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Demand and Supply Dynamics for Sequentially Released Products in International Markets: The Case of Motion Pictures

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Abstract
We develop an econometric model to study a setting in which a new product is launched first in its domestic market and only at a later stage in foreign markets, and where the product's performance ("demand") and availability ("supply") are highly interdependent over time within and across markets. Integrating literature on international diffusion, "success-breeds-success" trends, and the theatrical motion picture industry—the focus of the empirical analysis—we develop a dynamic simultanenous-equations model of the drivers and interrelationship of the behavior of consumers ("audiences") and retailers ("exhibitors"). Our findings emphasize the importance of considering the endogeneity and simultaneity of audience and exhibitor behavior, and challenge conventional wisdom on the determinants of box office performance (which is predominantly based on modeling frameworks that fail to account for the interdependence of performance and availability). Specifically, we find that variables such as movie attributes and advertising expenditures, which are usually assumed to influence audiences directly, mostly influence revenues*in*directly, namely through their impact on exhibitors' screen allocations. In addition, consistent with the idea that the "buzz" for a movie is perishable, we find that the longer is the time lag between releases, the weaker is the relationship between domestic and foreign market performance—an effect mostly driven by foreign exhibitors' screen allocations.

Keywords
dynamic simultaneous equations modeling, international release strategies, entertainment marketing, motion picture distribution and exhibition, channel management

Disciplines
Econometrics | Marketing | Operations and Supply Chain Management | Other Business | Other Economics

Demand and Supply Dynamics for Sequentially Released Products in International Markets: The Case of Motion Pictures

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We develop an econometric model to study a setting in which a new product is launched first in its domestic market and only at a later stage in foreign markets, and where the product's performance ("demand") and availability ("supply") are highly interdependent over time within and across markets. Integrating literature on international diffusion, "success-breeds-success" trends, and the theatrical motion picture industry—the focus of the empirical analysis—we develop a dynamic simultanenous-equations model of the drivers and interrelationship of the behavior of consumers ("audiences") and retailers ("exhibitors"). Our findings emphasize the importance of considering the endogeneity and simultaneity of audience and exhibitor behavior, and challenge conventional wisdom on the determinants of box office performance (which is predominantly based on modeling frameworks that fail to account for the interdependence of performance and availability). Specifically, we find that variables such as movie attributes and advertising expenditures, which are usually assumed to influence audiences directly, mostly influence revenues *in*directly, namely through their impact on exhibitors' screen allocations. In addition, consistent with the idea that the "buzz" for a movie is perishable, we find that the longer is the time lag between releases, the weaker is the relationship between domestic and foreign market performance—an effect mostly driven by foreign exhibitors' screen allocations.

(*Dynamic Simultaneous Equations Modeling; International Release Strategies; Entertainment Marketing; Motion Picture Distribution and Exhibition; Channel Management*)

1. Introduction

This study considers a setting in which a new product is launched first in an initial market (here its domestic market), and only at a later stage in subsequent markets (here a set of foreign markets) and where the product's sales performance ("demand") and availability ("supply") are highly interrelated within and across markets. That is, the product's performance in the initial market depends, among other factors, on the extent to which retailers make the product available to consumers. In turn, retailers quickly adapt the product's availability to the product's performance, i.e., to the extent to which consumers adopt the product. In subsequent markets, the product's availability and sales performance depend, among other things, on the product's performance in the initial market, and on the time lag between its introduction in the initial and subsequent markets. Here, as in the initial market, the extent to which consumers adopt the product depends on

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its availability, while the extent to which retailers make the product available in turn corresponds to consumer acceptance as it is revealed over time. In each market, a number of other factors influence the new product's availability and performance, including product attributes, advertising support, manufacturer/distributor characteristics, testimonials by third parties, word-of-mouth generated by previous consumers, the competitive environment, and seasonality.

A wide range of products can be characterized by highly *adaptive demand and supply dynamics* and are introduced in international markets by means of a *sequential release strategy*. A variety of media and entertainment products, including books, motion pictures, and video games, serve as particularly good examples. Many researchers have acknowledged the importance of considering the interdependence between availability and sales performance, either in a general setting (e.g., Reibstein and Farris 1995) or specifically in the context of international diffusion (e.g., Dekimpe et al. 2000c). However, research that investigates the interacting behavior of consumers and retailers is limited (Jones and Mason 1990 and Jones and Ritz 1991, which we discuss below, are two noteworthy exceptions)—particularly in an international setting. Our research specifically addresses key voids in existing research.

We focus on *motion pictures* in our empirical application, and do so for the following reasons. First, motion pictures are a prime example of products that are predominantly sequentially released. Second, although the industry has received increasing attention from marketing scholars as well as economists in recent years, there has been little emphasis on foreign (i.e., non-U.S.) markets. Two exceptions are Neelamegham and Chintagunta (1999), who focus on opening-week revenues only, and Walls (1997). The lack of attention is very unfortunate: not only are international markets crucial to the profitability of Hollywood studios, motion pictures are a major export market for the United States as a whole. Third, the challenge facing movie exhibitors—aligning the allocation of screens with the demand for motion pictures as it evolves over the course of a movie's run—is very similar to the task facing retailers in other (e.g., media and entertainment) industries who are seeking to effectively manage their shelf space. Here, we refer to the number of screens allocated to a movie also as its *shelf space, exhibition level*, or *supply*. Fourth, motion pictures have a short life-cycle, there are many releases in a relatively short time period, and production costs are generally high—characteristics that make these products interesting from a diffusion research and a managerial point of view. Fifth, research aimed at understanding market dynamics and informing motion picture distributors and exhibitors' decisions has considered either the demand side or the supply side of motion picture markets, with a strong emphasis on the former. There is a specific need for research that simultaneously considers supply and demand dynamics.

The latter argument also holds for international diffusion research in general. Although it has widely been recognized that diffusion patterns are influenced by both supply- and demand-side processes (e.g., Jain et al. 1991, Dekimpe et al. 2000a), research that explicitly considers both aspects in an international context is limited. Most international diffusion studies, including those that employ (a variant of) the Bass (1969) model, are intrinsically demand studies (see Dekimpe et al. 2000c). In investigating the diffusion of motion pictures, we consider both the drivers of the behavior of audiences (demand) as well those of exhibitors (supply), and their interdependencies. We operate under the premise that diffusion processes *across* countries can only be fully understood if the interaction between supply and demand *within* these countries is adequately analyzed, and vice versa.

Regarding dynamics *across* countries, to date, empirical studies of international diffusion have focused on either consumer durable goods (e.g., Gatignon et al. 1989) or industrial technology goods (Dekimpe et al. 2000a). By focusing on motion pictures or, more generally, entertainment products, our study broadens the scope of product contexts. Several characteristics of entertainment goods, including their experiential nature (their quality can be judged only through usage) and relatively short life-cycle, as well as the commonness of success-breeds-success trends in markets for popular culture, are likely to have important consequences for the appropriateness of sequential release strategies. Also, advances in digital technology bring *speed-to-market* issues to the forefront in these industries.

We address two research questions related to the international diffusion of motion pictures:

• To what extent and in what manner is the performance of a movie in a foreign (sequential) market influenced by its performance in the domestic (initial) market?

• To what extent and in what manner is the relationship between the performance in the domestic and foreign market moderated by the time lag between the movie's introduction in both markets?

The questions directly relate to research on the existence of an *experience effect* (Dekimpe et al. 2000c), a *lead effect* (e.g., Gatignon et al. 1989, Helsen et al. 1993, Kalish et al. 1995) or *demonstration effect* (e.g., Dekimpe et al. 2000b). Work on herds, cascades, positive feedback effects, and related success-breeds-success processes (e.g., Arthur 1989, Bikhchandani et al. 1992, Frank and Cook 1995) is also relevant. The idea that adopters in sequential markets learn from their counterparts in the initial market suggests that experience effects *strengthen* with longer release time lags. However, importantly, if success-breeds-success trends indeed play a role, we may expect *weaker* cross-country effects as release time increase—the idea that any buzz or momentum that innovations generate among adopters in initial markets may wear out quickly.

When it comes to dynamics *within* countries, we investigate the drivers of the behavior of both movie audiences and exhibitors within one domestic market (the United States) and the four largest European markets for motion pictures (France, Germany, Spain, and the United Kingdom). Our research questions are:

• What are the determinants of the behavior of motion picture exhibitors—as exemplified by the screens allocated to movies over the course of their runs?

• What are the determinants of the behavior of motion picture audiences—as exemplified by the revenues collected by movies over the course of their runs?

Crucially, we pay particular attention to the interdependence of the behavior of motion picture exhibitors and audiences.

We study the above questions using dynamic simultaneous-equations models. Main features of our modeling approach can be summarized as follows:

• We model the behavior of exhibitors and audiences in each market using an adaptive framework, whereby exhibitors allocate screens based on their expectations regarding audience demand, the behavior of audiences depends on the allocation of screens, which in turn affects exhibitors' expectations, and so on.

• We introduce an exponential smoothing procedure to derive our measure of expected revenues in a manner that resembles so-called adaptive expectations models, whereby the initial values—expected opening-week revenues—are constructed using data from a popular Internet market simulation.

• Our model accounts for the endogeneity of revenues and screens and incorporates the need to determine revenues and screens simultaneously, thereby directly addressing recommendations made by Sawhney and Eliashberg (1996) and Neelamegham and Chintagunta (1999).

• We take the perspective of an outside industry observer and employ an ex-ante (as opposed to ex-post) modeling approach in that we use only information that is available prior to a given week to model the behavior of exhibitors and audiences in that week.

