0.002*

Table 4.3. Fixed effect and Hausman-Taylor estimated models (cont.)

	Model 1						Model 2					
	Fixed Effect			Hausman and Taylor			Fixed Effect			Hausman and Taylor		
Variable	Coeff.		Std. Err.	Coeff.		Std. Err.	Coeff.		Std. Err.	Coeff.		Std. Err.
Wdw_1	-0.0023		*0.017*	-0.0009		*0.017*	0.0287		*0.022*	0.0291		*0.021*
Wdw_2	-0.0128		*0.019*	-0.0106		*0.019*	0.0197		*0.023*	0.0203		*0.023*
Wdw_3	0.0808	***	*0.023*	0.0822	***	*0.023*	0.0296		*0.026*	0.0290		*0.026*
Wdw_4	0.0592	**	*0.024*	0.0601	***	*0.023*	0.0462	*	*0.028*	0.0452	*	*0.027*
Wdw_5	0.2184	***	*0.022*	0.2184	***	*0.022*	0.2430	***	*0.027*	0.2417	***	*0.026*
Wdw_6	0.2139	***	*0.023*	0.2136	***	*0.023*	0.1833	***	*0.030*	0.1816	***	*0.029*
Wdw_7	0.0169		*0.017*	0.0161		*0.017*	-0.0620	***	*0.022*	-0.0634	***	*0.021*
Week_1	1.9232	***	*0.058*	1.9246	***	*0.058*	2.2535	***	*0.080*	2.2556	***	*0.078*
Week_2	1.7227	***	*0.052*	1.7240	***	*0.052*	2.0023	***	*0.083*	2.0048	***	*0.081*
Week_3	1.3285	***	*0.045*	1.3297	***	*0.045*	1.5466	***	*0.088*	1.5494	***	*0.086*
Week_4	1.0657	***	*0.039*	1.0667	***	*0.038*	1.1933	***	*0.093*	1.1962	***	*0.091*
Week_5	0.8294	***	*0.033*	0.8302	***	*0.032*	0.9061	***	*0.097*	0.9090	***	*0.094*
Week_6	0.6243	***	*0.028*	0.6249	***	*0.027*	0.7379	***	*0.097*	0.7407	***	*0.095*
Week_7	0.4220	***	*0.024*	0.4226	***	*0.024*	0.5601	***	*0.095*	0.5628	***	*0.093*
Week_8	0.2721	***	*0.021*	0.2725	***	*0.020*	0.4004	***	*0.090*	0.4029	***	*0.088*
Week_9	0.1400	***	*0.018*	0.1403	***	*0.018*	0.2575	***	*0.084*	0.2597	***	*0.082*
Week_10	0.0679	***	*0.017*	0.0681	***	*0.017*	0.1575	**	*0.075*	0.1594	**	*0.073*
Week_11							0.0792		*0.065*	0.0807		*0.063*
Week_12							0.0477		*0.054*	0.0489		*0.052*
Week_13							0.0464		*0.041*	0.0472		*0.040*
Week_14							0.0087		*0.030*	0.0091		*0.029*
Cons.	7.9010	***	*0.044*	-3.7769		*4.344*	7.9418	***	*0.073*	3.9693		*3.722*
Number of obs.	9,237			9,237			5,080			5,080		
Number of groups	947			947			340			340		
F test	F(32, 8258) = 8.427						F(43, 4697) = 3.174					
Wald test				Chi^2 (49) = 275.007						Chi^2 (60) = 143.064		
Hausman test	Chi^2 (32) = 0.98						Chi^2 (37) = 0.26					

Before analysing the elasticity of revenues with respect to theatres, we discuss the estimated coefficient of the control variables. All the variables that signal movie quality, such as the awards received, the presence of stars, and the budget, are important determinants of weekly revenues in Model 1. In addition, there is a positive impact on weekly revenues when the movie is released on a holiday. However, the effect of having an international star, a high budget or a holiday release are not significant in Model 2, when only films that remained on screen more than 15 weeks are considered. These results seem to indicate that, as expected, these variables have an important impact on the first weeks on screen. However, for films with a long life, their effect fades away as time passes.[48] No significant evidence is found in either model for other film features, such as MPAA rating or sequel.