Conventional wisdom on the drivers of box office performance in domestic and foreign markets is mostly based on single-equation analyses that demonstrate the significance of screen allocations but fail to account for the interdependence of screens and revenues. Our study further significantly adds to work by Jones and Ritz (1991), who also investigate the interaction between demand and supply dynamics in the context of motion pictures. They model the behavior of exhibitors and consumers as two parallel continuous-time processes but do not allow for feedback from the consumer adoption process to the retailer adoption process (i.e., do not have a fully adaptive framework), do not estimate the number of screens in the opening week, do not incorporate any other determinants of motion picture performance, and do not study international markets. Our framework is also relevant in light of research by Jones and Mason (1990), who opt for an approach similar to that of Jones and Ritz (1991) but do consider how the consumer adoption process impacts the retailer adoption process. They specify their model for the context of consumer electronics but lack empirical data to estimate it.

Our findings challenge conventional thinking in several respects. For example, we find that variables such as movie attributes and advertising expenditures which are usually assumed to influence audiences directly, mostly do so *in*directly, namely through their impact on exhibitors' screen allocations. In addition, consistent with the idea that the buzz for a movie is perishable, we find that the longer is the time lag between releases, the weaker is the relationship between domestic and foreign market performance—an effect that is mostly driven by foreign exhibitors' screen allocations.

Below we start by formulating our conceptual framework and hypotheses. We then describe the data, measures, model, and estimation issues, after which we discuss the findings. We end with a summary of key findings, managerial implications, and further research opportunities.

2. Conceptual Framework and Hypotheses

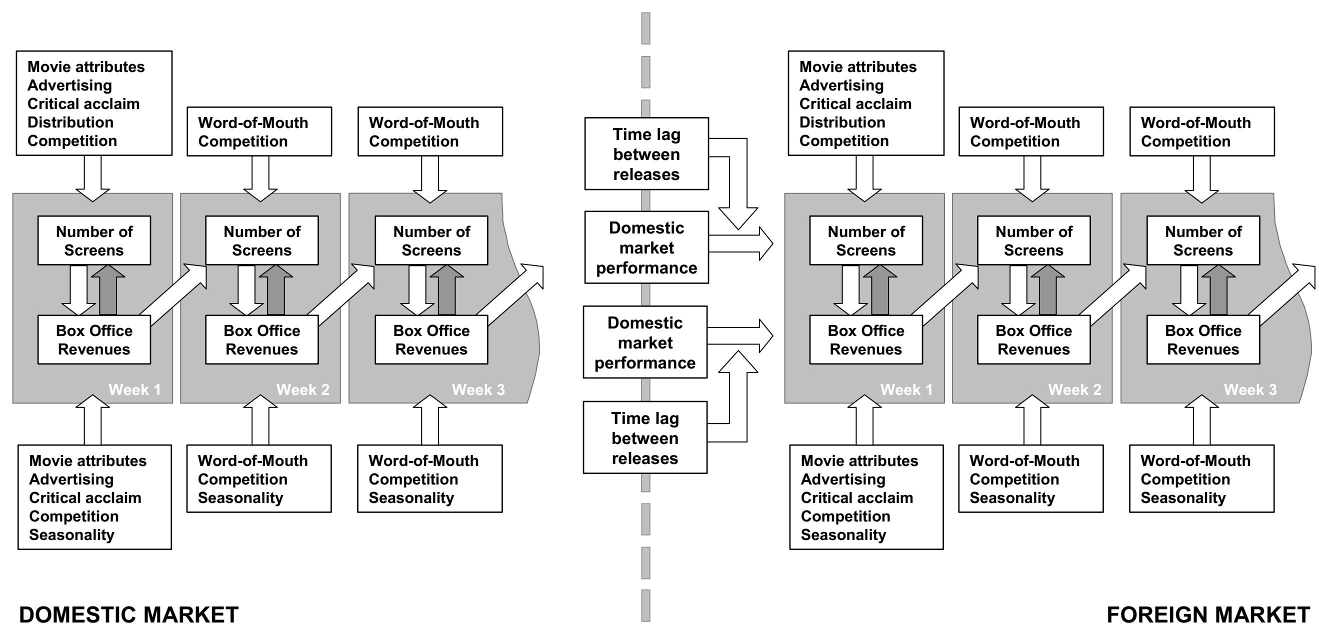
Integrating literature in the areas of international diffusion, success-breeds-success trends, and determinants of motion picture performance, we develop the hypotheses that guide the empirical analysis. Where applicable, this process was also informed by interviews with motion picture executives in both the U.S. and foreign markets.

Figure 1 depicts our conceptual framework. It reveals hypothesized relationships about dynamics across and within domestic and foreign markets. Table 1 lists all these hypotheses and provides insights into existing empirical evidence in the context of the motion picture industry. For brevity, we discuss only some general observations regarding the hypotheses below.

Hypotheses Regarding Dynamics Across Markets

Figure 1 reveals two differences between the domestic and foreign market, which directly relate to the two key hypotheses about international diffusion. First, it is likely that information about a motion picture's

Figure 1 **Conceptual Framework: Domestic and Foreign Market**



performance in the domestic market leaks to audiences and exhibitors in foreign markets, for example via word-of-mouth communication or media coverage. In case of a sequential release, this leads to a crucial difference in information availability, which in turn is likely to lead to differences in diffusion patterns across both markets (e.g., Putsis et al. 1997). We expect the relationship between performance in both markets to be positive, as expressed in Hypothesis 1, for two main reasons. On the one hand, the domestic market can act as a quality filter, i.e., reveal the true attractiveness of a media product. This is in line with international diffusion research findings, which has consistently provided evidence for cross-country lead or demonstration effects (e.g., Dekimpe et al. 2000a, b; Helsen et al. 1993; Kumar and Krishnan 2002; Mahajan and Muller 1994; Takada and Jain 1991; also see Dekimpe et al. 2000c). On the other hand, herds, cascades, superstars, positive feedback effects, and other success-breeds-success concepts—not necessarily related to a product's underlying quality—could also play a role (e.g., Arthur 1989, Rosen 1981, Bikhchandani et al. 1992, Frank and Cook 1995). The latter reflects the idea that initial performance differences in the lead market could set in motion the virtuous cycle (Shapiro and Varian 1999) that drives later performance, first in the domestic, and later in the foreign market. Several players feed this process: moviegoers jumping on the bandwagon of movies that were hits in other countries, media outlets giving disproportional attention to popular movies in their coverage of film markets, and exhibitors and distributors riding positive information cascades by giving more exposure to successful movies. It is likely that such dynamics extend beyond national borders.[1]

Second, extending the latter ideas, although empirical research is limited and existing evidence on the impact of timing is contradictory (Ganesh and Kumar 1996), the time lag between releases is likely to be a critical element in the emergence and development of success-breeds-success trends—on both the supply and demand side. The perishable nature of motion pictures, i.e., the idea that novelty wears out, makes an effect of the time lag probable. Evidence emerging from the motion picture industry confirms this view. For example, a decade ago, Friedman (1992) noted that motion pictures were opening overseas earlier than previously, to take advantage of the wide reach of publicity generated in America: "the impact of an American release can generate huge revenues overseas." In line with the latter, we expect the time lag between releases to moderate the relationship between domestic and foreign performance—both in terms of screens and revenues (Hypotheses 2).[2]

Hypotheses Regarding Dynamics Within Markets

As Figure 1 shows, in line with managerial practice in the motion picture industry, we make a conceptual distinction between the first week and subsequent weeks. The idea is that the importance of some factors is likely to diminish when initial box office performance data become available—i.e., after the first week.[3] For example, rather than hold on to a priori predictions of demand, exhibitors adapt supply to demand as it unfolds. Other factors—time-variant factors—play a role for the entire duration of a movie's run.

As far as the relationship between screens and revenues is concerned, we hypothesize that the number of screens allocated to a movie in its first week influences the box office revenues in that week (Jones and Ritz 1991; Hypothesis 3), for example because the availability of movies signals their attractiveness or popularity among other audience members, or because, due to the habitual nature of moviegoing behavior, exposure opportunities directly translate to

[1] A comment by Puttnam (1992) is interesting in this regard: "[British journalists] always decide how much space to give the opening of a movie based on its success in America."

[2] Although we test only for monotonic effects, we acknowledge that the relationship could potentially be nonmonotonic, where longer lag times initially *strengthen*, but further increases in lag time only *weaken* the relationship between performance in both markets. This is consistent with the idea that a buzz needs some time to develop and reach the foreign market but can also rapidly weaken, for example, if supply fails to meet demand.

[3] Strictly speaking, these variables may also have an impact on the exhibition intensity after the first week—for example, if contracts negotiated before the start of a movie have an impact beyond the opening week. In the model, this "persistence" is captured by the relationship between screens and revenues across time.

Table 1 Hypotheses, Existing Empirical Evidence, and Summary of Findings

Hypotheses	Existing Empirical Evidence for the Motion Picture Industry	Findings: US	FRA	GER	SPA	UK
Hypotheses Regarding Dynamics Across Markets						
1. The stronger a movie's domestic market performance:						
(a) the higher its number of screens in the opening week in the foreign market.	(a) No evidence	—	✓	✓	✓	
(b) the higher its revenues in the opening week in the foreign market.	(b) Some evidence (Neelamegham and Chintagunta 1999)	—	✓	✓	✓	✓
2. The longer the time lag between a movie's domestic and foreign release, the weaker the relationship between…						
(a) its domestic market performance and its opening-week number of screens in the foreign market.	(a) No evidence	—	✓	✓	✓	
(b) its domestic market performance and its opening-week revenues in the foreign market.	(b) No evidence	—	✓			
Hypotheses Regarding Dynamics Within Markets						
3. The higher a movie's number of screens in any given week, the higher its revenues in the same week.	Strong evidence for a relationship with weekly revenues (Jones and week, the higher its revenues in the same week. 1991, Sawhney and Eliashberg 1996), opening week revenues Ritz and Chintagunta 1999), and cumulative rentals or revenues (e.g., Litman 1982, Litman and Kohl 1989, Sochay 1994, Litman and 1998)	✓	✓	✓	✓	✓
4. The higher a movie's expected revenues in any given week, the higher its number of screens in the same week.	No evidence	✓	✓	✓	✓	✓
5. The higher a movie's production budget, the higher its number of screens in the opening week.	No evidence Strong evidence for a relationship with *revenues* (Litman 1982, Litman and Kohl 1989, Litman and Ahn 1998, Prag and Casavant 1994, Wallace et al. 1993, Zufryden 2000)		✓		✓	
6. The higher a movie's star power:						
(a) the higher its number of screens in the opening week.	(a) No evidence		✓	✓	✓	
(b) the higher its revenues in the opening week.	(b) Contradictory evidence: • Strong evidence (Levin and Levin 1997, Litman and Kohl 1989, Sochay 1994, Neelamegham and Chintagunta 1999, Sawhney and Eliashberg 1996, Wallace et al. 1993) • Limited or no evidence (Austin 1989, De Vany and Walls 1999, Litman 1983, Litman and Ahn 1998, Ravid 1999)	✓				
7. The higher a movie's director power:						
(a) the higher its number of screens in the opening week.	(a) No evidence					
(b) the higher its revenues in the opening week.	(b) Some evidence (Litman 1982, Litman and Kohl 1989, Sochay 1994, Litman and Ahn 1998)					
8. The higher a movie's advertising expenditures:						
(a) the higher its number of screens in the opening week.	(a) No evidence	✓	—	—	—	✓
(b) the higher its revenues in the opening week.	(b) Some evidence (Prag and Casavant 1994; Zufryden 1996, 2000; Lehmann and Weinberg 2000; Moul 2001)	✓	—	—	—	

Table 1 (cont'd.)

Hypotheses	Existing Empirical Evidence for the Motion Picture Industry	Findings US	FRA	GER	SPA	UK
Hypotheses Regarding Dynamics Within Markets (cont'd)						
9. The higher a movie's critical acclaim:						
(a) the higher its number of screens in the opening week.	(a) No evidence	×				×
(b) the higher its revenues in the opening week.	(b) Contradictory evidence: • No evidence for relationship with opening-week revenues (Eliashberg and Shugan 1997). • Strong evidence for a positive relationship with cumulative rentals or revenues (Jedidi et al. 1998, Litman 1982, Litman and Kohl 1989, Litman and Ahn 1998, Prag and Casavant 1994, Ravid 1999, Sawhney and Eliashberg 1996, Eliashberg and Shugan 1997, Zufryden 2000). • Some evidence for a U-shaped relationship with cumulative rentals (Wallace et al. 1993)	✓				✓
10. A movie distributed by one of the "majors" opens on a higher number of screens than a movie not distributed by a "major."	No evidence Contradictory evidence for the relationship with *revenues*: • Some evidence for a positive relationship with opening-week revenues in United States but not in foreign markets (Neelamegham and Chintagunta 1999) • Some evidence for a positive relationship with cumulative revenues (Litman 1983, Litman and Kohl 1989) • No evidence for a positive relationship with cumulative revenues (Sochay 1994, Litman and Ahn 1998)					
11. The more positive the word-of-mouth communication for a movie in any given week:						
(a) The higher its number of screens in the same week.	(a) No evidence	✓	✓	✓	✓	✓
(b) the higher its revenues in the same week.	(b) No evidence (Neelamegham and Chintagunta 1999)	✓	✓	✓	✓	
12. The weaker a movie's competitive environment in any given week:						
(a) the higher its number of screens in the same week.	(a) No evidence	✓	✓	✓	✓	✓
(b) the higher its revenues in the same week.	(b) Some evidence for a negative relationship with cumulative revenues (Sochay 1994, Litman and Ahn 1998) and weekly revenues (Jedidi et al. 1998, Zufryden 2000)	✓	✓	✓	✓	✓
13. The more a movie plays in a "high-season" week, the higher its revenues.	Some evidence: • Some evidence for a positive relationship with cumulative rentals or revenues (e.g., Litman 1982, Litman and Kohl 1989, Radas and Shugan 1998) • Contradictory evidence for a positive relationship with weekly revenues: • Some evidence (Zufryden 2000) • Limited or no evidence (Ravid 1999, Einav 2001)		✓		✓	✓

Notes. FRA = France, GER = Germany, SPA = Spain, UK = United Kingdom. ✓ = significant with $p = 0.05$ in the hypothesized direction; × = significant with $p = 0.05$ but not in the hypothesized direction; — = not applicable. Reported results for Hypotheses 11–13 are based on estimates for $t = 1$ and $t \geq 2$.

admissions. Revenues in the first week, in turn, influence the number of screens allocated to the movie in its second week, which again drives revenues, and so on (e.g., De Vany and Walls 1996). Specifically, we hypothesize that exhibitors allocate screens based on expectations of revenues (Hypothesis 4). Expected revenues are updated each week on the basis of earlier expectations and realized revenues in previous week(s). In a movie's opening week, when no information on actual revenues is available, exhibitor's expectations are determined by a variety of objective and subjective criteria (including the buzz for a movie).[4]

Table 1 reveals the complete lack of research on determinants of the *screens* allocated to movies. Most research on the behavior of exhibitors is normative in nature (e.g., Eliashberg et al. 2000, 2001; Swami et al. 1999) and does not provide direct insights into the drivers of screen allocations. Without exception, hypotheses on exhibitors' screen allocations (Hypotheses 1a, 2a, 3, 5, 6a, 7a, 8a, 9a, 10, 11a, and 12a) are thus not grounded in existing empirical evidence. However, because we hypothesize that screens drive revenues, existing research on the determinants of *revenues* is relevant—the hypotheses implictly reflect the idea that relationships between determinants and first-week *revenues* can at least partly be explained by relationships between these determinants and first-week *screens*. When it comes to the role of production budget (Hypothesis 5) and the involvement of a major distributor (Hypothesis 10), our hypotheses imply that the number of first-week screens mediates the relationship between these determinants and first-week revenues. We do not hypothesize a direct effect on the behavior of audiences but again list relevant empirical evidence on the revenues side.

[4] Drawing on interviews with motion picture executives, we recognize that screen allocations, particularly early in a movie's run, are often the outcome of a negotiation process between exhibitors and distributors rather than a decision made purely by exhibitors. We note in this respect that our view of adaptive exhibitors does not contrast with a situation in which exhibitors adhere to a contract with a distributor and maintain a certain number of screens for a number of weeks, provided that the revenues are satisfactory. Exhibitors are known to pull a movie despite contractual agreements with a distributor if it bombs.

Although the abundance of research on the determinants of *revenues* generally appears to lead to well-supported hypotheses, some caveats apply here as well. First, as indicated, conventional wisdom reported in the table is largely based on studies based on single-equation analyses that fail to account for the interplay between screens and revenues (e.g., Litman 1982, Litman and Kohl 1989, Sochay 1994, Prag and Casavant 1994, Wallace et al. 1993). This may have led to incorrect conclusions about the role and significance of determinants. Second, studies referred to in Table 1 employ a variety of measures for the dependent variable, most notably cumulative revenues, cumulative rentals, weekly revenues, and opening-week revenues. Direct evidence in support of our hypotheses is often limited. Third, measures of determinants, the indendepent variables, vary widely. In some cases, variations in measurements may underlie contradictory findings on the impact of determinants. In other cases, for example Neelamegham and Chintagunta's (1999) finding on the impact of word-of-mouth communication on revenues (Hypothesis 11b), shortcomings in measures may explain the lack of empirical support for hypotheses. Fourth, with the exception of work by Neelamegham and Chintagunta (1999), existing empirical research on the role of determinants focuses solely on the United States.

3. Data, Measures, Model, and Estimation

Data

Our sample consists of all movies that (a) were produced or co-produced in the United States, (b) were released in the United States in 1999, and (c) appeared at least once in the U.S. box office top 25. This leads to a total of 164 movies. In addition to the United States (the domestic market), the focus is on four foreign countries: France, Germany, Spain, and the United Kingdom. Two main considerations played a role in selecting these markets: they rank highest in Europe in terms of annual movie admissions (EAO 2001), and box office data collection procedures are similar across countries.

Our dataset includes weekly box office revenues and the weekly number of screens for all movies, for both the United States and the foreign countries in which they were released, obtained from AC Nielsen EDI. Unlike many previous studies on motion pictures (e.g., De Vany and Walls 1996, Neelamegham and Chintagunta 1999), box office data are available for the entire duration of the movies' run. Our data cover 7,462 unique country-movie-week combinations. In addition, we use data on a wide range of other characteristics, including production budget, genre, star power, director power, ratings, distributor characteristics, and critical reviews, obtained from such sources as *Entertainment Weekly*, the *Internet Movie Database*, *The Hollywood Reporter*, and *Variety*. For the United States and United Kingdom, we have information on total advertising expenditures, collected by *Competitive Media Reporting* (CMR) and *ACNielsen MMS*, respectively. As described below, we use data obtained from the *Hollywood Stock Exchange* (HSX) to develop a measure of expected first-week revenues. In constructing measures of competition, we employ data for 537 movies playing alongside our sample of 164 movies between January 1, 1999 and June 21, 2000 in the United States, and between January 1, 1999 and December 21, 2000 in the foreign markets (when the last remaining movie ends its run in each market). Finally, in constructing a measure of seasonality, we turn to Vogel (2001) for aggregate weekly U.S. box office revenues from 1969 to 1984, as well as to *ACNielsen EDI* and *Variety* for weekly box office data for all five markets for 1998.