The presence of more (and stronger) new competitors has in both models a significant negative impact on weekly box-office revenue. These results are in line with the evidence obtained by, among others, Ainslie et al. (2005), Basuroy et al. (2006) and Gutierrez-Navratil et al. (2012). Regarding the time and seasonality variables, we observe that the seasonal variations in the underlying demand have significant effects on movie performance in both models, explaining almost 25% of the intra-annual variations, once other factors have been controlled for. As expected, the coefficients of

[48] Brewer et al. (2009) also obtain evidence that variables such as genre and MPAA rating cease to be relevant after the release. After a given number of weeks, more information is available to consumers and there is evidence of increasing returns to information and a non-linear effect of the 'star power'. In a cross-sectional study, those authors determine that indicators of approval of the industry in terms of awards (or nominations), word-of-mouth, and praise from movie goers outweigh other signals.

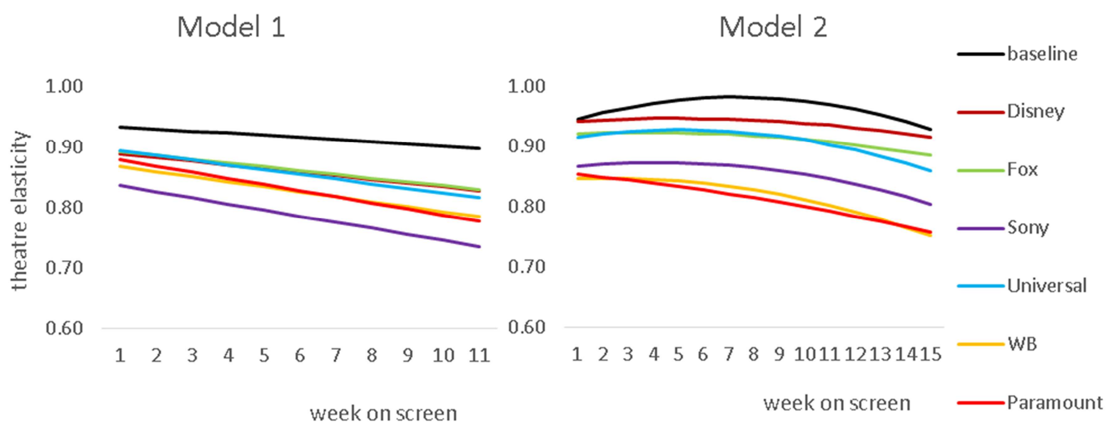
the dummies for each week of the movie run show a clear pattern of decaying revenue over time.

The importance of the number of theatres distinguished by distributor[49], with non-Majors being the reference category in the estimations, is analysed using the estimated elasticity of box-office revenues with respect to the number of theatres. As these elasticities change week by week, we have interacted theatre variable with a trend. As Model 2 involves longer runs, it also includes the theatre variable interacted with a quadratic trend to allow these changes to differ over time.[50] The estimated theatre elasticities are close in both models, but lower than one, as expected. On the distributor side, assuming a low marginal cost associated with the marginal theatre, it is in a distributor's interest to obtain the maximum number of theatres for its movies, thus driving theatre elasticity well below one. On the other hand, exhibitors are interested in obtaining a theatre elasticity as close to one as possible in order to increase their revenues.[51] Therefore, once other factors have been controlled for, low theatre elasticity may be associated with two different environments. First, there will be a *push effect* when the distributors have high bargaining power, forcing the exhibitor to allocate a large number of theatres. Second, there will be a *pull effect*

[49] Using Wald tests, we find that these differences in the theatre elasticity of box-office revenue among the six Majors are statistically significant, which justifies make distinguishing between Majors when estimating elasticities.
[50] In Model 1, the quadratic term of the trend is not significant in any case, and we have excluded it from the model.
[51] A theatre elasticity of revenues close to one implies a theatre elasticity of occupancy rate next to zero, indicating that when additional theatres are assigned to a movie the occupancy rate of the theatres of this movie does not decrease.

when the exhibitors have enough incentives to allocate their screens to a particular distributor. Figure 4.2 displays the results graphically.

Figure 4.2. Theatre elasticity of box-office revenues per distributor



Regarding the theatre elasticities represented on the left in Figure 4.2, it is worth mentioning that the elasticities for non-major distributors (our estimation benchmark) are quite close to one, and consistently higher than the estimated elasticity for all the Majors throughout the whole movie run. Since, assuming identical conditions for the sharing of box-office revenue, exhibitors will maximize their revenues at the point where all movies have the same theatre elasticity, this result seems to indicate that non-Majors have lower bargaining power in the sense they are less able to face exhibitors to allocate additional theatres to their films compared to Majors distributors, that is, their *push effect* is smaller.