Measures

We describe the variables, their operationalizations, and their sources, in Table 2.

Note that in the creation and selection of variables, the ex-ante nature of our modeling approach played a crucial role: we base our variables only on information that is available to relevant players at the time the variable enters the model. Below, for brevity, we clarify only measures for expected first-week revenues, word-of-mouth communication, and competition.

Our measure of expected first-week revenues, $REVENUES_1^{**}$, is based on data obtained from the Hollywood Stock Exchange (www.hsx.com). HSX, a popular online market simulation with nearly 400,000 registered accounts by the end of 1999, allows its users to trade in, among other things, movie stocks. Participants start with a total of 2 million so-called Hollywood dollars, and can manage their portfolio by strategically buying and selling stocks. Typically, stocks for a particular movie will be available months, sometimes years, in advance. The first Saturday after a movie's wide U.S. release—i.e., before early box office figures are available—trading is halted. When trading resumes on Monday, prices are adjusted based on the movie's opening weekend gross, using a set of standard multipliers.[5] Encouraged by HSX's popularity and its potential power as a research tool (e.g., Pennock et al. 2001), we construct an expectation of opening weekend revenues based on the halt prices and multipliers. Table 3 lists three examples.

Opening-weekend expectations constructed using HSX data are available only for movies that opened "wide," which is the case for 138 movies (84%) in our sample. As detailed in Table 2, we use historical data to generate first-weekend expected revenues for the 26 movies (16%) that opened "limited," to transform all first-*weekend* to first-*week* expectations, and to obtain expected first-week revenues in foreign markets.

We capture word-of-mouth (*WOM*) for a movie by means of the revenues per screen collected in the previous week. Revenues per screen is the primary measure used by industry experts to assess a movie's weekly performance relative to other movies and to judge its growth potential, i.e., the likelihood that the movie has playability (Vogel 2001).[6] Practitioners often use terms such as *playability, legs, longevity*, and *driven by word-of-mouth* interchangeably to indicate the extent to which a movie can maintain an audience throughout its run, and contrast this with *marketability*, which refers to a movie's ability to secure a large opening audience.[7] We note that our

[5] For example, for a movie opening on a Friday, the adjusted price is 2.9* the opening weekend gross (in $ millions).

[6] For example, David Dinerstein, Miramax VP of Marketing, commented regarding the movie *Pulp Fiction*: "We felt we had the movie, and with the per-screen average as high as it was [$6,960], we would continue to gross on that" (Lukk 1997).

[7] Strictly speaking, word-of-mouth communication is the key driver of a movie's playability or legs. Industry insiders widely acknowledge a movie's playability to be as important to its financial success as its marketability (Daniels et al. 1998).

Table 2 Variables, Descriptions, Measures, and Sources

Variable	Description	Measure	Source
REVENUES	Weekly revenues.	Weekly revenues (in 000, local currency)[1]	*ACNielsen EDI*
SCREENS	Weekly number of screens	Weekly number of screens	*ACNielsen EDI*
$REVENUES_1^{**}$	Expected revenues, first week	U.S., first-weekend revenues: • Wide openers (>650 screens): expected first-weekend revenues = [HSX halt price] ∗ [HSX multiplier] • Limited openers (≤650 screens): expected first-weekend revenues = \$350,000 (average first-weekend revenues for similar limited openings in 1998) Foreign markets, first-weekend revenues: • [U.S. first-weekend revenues] ∗ [yearly foreign admissions as % of U.S. admissions] ∗ [% of foreign box office grosses collected by U.S.-produced movies] ∗ [local currency versus U.S.\$ exchange rate] Expected first-week revenues (in 000) = [expected first-weekend revenues (in 000)] ∗ [100/72] (opening weekend revenues were on average 72% of opening week revenues in 1998)	*Hollywood Stock Exchange (HSX)*
$REVENUES^{**}$	Expected revenues, beyond first week	Constructed using double exponential smoothing (Equations (5)–(7))	—
BUDGET	Production budget	Production budget (in \$000)[2]	*Internet Movie Database*, *Variety*
STAR	Star power	Movies are scored (on a 1–100 scale) according to their highest rated star	*Hollywood Reporter Star Power Index* (1998 edition)
DIRECTOR	Director power	Movies are scored (on a 1–100 scale) according to their director	*Hollywood Reporter Director Power Index* (1998 edition)
AD_EXP	Advertising expenditures	Advertising expenditures (in 000, local currency): United States and United Kingdom only	United States: *Competitive Media Reporting* (CMR); United Kingdom: *ACNielsen MMS*
REVIEWS	Critical reviews	American grades assigned by leading newspaper critics (Roger Ebert, *Chicago Sun-Times*; Jami Bernard, Knight-Ridder Syndicate; Carrie Rickey, *Philadelphia Inquirer*; Mike Clark, *USA Today*; Rita Kempley, *The Washington Post*; Keneth Turan, *Los Angeles Times*; and EW), converted to a 1–5 scale	*Entertainment Weekly* (EW)
DISTR_MAJOR	Major distributor	Dummy, indicating whether a movie is distributed by a major distributor (coded per country): Paramount, Sony Pictures (Columbia Pictures, TriStar), The Walt Disney Company (Buena Vista, Touchstone, and Hollywood Pictures), Twentieth Century Fox, Universal, and Warner Bros (New Line, Fine Line).	*ACNielsen EDI*

Table 2 (cont'd.)

Variable	Description	Measure	Source
WOM	Word-of-mouth communication	Revenues per screen in the previous week.	*ACNielsen EDI*
COMP_SCR_NEW	Competition for "screen space" from new releases	New releases, weighted by production budget, for each calender week in each country: • Number of new releases ∗ every $10 million of their production budget.[3]	*ACNielsen EDI*, *Internet Movie Database*, *Variety*
COMP_SCR_ONG	Competition for "screen space" from ongoing movies	Average age of ongoing releases, for each calender week in each country:[4] • United States: Average age (in weeks) of the Top 25 movies in the previous week (excluding the movie under consideration) • Foreign markets: Average age (in weeks) of the Top 10 movies in the previous week (excluding the movie under consideration)	*ACNielsen EDI*

COMP_REV	Competition for the attention of audiences	Presence of similar movies, weighted by their age, for each week of a movie's run:
		• United States: Number of instances in which a movie's genre or MPAA rating is the same as that of any of the (other) Top 25 movies on release, divided by the age (in weeks) of each of those competing movies
		• Foreign markets: Number of instances in which a movie's genre is the same as that of any of the (other) Top 10 movies on release, divided by the age (in weeks) of each of those competing movies:
		  • Genre has 5 categories (action, comedy, drama, romance, and/or thriller)
		  • MPAA rating has 4 categories (G, PG, PG-13, or R)[5]
			ACNielsen EDI, *Internet Movie Database*

SEASON	Seasonality	Seasonality (on a scale of 0–100), for each calender week in each country: • United States: Normalized weekly revenues over 1969–1984 • Foreign markets: Normalized weekly revenues over 1998	*ACNielsen EDI*
US_PERF	Domestic (U.S.) market performance	Average of revenues per screen over the first two weeks of a movie's U.S. run (in 000).	*ACNielsen EDI*
TIME_LAG	Time lag between domestic (U.S.) and foreign release	Number of days between a movie's U.S. and each foreign market release	*ACNielsen EDI*

[1]In France, the variable *REVENUES* reflects movie admissions. The difference is marginal if we consider that ticket prices are uniform within each market.

[2]Data for 139 movies (85%) were available; missing values were replaced with the mean.

[3]For example, if in a given week movie X is confronted with two new releases, movie Y with a budget of $50 million and movie Z with a budget of $115 million, movie X is assigned a score of $5+11=16$.

[4]Higher scores represent *weaker* competition.

[5]Consider a movie X with genre action and rating PG-13, that in a given week is playing alongside two other movies, movie Y in its first week of release with genre "action" and rating R, and movie Z in its fourth week of release with genre action and rating PG-13. This leads to the following overall score for movie X's competitive environment in this particular week: $(1/1)+(2/4)=1.5$.

Table 3 Constructing Expected Opening Weekend Revenues Using HSX Data: Three Examples

	"Bats"	"Inspector Gadget"	"The General's Daughter"
HSX halt price (in H$)	20.01	51.13	49.00
Multiplier	2.90	2.90	2.90
Expected 1st weekend BO			
(=(halt price/multiplier) ∗ $m)	6,900,000	17,631,034	16,896,552
Actual 1st weekend BO	4,720,000	21,890,000	22,330,000
Prediction percentage error			
(=(expected − actual)/actual)	46%	−19%	−24%

choice for a measure of word-of-mouth based only on previous-period (rather than cumulative) data is consistent with previous research based on a discrete-time modeling framework (Hahn et al. 1994, Lilien et al. 1981). It is also in line with work by De Vany and Walls (1996) and Moul (2001), both in the context of motion pictures.

Measures of the strength of a movie's competitive environment featured in previous research roughly fall in two categories: first, an ex-ante measure, the number of new releases introduced at each stage of a movie's run (e.g., Jedidi et al. 1998, Zufryden 2000) and, second, an ex-post measure, revenues accruing to movies at the top of the charts as a percentage of the total revenues for that week (e.g., Sochay 1994, Litman and Ahn 1998). Here, using ex-ante measures of competition, we differentiate between competition for screens (i.e., screens allocated by *exhibitors*) and for revenues (i.e., attention from *audiences*).

We use two variables to measure competition for screens. First, to capture competition for screens from new releases (*COMP_SCR_NEW*), we count the number of new releases in the current week's Top 25 (in the United States) or Top 10 (in the foreign markets), but acknowledging that some movies have a larger impact than others when they enter the market, we score new releases according to their production budgets. Note that production budgets relate to several attributes (e.g., star power, advertising expenditures, and special effects) and reflect the stakes involved for distributors. Second, focusing on ongoing movies, we construct a measure (*COMP_SCR_ONG*) that reflects the amount of shelf space that may become available—or can be made available—at each stage of a movie's run. To that end, for each movie at each stage of its run, we calculate the average age of the Top 25 (in the United States) or Top 10 (in the foreign markets) movies in the previous week. The underlying idea is in line with exhibition practices: the lower the average age of movies on release in the previous week, the more difficult it is for exhibitors to free up screens, and hence the stronger the competition for screens experienced by the movie under consideration.

Our measure of competition for audience attention (*COMP_REV*) captures the idea that a movie generally experiences stronger competition from movies that are similar in certain respects, as well as the phenomenon that the influence of competing movies decreases the longer they are on release. In the domestic market, we opt to express similarity in terms of two key attributes that define a movie's potential audience: genre and MPAA ratings. In the foreign market, lacking reliable data on ratings, we focus on genre only.

Model

Several key considerations underlie our model specification:

- First, as we are interested in the drivers of the behavior of both motion picture exhibitors and audiences, we construct a system of two interdependent equations: one equation with revenues as the dependent variable (the revenues equation) and one with screens as the dependent variable (the screens equation).
- Second, recognizing that movies collect revenues over a period of weeks or months and the role of determinants can vary for different stages of a movie's run (e.g., Radas and Shugan 1998, Sawhney and Eliashberg 1996), we develop a system of *dynamic* equations.

• Third, addressing recommendations by Sawhney and Eliashberg (1996) and Neelamegham and Chintagunta (1999) to account for the endogeneity of the number of screens when estimating revenues, we treat both screens and (expected) revenues as endogenous variables.

• Fourth, we assume that in each time period (i.e., week), the errors in the two equations may be correlated. This implies that we take into account that exogenous factors not included in our model specification could simultaneously "shock" both revenues and screens.[8]

• Fifth, we opt for a multiplicative or, more specifically, a log-linear formulation (e.g., Zufryden 1996). This mostly follows from our aim to incorporate that when a movie has not been allocated any screens, by definition, it will not collect any revenues, and similarly, when exhibitors do not expect to collect any revenues with a particular movie, they will not allocate any screens to it. Another advantage of the log-linear form is that the estimated coefficients directly represent the elasticity of the right-hand-side variable with respect to changes in the left-hand-side variable.

• Sixth, we take an ex-ante (as opposed to ex-post) modeling approach, in the sense that our model only uses information that is available before or at a certain time period t to model the behavior of exhibitors and audiences at that time period.

• Finally, we distinguish a movie's opening week from its run in later weeks. On the revenues side, this is based on the realization that, in assessing a movie's quality in its opening week, potential audiences have to rely on external sources, whereas they can rely on word-of-mouth communication among consumers later in a movie's run. On the screens side, exhibitors are forced to allocate screens based just on expectations in a movie's opening week, while they can lean on information about realized demand in later weeks. We note that the resulting model specification—a system with two pairs of equations—is in line with the widely held view that a movie's opening week generally drives its success (or failure) in later weeks.

[8] One example of such a factor is a Best Picture Oscar Academy Award nomination for a movie still on release—this may cause an increase in screens and audience attention.

Revenues Equations. Turning to the mathematical model, Equation (1) expresses the opening week revenues, and Equation (2) reflects the revenues beyond the opening week.

$$REVENUES_{it} = e^{\alpha_0} \cdot SCREENS_{it}^{\alpha_1} \cdot X_{Rit}^{\alpha_2} \cdot Z_{Ri}^{\alpha_3} \cdot e^{\varepsilon_{Rit}} \quad \text{for } t = 1, \quad (1)$$

$$REVENUES_{it} = e^{\alpha_0} \cdot SCREENS_{it}^{\alpha_1} \cdot X_{Rit}^{\alpha_2} \cdot e^{\alpha_3 D_{Rit}} \cdot e^{\varepsilon_{Rit}} \quad \text{for } t \geq 2. \quad (2)$$

Here, $REVENUES_{it}$ denotes the box office revenues for a movie i at time t, $SCREENS_{it}$ the number of screens (shelf space) allocated to a movie i at time t, X_{Rit} vectors of time-variant variables, Z_{Ri} vectors of time-invariant variables, D_{Rit} vectors of dummy variables, and ε_{Rit} the error term. As far as the vectors of covariates are concerned, X_{Rit} consists of the variables WOM_{it}, $COMP\_REV_{it}$ and $SEASON_{it}$, Z_{Ri} includes the variables $STAR_i$, $DIRECTOR_i$, AD_EXP_i (for the United States and United Kingdom only), and $REVIEWS_i$. For the foreign markets, Z_{Ri} includes US_PERF_i and, to assess a moderating role of $TIME\_LAG_i$, $[TIMELAG_i * US\_PERF_i]$. D_{Rit} covers $(t-1)$ time dummies (as explained in the "Estimation" section).

Screens Equations. Equations (3) and (4) express the number of screens allocated to a movie in its opening week and in its second week and onward, respectively:

$$SCREENS_{it} = e^{\beta_0} \cdot (REVENUES_{i1}^{**})^{\beta_1} \cdot X_{Sit}^{\beta_2} \cdot Z_{Si}^{\beta_3} \cdot e^{\beta_4 D_{Si}} \cdot e^{\varepsilon_{Sit}} \quad \text{for } t = 1, \quad (3)$$

$$SCREENS_{it} = e^{\beta_0} \cdot (REVENUES_{it}^{**})^{\beta_1} \cdot X_{Sit}^{\beta_2} \cdot e^{\beta_3 D_{Sit}} \cdot e^{\varepsilon_{Sit}} \quad \text{for } t \geq 2. \quad (4)$$

Here, $REVENUES_{i1}^{**}$ denotes the expected opening-week revenues, $REVENUES_{it}^{**}$ expected revenues beyond the opening week, X_{Sit} vectors of time-variant variables, Z_{Si} vectors of time-invariant variables, D_{Sit} vectors of dummy variables, and ε_{Sit} the error term. X_{Sit} includes the variables WOM_{it}, $COMP\_SCR\_NEW_{it}$ and $COMP\_SCR\_ONG_{it}$, Z_{Si} includes the variables $BUDGET_i$, $STAR_i$, $DIRECTOR_i$, AD_EXP_i (for the United States and United Kingdom only), $REVIEWS_i$ and, for the foreign markets, US_PERF_i and moderator $[TIMELAG_i * US\_PERF_i]$, and D_{Sit} includes $DISTR\_MAJOR_i$ (in Equation (3) only) as well as $(t-1)$ time dummies (in Equation (4) only).

Variable $REVENUES^{**}_{it}$ in Equation (4) deserves further attention. We use an adaptive expectations framework to construct this variable (e.g., Judge et al. 1985). Specifically, we assume that the number of screens that exhibitors allocate to a movie is influenced by the anticipated revenues for that movie. We derive the anticipated value by means of an exponential smoothing procedure, in which last week's anticipated value is updated by a fraction of the prediction error:

$$REVENUES^{*}_{t} = REVENUES^{*}_{t-1} + \lambda(REVENUES_{t-1} - REVENUES^{*}_{t-1}) \qquad \text{for } t \geq 2. \quad (5)$$

The above equation entails so-called single exponential smoothing. $REVENUES^{*}_{it}$ represents the anticipated revenues ($*$ indicates simple smoothing), and λ represents the smoothing parameter (which varies between 0 and 1). Because the evolution of box office revenues is likely to exhibit a downward trend, we opt for a double exponential smoothing procedure. Applied to the modeling problem at hand, with T_t denoting the trend and γ representing a second smoothing parameter (which also varies between 0 and 1), we assume:[9]

$$T_t = \gamma(REVENUES^{*}_{t} - REVENUES^{*}_{t-1}) + (1-\gamma)T_{t-1} \qquad \text{for } t \geq 2, \quad (6)$$

where $T_1 = 0$.

The anticipated revenues $REVENUES^{**}_{t}$ (with ** representing double smoothing) are now derived in the following manner (see, for example, Moskowitz and Wright 1979):

$$REVENUES^{**}_{t} = REVENUES^{*}_{t} + \frac{1-\gamma}{\gamma}T_t \qquad \text{for } t \geq 2. \quad (7)$$

[9] While a double smoothing procedure with *exponential* trend may appear more appropriate in this context, its average fit turns out to be worse than double smoothing with *linear* trend as employed here.

Estimation

Our estimation can be divided into two steps: (1) estimation of the double smoothing parameters and (2) estimation of the system of equations.