Additionally, there are no large differences between the Majors. In fact, the estimated theatre elasticities for Disney, Fox and Universal are barely distinguishable from each other. This finding indicates that, in general, theatres are involved in a similar allocation of films distributed by Majors. A slightly different pattern can be observed for Sony and, to a lesser degree, for WB and Paramount, with lower estimated theatre elasticities. It seems that Sony, WB and Paramount, despite their different number of released films, have a release strategy consisting of a larger average of release theatres than any other Major,[52] a fact that may explain their lower theatre elasticity. As stated above, there could be several reasons explaining how these firms manage to follow a different strategy. First, it could be that these Majors offer better conditions to the exhibitors in their revenue-sharing contracts, seeking to enhance the *pull effect*.[53] This would imply a different risk-sharing strategy between Sony, WB and Paramount and the exhibitors, with implications for the rest of the exhibition weeks. Second, a non-competing alternative would be that these Majors have greater bargaining power, allowing them to sign more theatres on average than their rivals.[54] Third, another relevant determinant of the (opening) theatres is the expected box-office revenues that are linked to the budget (including advertising and marketing expenditures) and the film's other aspect of marketability (stars, rating…). However, this should not be the case in our analysis, since the results have already accounted for this factor through the set of explanatory variables for the observable characteristics, and by the film-specific effect for the unobserved ones.

[52] In our sample, the average number of opening screens is 2,658; 2,647 and 2,562 for Sony, WB and Paramount, respectively, and 2,221 for the other three Majors.

[53] A lower rental ratio would be consistent with the observed lower theatre elasticity, since exhibitors would have a greater incentive to allocate screens to those distributors, even if the total revenue by screen is not as high as it could be for movies distributed by other companies.

[54] This is consistent with the market shares of WB and Sony over the years analysed, as the two largest distributors (see www.boxofficemojo.com and www.the-numbers.com).

In addition, to capture differences in elasticities among distributors, one contribution of the Chapter is the analysis of changes over time in the estimated elasticities. This analysis provides additional insight about differences in performance among distributors. In particular, Figure 4.2 shows that all theatre elasticities follow a decreasing trend that is much more pronounced for the Majors as the estimated trend slope for the six Majors is, on average, more than twice that for non-Majors. Again, this result could be explained by the greater market power of the Majors, which may impose a longer minimum playing time for their movies than non-Majors, regardless of the film's performance. This leads to difficulties for the exhibitor in adjusting the number of theatres according to the film's performance.[55] The use of profit-sharing contracts with different sliding scales for the exhibitor could also generate greater incentives to keep movies on screen for longer, even with decreasing revenues.

In Model 2, we consider a longer timeframe (15 weeks) and focus our attention on movies with a longer life on screen. Therefore, when discussing the results, it is important to keep in mind that only the most successful movies with especially long runs are considered, reducing attrition and providing a homogeneous sample of movies. These changes in the sample lead to differences in the results between the two estimated models. However, as in Model 1, theatre elasticities are higher for non-Major movies, giving additional insights into the existence of differences between the

[55] Whereas the financial performance of a film is found to be nearly impossible to forecast in the 'nobody knows' environment, Hand (2002) finds that the level of admissions can be foreseen , at least in the short term.

standard contract offered to the exhibitors by non-Majors and Majors; an outcome that we attribute to the differences in market power.

Finally, in Model 2, the coefficients of the quadratic trends are statistically significant for all the distributors, but especially for the non-Majors. As show in Figure 4.2, this implies that all elasticities increase up to a certain point and then decreases. The temporal patterns are likely connected to word-of-mouth effects. Indeed, the word-of-mouth effect should be important as we are considering here the most successful movies (otherwise these films would not survive beyond the fifteenth week). Therefore, it is quite likely that the word-of-mouth effect was not fully anticipated for these movies when the exhibition contracts were signed. As we indicate above, the rise in theatre elasticity may be due to an increase in the attendance rate. Hence, theatres fill up more and more each week. However, exhibitors cannot freely adjust the number of screens allocated to a film because they are bound by their contractual obligations to exhibit other movies. This leads to a suboptimal allocation of screens, especially in the case of sliding-scale contracts. The adjustment will be easier if the same distributor has more than one film during the run of the more successful movies, since it can reallocate the theatres or screens with the exhibitor.[56] This could explain why the quadratic effect is less intense for the Majors. However, non-Majors, which may additionally have a larger bias in their forecasted

[56] Some data reflect plenty of informal contracting and renegotiation. Using evidence from a Spanish exhibitor, Gil (2013) reports that nearly one-half of formal exhibition contracts are renegotiated and that informal contracts are extensively used (about 34% of the contracts the author analyses). This is explained in terms of deviations from the expected performance of the film, providing evidence that exhibitors learn during the film’s run and accommodate their choices to maximize revenues. As distributors make the contract proposal, they should also anticipate the subsequent decisions made by exhibitors.

success, will have fewer possibilities of adjustment through screens or theatres, since this adjustment will imply new arrangements with more than one distributor. After several weeks in theatres, the word-of-mouth effect starts to fade, the potential demand reduces, and we find that theatre elasticity decreases again.