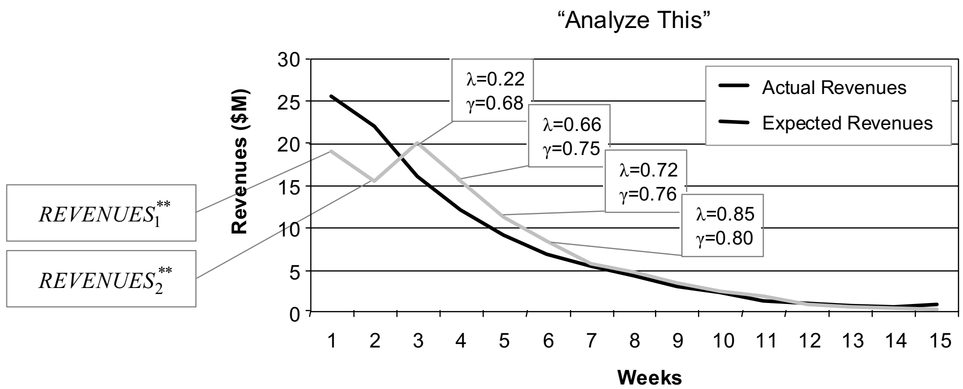
In the first step, we derive expected revenues ($REVENUES^{**}_{it}$) by means of the double exponential smoothing procedure expressed in Equations (5)–(7), i.e., by estimating λ and γ. To ensure that our measure is ex-ante, we perform a succession of smoothing procedures for each movie, using all revenue information available *prior* to the week for which the expected revenues are computed. That is, in week 5, expected revenues are calculated using actual and predicted values for week 1 through 4; in week 6, expected revenues are calculated using actual and predicted values for week 1 through 5, and so on. Given that we need at least two weeks of data to estimate the smoothing parameters, the smoothing procedure is first performed to generate a movie's expected revenues in week 3. Lacking sufficient information to estimate smoothing parameters in week 2, we calculate $REVENUES^{**}_{i2}$ by averaging *actual* and *expected* opening-week revenues (i.e., *REVENUES* and $REVENUES^{**}_{i1}$), and then multiplying that average by 0.70.[10] For $t \geq 3$, we minimize the sum of squared differences between actual and predicted revenues—the dominant model-fitting criterion in exponential smoothing (e.g., Gardner 1999)—to estimate values for λ and γ for each movie separately. Figure 2 illustrates the double smoothing procedure for one example, *Analyze This*, a good representation of the most common temporal pattern of weekly revenues.

In the second step, we estimate the system of Equations (1)–(4). We begin by linearizing Equations (1)–(4), i.e. rewriting them in terms of natural logarithms:

$$LN(REVENUES_{it}) = \alpha_0 + \alpha_1 LN(SCREENS_{it}) + \alpha_2 LN(X_{Rit}) + \alpha_3 LN(Z_{Ri}) + \varepsilon_{Rit} \qquad \text{for } t=1, \quad (8)$$

[10] The latter follows from an analysis of 1998 U.S. box office data, which reveal that the median drop in revenues from the first to the second week is approximately 30%.

Figure 2 **Estimating Double Exponential Smoothing Parameters: An Example**



$$LN(REVENUES_{it}) = \alpha_0 + \alpha_1 LN(SCREENS_{it}) + \alpha_2 LN(X_{Rit}) + \alpha_3 D_{Rit} + \varepsilon_{Rit} \quad \text{for } t \geq 2, \quad (9)$$

$$LN(SCREENS_{it}) = \beta_0 + \beta_1 LN(REVENUES^{**}_{i1}) + \beta_2 LN(X_{Sit}) + \beta_3 LN(Z_{Si}) + \beta_4 D_{Si} + \varepsilon_{Sit} \quad \text{for } t = 1, \quad (10)$$

$$LN(SCREENS_{it}) = \beta_0 + \beta_1 LN(REVENUES^{**}_{it}) + \beta_2 LN(X_{Sit}) + \beta_3 D_{Sit} + \varepsilon_{Sit} \quad \text{for } t \geq 2. \quad (11)$$

We employ a three-stage least-squares (3SLS) procedure to estimate the system of Equations (8)–(11). OLS is inconsistent because the endogenous variable *SCREENS* used as a regressor in the revenues equation is contemporaneously correlated with the disturbance term in the same equation; the presence of lagged endogenous variables also makes it biased. Furthermore, as the errors across equations may be correlated, a 3SLS procedure is more efficient than a two-stage least-squares (2SLS) procedure (e.g., Zellner 1962, Zellner and Theil 1962). We note that, in general terms, Equations (8)–(11) represent a triangular system with a nondiagonal disturbance covariance matrix (if it were not for the assumption of simultaneity, the model could be regarded as recursive). In such cases, 3SLS estimation is preferred (Lahiri and Schmidt 1978). To our knowledge, empirical applications based on this particular type of model specification have not been published.

In the system of Equations (8)–(11), we treat *SCREENS* and *REVENUES* as endogenous, and the other variables as exogenous.[11] When estimating Equations (9) and (11) we exclude lagged endogenous variables—and terms that incorporate such variables, i.e., both *REVENUES*** and *WOM*—from the instruments set to alleviate potential estimation problems related to autocorrelation (Greene 1997). Instead, in an aim to select instruments that are correlated with the lagged endogenous variables but independent of each of the errors, we turn to the set of time-invariant exogenous variables used in estimating opening week Equations (8) and (10). We employed a variation of Hausman's specification test (Wu 1973) to test for the appropriateness of a model that accounts for both endogeneity and simultaneity. The findings lend support to our approach. For each country and each set of equations, an instrumental variables' (IV)

[11] Acknowledging that an intricate relationship may exist between the timing of foreign releases, performance in the domestic market, and a range of exogenous variables, we explore the question whether it deserves recommendation to treat *TIME_LAG* as an endogenous variable in Equations (8) and (10). We find that the release time lag is negatively correlated with several key movie attributes and advertising expenditures but that we can explain only a small portion of the variance in time lags (with Adjusted R^2 ranging from 0.12 to 0.18). Even though strictly speaking the direct use of *TIME_LAG* in Equations (8) and (10) may violate the assumption of error term independence (e.g., Dubin and McFadden 1984), we therefore opt not to replace it with a fitted value.

method (i.e., either 2SLS or 3SLS) is preferred over OLS. Specifically, for all five countries, 3SLS emerges as the preferred estimator for Equations (9) and (11) (i.e., $t \geq 2$); for three out of five countries (France, Germany, and the United Kingdom), it emerges as the preferred estimator for Equations (8) and (10) (i.e., $t = 1$).

In the case of panel data, it is usually recommended to account for unobserved individual or time effects, in either a fixed effects or random effects framework (e.g., Hausman and Taylor 1981, Baltagi 1995), or to opt for first-differencing (Arellano and Honore 1999). However, capturing individual-specific effects using either a fixed or random-effects specification in a model with lagged endogenous variables leads to inconsistent estimators (Baltagi 1995). Another disadvantage of a fixed-effects specification is that parameters of time-invariant but cross-sectionally varying variables (such as movie attributes in our model) cannot be estimated directly. Also because a Holtz-Eakin (1988) test for the presence of individual effects in dynamic models reveals that such effects do not pose a large enough problem here to warrant these or other (e.g., first-differencing) transformations, we opt for a model that does not capture unobserved *individual*-specific effects. We do account for *time*-specific fixed effects in estimating our model, by including a set of $(t-1)$ dummies in Equations (9) and (11).

4. Findings

Table 1, which we referred to in the discussion of hypotheses, provides an overview of the key results regarding all hypotheses for each of the five countries separately. We discuss the main findings below. Table 4 provides descriptive statistics for key variables.

Results for the Opening Week, United States

The United States motion picture market serves as a useful benchmark in at least two respects. First, it has—by far—received the most attention from academics, and comparing the fit of our model to that of previous studies is interesting in its own right—particularly given the new framework to estimating revenues that we propose here. Second, noteworthy in the context of one of our key objectives to study sequential release patterns, the United States is generally the first market in which U.S.-produced movies are released,[12] and we can therefore assume spill-over of information from other markets to be negligible.

Moving to the system of Equations (8) and (10) for the United States, Table 5 reports the results for OLS, 2SLS, and 3SLS estimation, with the former two serving to indicate how the results would differ if endogeneity and simultaneity of screens and revenues are not taken into account.[13]

First, we note the high Adjusted R^2 values—using 3SLS, 0.80 for the screens equation and 0.87 for the revenues equation—which exceed those of most previous empirical research. The model appears to fit the data very well. Also using 3SLS, the number of screens (*SCREENS*), star power (*STAR*), advertising expenditures (*AD_EXP*), critical reviews (*REVIEWS*), and competition from movies with a similar target audience (*COMP_REV*) emerge as key predictors of *REVENUES* in the opening week. All have the hypothesized direction. $REVENUES_1^{**}$, *AD_EXP*, and *REVIEWS* in turn emerge as significant predictors of first-week screens.

Contrary to our hypothesis, *REVIEWS* has a negative coefficient, implying that less positive critical reviews correspond with a higher number of opening screens. We think two explanations are most compelling. First, it could reflect the negotiating power of distributors who, believing that movies with a low perceived quality will generate negative word-of-mouth, may push for a wide opening so they can recoup a large share of the negative cost of the movie in its opening week. Second, it could reflect distributors' confidence in the fact that movies with positive critical reviews tend to have longer runs (e.g., Eliashberg and Shugan 1997) and can build momentum even after a limited opening (which requires less

[12] Only 8% of the movies in our sample have generated foreign box office revenues at the time of their U.S. release; amounts are usually marginal compared to U.S. opening week revenues.

[13] Recall that the Hausman tests revealed that both 2SLS and 3SLS were preferred over OLS, but 2SLS and 3SLS were equally appropriate in estimating Equations (8) and (10).

Table 4 Key Descriptive Statistics

Variable	*N*	Mean	Median	SD	Minimum	Maximum
Attributes						
BUDGET	139	36,879.42	30,000.00	29,762.84	22.00	170,000.00
STAR	164	46.28	48.39	33.67	1.00	99.73
DIRECTOR	164	25.28	13.82	28.63	1.00	97.53
AD_EXP (U.S.)	164	10,455.01	10,005.90	6,626.67	6.20	27,827.80
AD_EXP (U.K.)	164	1,063.00	782.40	912.82	32.50	4,397.00
REVIEWS	158	3.15	3.33	0.84	1.00	4.67
United States						
SCREENS ($t = 1$)	164	1,658.73	1,870.00	999.82	1.00	3,309.00
REVENUES ($t = 1$)	164	10,964.91	6,947.73	12,569.02	6.81	63,674.40
Total *REVENUES*	164	43,712.51	22,059.95	58,542.32	752.12	431,088.30
Length of run (weeks)	164	16.21	16.00	6.66	2.00	30.00
France						
SCREENS ($t = 1$)	140	223.59	172.50	190.52	2.00	793.00
REVENUES ($t = 1$)	140	237.40	91.94	374.93	0.08	2,257.20
Total *REVENUES*	140	765.39	205.99	1,404.17	0.08	7,917.21
Length of run (weeks)	140	5.42	5.00	3.93	1.00	17.00
US_PERF	140	9.64	5.86	12.79	0.78	85.63
TIME_LAG	140	131.89	115.00	108.31	0.00	514.00
Germany						
SCREENS ($t = 1$)	138	276.69	245.00	229.23	1.00	1,001.00
REVENUES ($t = 1$)	138	2,876.92	1,199.07	4,445.93	1.61	32,236.48
Total *REVENUES*	138	9,650.27	3,400.41	16,187.10	3.09	99,859.53
Length of run (weeks)	138	9.67	8.00	7.34	1.00	30.00
US_PERF	138	8.97	5.66	11.89	0.78	85.63
TIME_LAG	138	139.83	124.00	97.42	0.00	529.00
Spain						
SCREENS ($t = 1$)	127	144.45	149.00	81.95	0.00	352.00
REVENUES ($t = 1$)	127	150,300.81	87,873.21	192,194.19	486.00	1,311,916.91
Total *REVENUES*	127	506,390.40	205,766.47	744,549.40	514.00	4,381,326.72
Length of run (weeks)	127	10.35	9.00	6.89	1.00	30.00
US_PERF	127	8.18	5.21	10.18	0.78	78.57
TIME_LAG	127	117.34	110.00	76.51	0.00	360.00
United Kingdom						
SCREENS ($t = 1$)	138	179.37	183.50	136.61	1.00	481.00
REVENUES ($t = 1$)	138	1,053.44	442.37	1,937.28	0.64	15,466.54
Total *REVENUES*	138	4,179.38	1,373.09	7,803.46	3.80	51,031.27
Length of run (weeks)	138	10.21	9.00	6.90	1.00	30.00
US_PERF	138	9.88	6.20	12.74	0.96	85.63
TIME_LAG	138	112.38	99.00	75.51	0.00	319.00

advertising support). The negative relationship could also reflect distributors and exhibitors' perceived distinction between critical acclaim and popular appeal (e.g., Austin 1983), but we note that our finding of a positive relationship between *REVIEWS* and opening week revenues (*REVENUES*) suggests that this perception does not match reality for the set of movies under consideration here.

If we compare 3SLS (or 2SLS) with OLS, although we do not see any major changes in the significance of variables, some interesting differences in coefficients emerge. A first example, in the revenues

Table 5 United States, Opening Week: OLS, 2SLS, and 3SLS

	OLS			2SLS			3SLS		
Variable	Coefficient	SE	P	Coefficient	SE	P	Coefficient	SE	P
U.S., Week 1: Supply Equation, with LOG*(SCREENS) as Dependent Variable*									
CONSTANT	−1.61	2.23	0.47	−1.61	2.23	0.47	−0.29	2.14	0.89
LOG($REVENUES_1^{**}$)	**1.40**	**0.08**	**0.00**	**1.40**	**0.08**	**0.00**	**1.41**	**0.08**	**0.00**
LOG(*BUDGET*)	0.01	0.10	0.90	0.01	0.10	0.90	−0.02	0.10	0.87
LOG(*STAR*)	0.04	0.06	0.50	0.04	0.06	0.50	0.04	0.05	0.47
LOG(*DIRECTOR*)	−0.03	0.05	0.52	−0.03	0.05	0.52	−0.03	0.05	0.57
LOG(*AD_EXP*)	**0.26**	**0.11**	**0.02**	**0.26**	**0.11**	**0.02**	**0.25**	**0.11**	**0.02**
LOG(*REVIEWS*)	**−1.49**	**0.28**	**0.00**	**−1.49**	**0.28**	**0.00**	**−1.48**	**0.28**	**0.00**
LOG(*DISTR_MAJOR*)	0.12	0.20	0.54	0.12	0.20	0.540	0.10	0.19	0.61
LOG(*COMP_SCR_NEW*)	−0.06	0.22	0.78	−0.06	0.22	0.78	−0.19	0.21	0.36
LOG(*COMP_SCR_ONG*)	0.05	0.17	0.78	0.05	0.17	0.78	0.07	0.16	0.65
	$R^2 = 0.82$, Adj. $R^2 = 0.80$			$R^2 = 0.82$, Adj. $R^2 = 0.80$			$R^2 = 0.81$, Adj. $R^2 = 0.80$		
U.S., Week 1: Demand Equation, with LOG*(REVENUES) as Dependent Variable*									
CONSTANT	0.39	1.23	0.75	0.83	1.25	0.51	0.27	1.22	0.82
LOG(*SCREENS*)	**0.74**	**0.03**	**0.00**	**0.81**	**0.04**	**0.00**	**0.81**	**0.04**	**0.00**
LOG(*STAR*)	**0.11**	**0.04**	**0.00**	**0.10**	**0.04**	**0.01**	**0.10**	**0.04**	**0.01**
LOG(*DIRECTOR*)	0.01	0.03	0.79	0.00	0.03	0.90	0.00	0.03	0.91
LOG(*AD_EXP*)	**0.58**	**0.07**	**0.00**	**0.20**	**0.07**	**0.00**	**0.20**	**0.07**	**0.01**
LOG(*REVIEWS*)	**0.55**	**0.01**	**0.00**	**0.75**	**0.03**	**0.00**	**0.77**	**0.03**	**0.00**
LOG(*COMP_REV*)	**−0.22**	**0.06**	**0.00**	**−0.22**	**0.07**	**0.00**	**−0.20**	**0.06**	**0.00**
LOG(*SEASON*)	0.00	0.27	0.99	−0.11	0.27	0.69	0.02	0.27	0.95
	$R^2 = 0.88$, Adj. $R^2 = 0.87$ $N = 164$, Missing $= 8$			$R^2 = 0.88$, Adj. $R^2 = 0.87$ $N = 164$, Missing $= 8$			$R^2 = 0.88$, Adj. $R^2 = 0.87$ $N = 164$, Missing $= 8$		

equation, the coefficient for *REVIEWS* increases from 0.55 in OLS to 0.75 and 0.77 in 2SLS and 3SLS, respectively—a significant difference. A second example, also concerning the revenues equation, the coefficient for *AD_EXP* drops from 0.58 in OLS to 0.20 in 2SLS and 3SLS—another significant difference. In both cases, the coefficients in the screens equation remain unchanged.[14] This implies that not taking into account the endogeneity of the *SCREENS* variable leads to an overestimation of the positive influence of advertising expenditures and an underestimation of the positive influence of reviews on revenues. For instance, because we can interpret the coefficient for advertising expenditures (*AD_EXP*) as the elasticity of *REVENUES* with respect to *AD_EXP*, OLS wrongly suggests that (all else being equal) a 1% increase in advertising expenditures corresponds to about 0.5% increase in revenues; 3SLS estimations show this to be less than 0.25%.

Results for the Opening Week, Foreign Markets

We present 3SLS estimates for the opening week (Equations (8) and (10)) in each of the foreign markets in Table 6.

Several key insights emerge. First, the model's fit is reasonably good, and in line with magnitudes reported in previous empirical research. However, the Adjusted R^2 particularly for the screens equation (ranging from 0.46 in the United Kingdom to 0.48 in France), but also for the revenues equation (ranging from 0.77 in Spain to 0.88 in France) are lower than their counterparts for the United States.

Several variables are found to be significant predictors of opening week revenues. Most important is

[14] Because there is no endogenous variable among the regressors in the screens equation, the coefficients for OLS and 2SLS estimations are the same for this equation.