4.5. Conclusions

In this Chapter, we have analysed theatre elasticity from box-office revenue models. Given the lack of information on contracts as the main instrument for distributors when implementing their strategies, estimated theatre elasticities provide only indirect evidence of the different distributors' behaviour and their influence on the process of theatre allocation.

We have estimated weekly box-office revenues using the Hausman-Taylor estimator, which allows us to control for the individual effects of each film (so we control for the unobserved heterogeneity among films). Our results for other variables are in line with the usual findings in the literature. For instance, we find that awards, the presence of stars, the budget, or being released on a holiday, are important determinants of revenue during the first weeks. However, no significant evidence is found for MPAA ratings or sequels. Seasonal variations in the underlying demand for movies in the U.S., characterized using a Moving Average Convergence Divergence Analysis, have significant effects on movies. As expected, the estimated coefficients of the dummies for each week of the movie run reveal a clear pattern of decaying revenue over time.

The main contribution of our approach is the estimation of theatre elasticity by firms. The theatre elasticity for non-Majors is very close to one throughout a movie's entire run, and significantly higher than the estimated elasticity for all the Majors. The lower theatre elasticity found for Majors may be associated with two different situations: first, a *pull effect* when the exhibitors have incentives, which can be specified in the exhibition contracts, to allocate more theatres to a particular film; second, a *push effect* if the distributors have high bargaining power, forcing the exhibitors to allocate a large number of theatres to their films. This non-competing alternative is consistent with the differences in market shares between non-Majors and Majors.

In addition, theatre elasticity follows a downward trend, which is steeper for Majors than for non-Majors, with the estimated trend for the Majors' slope being on average more than double. Again, this result could be explained by the higher market power of the Majors, which can impose a longer minimum playing time on their movies than the non-Majors. This situation leads to lower theatre elasticity, since the exhibitor would be unable to adjust the number of theatres according to the performance of the film. Additionally, we find differences between the Majors, indicating that, in general, theatres are similarly but not homogeneously allocated. These differences are related to the Majors' relative market share and their releasing policy.

When we consider solely the most successful movies, we observe an inverse U-shape in the theatre elasticity for films from all the distributors, but especially from the non-Majors. We expect a large and positive word-of-mouth effect for those movies; otherwise, they would not survive beyond the fifteenth week. If this effect is not fully anticipated when the exhibition contracts are signed, and theatres record higher attendances each week, theatre elasticity will rise during the first weeks on screen.

Considering this new evidence on the relevance of theatre allocation over the movie run as one of the main determinants of a movie's commercial success, and accounting for the impact that market power may have on this variable, there are certain policy implications that can be derived from our analysis. First, given the relevance of the contract terms for specifying the screens allocated to each film, it is advisable to control for the possible presence of abusive clauses, especially among those distributors with the largest market shares. Second, since word-of-mouth could be a particularly crucial effect in the case of surprise successes, it might be appropriate to include flexible clauses in the exhibition contracts that allow the number of theatres (screens) and weeks to be increased. Third, the inclusion of flexible clauses can also be used for the downward adjustment of the number of theatres when a particular film underperforms. This will allow adjusting the use of the theatres to movies with greater demand, increasing social welfare.

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Chapter 5: Conclusions

Although the analysis of the motion picture industry is a well-consolidated research field, there are still several interesting topics to be explored from the point of view of the organization and the strategic decisions of the agents participating in this sector. Following an industrial economics approach, this thesis aims to extend the knowledge of the movie market through three essays focused on the decisions of film distributors regarding two key strategic variables, namely the release date and the number of movie theatres.

These essays examine three different but highly interrelated issues that allow us to better understand firms' performance in the movie industry. The first essay clearly demonstrates the relevance of release dates as a strategic competition variable as well as the asymmetric nature of this source of competition among distributors. Once we have shown that temporal competition is a critical determinant of films' box-office revenues, the second essay tries to test whether some distributors have been able to better mitigate temporal competition by separating the release dates of their films. Having found some evidence on coordination of release-dates among Major Distributors, the final essay examined the relationship between Major Distributors' market power and the theatre allocation process.

The first essay, in Chapter 2, aimed to evaluate the role of temporal competition within the movie distribution market. More specifically, we have measured to what extent movies' box office receipts are affected by the temporal distribution of rival films. We have found that past, present and future rival releases have different effects on the total box office revenues of a particular film. In particular, we have found that the effect of competing films released simultaneously is always higher than the effect of films released in previous or posterior weeks. Another interesting result is that when considering all the films together, future releases always have a higher effect than previous releases. In general, we have found a decreasing impact of rival movies when their release dates move further from the release week of the reference film.

Overall, the results obtained in the first essay about the temporal pattern of competition effects show evidence of a clear asymmetry between the effect of past and future film releases. These findings are useful for film studios and distributors, which often carry out intense market research before releasing their movies in order to discover audience's preferences and anticipate market responses. Managers should take into account these temporal competition asymmetries in order to improve their release timing decisions to better defend or capture market share from their competing movies.

The previous literature suggests that the competition effect should depend on the characteristics of movies. Therefore, we have also examined the differential effects of films aimed at different target audiences, i.e. films with different ratings. This has permitted us to observe that in the case of restricted films the greatest influence of rival movies corresponds to previous releases. Such differing patterns with respect to the impact of previous or future releases suggest that managers should also consider the type of audience in order implement potentially different releasing policies.

According to this first essay, the coincidence of film releases may have important negative effects on box-office revenues. As a consequence, distributors might be interested in coordinating their release schedules. Despite the film market in most countries being dominated by a small number of distributors linked to the Hollywood Major film studios, there has been little attention given in the literature to the question of collusion in release dates. The second essay, in Chapter 3, tries to fill this gap with a study of the distributors' decisions regarding their films' release schedule. More concretely, we have examined the presence of potential collusive behaviour among the movie Major Distributors, considering the importance of release dates as a key variable to avoid the negatives effects of competition. We have tried to test whether Major Distributors have been able to somehow coordinate their release schedules, reducing the clustering of their film releases and thereby lessening temporal competition. Our results in this chapter can then be taken as an indirect evidence of collusive behaviour, which empirically support the arguments used by the Spanish Competition Authority in 2006 to fine the Spanish Major Distributors for anti-competitive practices.

The empirical evidence found in the second essay shows the temporal distance that separates the release of any two films increases considerably for pairs of films belonging to the alleged cartel. In general, our results suggest that Majors achieve a larger degree of coordination in their release schedules than other distributors in the motion picture market. Moreover, the results in this essay seem to indicate that the Major Distributors set their release schedules jointly as if they were the same firm selecting the release dates of their own films. Even though it is legitimate for a single distributor to separate their own releases to avoid cannibalizing its own films revenues, this behaviour is censurable when it is the result of a coordinated strategy by a group of firms. All the results obtained in this chapter seem to suggest that the Majors, compared to other distributors, use their dominant market position to better reduce the clustering of their film releases. General speaking, these outcomes suggest that collusive behaviour or other practices (e.g. abuse of dominant position or first-mover advantages) make market power less evenly distributed in the market.

As a consequence of these results one would expect Major Distributors to have an influence on the subsequent theatre allocation process. Thus, the third essay, in Chapter 4, focuses on the study of the theatre allocation as a key strategic decision variable that can be modified over the movie run. Considering the structure of the distribution market, we have explored whether different types of distributors follow different theatre allocation strategies and have examined the effect they have in terms of distribution intensity. These strategies should have an impact on the clauses that Majors include in their exhibition contracts. Since the terms of contracts are inside information between distributors and exhibitors set on a case-by-case basis and are not available to researchers, we need some indirect indicator of these terms. To obtain this, we have estimated the theatre elasticity of box-office revenues throughout the whole life-cycle of movies for the different distributors in order to provide indirect evidence on the distributors' strategies and their negotiation power in the theatre allocation process.

The estimated theatre elasticities for all the Major Distributors are significantly lower than those corresponding to non-Major throughout the entire movie run. This provides evidence of different commercial strategies between both types of distributors. The Majors' lower theatre elasticities can be the outcome of two possible scenarios. The first is a "pull effect", when exhibitors have enough incentives to allocate their screens to a particular distributor. Second, there may be a "push effect" when the distributors have high bargaining power and can force the exhibitor to allocate a large number of theatres, which will in turn tend to yield small theatre elasticities. This latter alternative is consistent with the observed differences in market shares between non-Majors and Majors. In sum, our results provide indirect evidence about the Major Distributors bargaining power and their ability to establish different contract terms with the exhibitors.

The three essays included in this thesis allow us to better understand market competition in the movie industry and firms' performance using the release dates of their films or the number of theatres allocated to them as key strategic competition variables. Overall, our results seem to indicate that market power is not evenly distributed in the market either between distributors and exhibitors or among distributors. Cinemagoers, movie market participants and competition authorities should therefore be aware of the likely appearance of anticompetitive issues in this market in the near future.