Table 6 Foreign Markets, Opening Week: 3SLS

	France			Germany			Spain			United Kingdom		
Variable	Coefficient	SE	*P*	Coefficient	SE	*P*	Coefficient	SE	*P*	Coefficient	SE	*P*
Foreign Markets, Week 1: Supply Equation, with LOG*(SCREENS) as Dependent Variable, 3SLS Estimates*												
CONSTANT	1.62	1.20	0.18	0.99	1.58	0.53	−0.49	1.29	0.71	2.36	1.74	0.18
LOG(*REVENUES*$_1^{**}$)	**0.39**	**0.07**	**0.00**	**0.38**	**0.07**	**0.00**	**0.24**	**0.05**	**0.00**	**0.35**	**0.08**	**0.00**
LOG(*BUDGET*)	**0.23**	**0.10**	**0.03**	0.17	0.10	0.07	**0.30**	**0.10**	**0.00**	0.03	0.10	0.75
LOG(*STAR*)	**0.22**	**0.06**	**0.00**	**0.12**	**0.05**	**0.01**	**0.11**	**0.05**	**0.04**	−0.06	0.07	0.43
LOG(*DIRECTOR*)	−0.04	0.05	0.49	−0.20	0.25	0.44	0.01	0.04	0.80	−0.01	0.06	0.80
LOG(*AD_EXP*)	—	—	—	—	—	—	—	—	—	**0.18**	**0.04**	**0.00**
LOG(*REVIEWS*)	−0.05	0.34	0.89	−0.41	0.37	0.26	−0.19	0.26	0.48	**−0.82**	**0.34**	**0.02**
LOG(*DISTR_MAJOR*)	0.06	0.18	0.73	−0.15	0.16	0.36	0.13	0.11	0.25	0.18	0.17	0.28
LOG(*COMP_SCR_NEW*)	0.11	0.21	0.50	**−0.13**	**0.06**	**0.02**	−0.12	0.21	0.55	0.32	0.42	0.45
LOG(*COMP_SCR_ONG*)	−0.45	0.35	0.20	0.34	0.36	0.34	0.05	0.24	0.85	0.47	0.24	0.05
LOG(*US_PERF*)	**0.84**	**0.15**	**0.00**	**0.95**	**0.16**	**0.00**	**0.38**	**0.13**	**0.00**	0.06	0.22	0.80
LOG(*TIME_LAG*US_PERF*)	**−0.31**	**0.11**	**0.01**	**−0.28**	**0.13**	**0.03**	**−0.23**	**0.10**	**0.03**	−0.06	0.16	0.71
	$R^2 = 0.53$, Adj. $R^2 = 0.48$			$R^2 = 0.50$, Adj. $R^2 = 0.47$			$R^2 = 0.47$, Adj. $R^2 = 0.46$			$R^2 = 0.51$, Adj. $R^2 = 0.46$		
Foreign Markets, Week 1: Demand Equation, with LOG*(REVENUES) as Dependent Variable, 3SLS Estimates*												
CONSTANT	−1.74	0.94	0.07	**−2.47**	**1.01**	**0.02**	0.21	1.25	0.87	**−3.36**	**1.41**	**0.02**
LOG(*SCREENS*)	**1.43**	**0.09**	**0.00**	**1.51**	**0.07**	**0.00**	**1.89**	**0.14**	**0.00**	**1.51**	**0.13**	**0.00**
LOG(*STAR*)	0.03	0.05	0.52	−0.03	0.04	0.51	−0.09	0.06	0.14	−0.00	0.05	0.98
LOG(*DIRECTOR*)	−0.05	0.04	0.18	−0.02	0.03	0.56	−0.08	0.04	0.07	−0.09	0.05	0.07
LOG(*AD_EXP*)	—	—	—	—	—	—	—	—	—	−0.04	0.05	0.43
LOG(*REVIEWS*)	0.46	0.25	0.07	0.37	0.23	0.11	0.33	0.27	0.22	**0.86**	**0.41**	**0.04**
LOG(*COMP_REV*)	**−0.10**	**0.05**	**0.03**	**−0.07**	**0.02**	**0.00**	**−0.01**	**0.01**	**0.00**	**−0.56**	**0.21**	**0.01**
LOG(*SEASON*)	**0.98**	**0.49**	**0.05**	**0.39**	**0.18**	**0.03**	0.34	0.21	0.11	**0.54**	**0.23**	**0.02**
LOG(*US_PERF*)	**0.30**	**0.12**	**0.02**	**0.17**	**0.08**	**0.04**	**0.22**	**0.10**	**0.03**	**0.90**	**0.16**	**0.00**
LOG(*TIME_LAG*US_PERF*)	**−0.21**	**0.08**	**0.01**	0.01	0.08	0.90	0.08	0.11	0.47	−0.15	0.12	0.23
	$R^2 = 0.88$, Adj. $R^2 = 0.88$			$R^2 = 0.88$, Adj. $R^2 = 0.87$			$R^2 = 0.78$, Adj. $R^2 = 0.77$			$R^2 = 0.82$, Adj. $R^2 = 0.81$		
	$N = 140$, Missing $= 16$			$N = 138$, Missing $= 14$			$N = 127$, Missing $= 9$			$N = 138$, Missing $= 9$		

again *SCREENS*, which is highly significant in all four markets. Interestingly, we note that the estimated elasticities of *REVENUES* with respect to *SCREENS* in the foreign market are all higher than one, contrary to the elasticity reported for the United States (see Table 5). This suggests that, whereas the relationship between screens and revenues is concave in the United States, it is convex in each of the four foreign markets—which in turn is in line with the dominant belief in the industry that the United States was overscreened and foreign markets were largely underscreened in the period under investigation. The competition variable *COMP_REV* also arises as a key variable and is significant in all four markets. *SEASON* is significant in all but one (Spain) foreign market. *REVIEWS* is significantly (and positively) related to revenues in the United Kingdom only. Our measure of U.S. performance (*US_PERF*) is significant in three markets (Germany, Spain, and the United Kingdom), while the interaction term [$TIME\_LAG * US\_PERF$][15] is significantly related to revenues in France only.

[15] Pair-wise correlation analyses show that the correlation between *TIME_LAG* and *US_PERF* is insignificant for each of the foreign markets, but that the former is significantly correlated with both revenues and screens. Although the issue is debated, it is generally seen as desirable that the moderator and dependent variable are not correlated (Baron and Kenny 1986). Strictly speaking, *TIME_LAG* should therefore be treated as a "quasi" moderator (e.g., Sharma et al. 1981). As far as possible negative effects of multicollinearity are concerned, it is encouraging to find that if we substitute the interaction term for *TIME_LAG*, the coefficients and standard errors of all other variables remain largely unchanged.

As far as the screens equation is concerned, expected first-week revenues ($REVENUES_1^{**}$) are highly significant in all four markets; *BUDGET* is significant in three markets (France, Germany, and Spain); *STAR* is significant in two markets (France and Spain); and *AD_EXP* is significant in the United Kingdom—all with positive coefficients. Interestingly, like in the United States, critical reviews (*REVIEWS*) are *negatively* related to the number of screens allocated to a movie in the United Kingdom. The competition variables *COMP_SCR_NEW* and *COMP_SCR_ONG* generally do not emerge as significant predictors (even though they are positively correlated with screens in several countries); *COMP_SCR_NEW* is negatively related to screens in Germany only. Finally, both *US_PERF* and [$TIME\_LAG * US\_PERF$] are significant in France, Germany, and Spain.

Thus, we have fairly strong evidence to support the hypothesis that the stronger a movie's U.S. performance, the more screens exhibitors allocate to that movie in its opening week in a foreign market, and the higher the demand for that movie is among foreign audiences. Furthermore, while we find only limited evidence that the time lag between releases moderates that relationship on the demand side, we observe fairly strong evidence that it acts as a moderator on the screens side. The shorter the time between the release in the United States and in each of those foreign markets, the stronger this relationship is. The fact that the effect is more pronounced for exhibitors could be related to the availability of information on a movie's domestic market performance. It may also reflect a strong concern among exhibitors that, if the time lag is long, successful movies can lose much of the hype that surrounds them—interestingly, a perception that we in turn find little support for. Finally, it could point to a lack of attention on the side of distributors for movies that have been in the market place for some time.

Results for the Second Week and Beyond, United States

Having explored the drivers of behavior of exhibitors and audiences regarding a movie's opening week, we now move to the remainder of movies' theatrical lifecycles. Turning to the system of Equations (9) and (11), the following findings arise for the United States.

Again, the fit of our model is excellent as far as the revenues equation is concerned (Adjusted $R^2 = 0.93$) and fairly good as far as the screens equation is concerned (Adjusted $R^2 = 0.74$). As hypothesized, *SCREENS*, *COMP_REV*, and *WOM* emerge as significant predictors of revenues throughout a movie's run, while $REVENUES^{**}$, *COMP_SCR_NEW*, and *WOM* emerge as significant predictors of the number of screens allocated to movies throughout their run, all in the hypothesized directions. Week-by-week tests (not reported here) provide two additional insights. First, *COMP_SCR_ONG* (reflecting competition from ongoing movies) is mostly correlated with screens in the early stages of a movie's run. Second, *WOM* and *SCREENS* are negatively related in the second and third week. This may be explained by distributor power (e.g., contractual arrangements between exhibitors and distributors that stipulate a certain exhibition level regardless of performance), exhibitor inertia (i.e., exhibitors' inability to quickly adjust exhibition levels to early indications of the appeal of movies), or shortcomings in our measure (i.e., reflect that revenues per screen in early weeks represent not just a movie's playability, but also its marketability). Across all weeks, the association is positive. Finally, although we report only 3SLS results, we again note that we find marked differences in coefficients across the three estimation methods.

Results for the Second Week and Beyond, Foreign Markets

Do similar patterns arise in the foreign markets after the opening week? Table 8 displays the 3SLS estimation results for the each of four foreign markets.

Our model appears to have a reasonably good fit in each country: the Adjusted R^2 for the revenues equations vary between 0.76 for the United Kingdom and 0.88 for Germany, while those for the screen equations range from 0.55 for France to 0.64 for Germany. Exhibition levels (*SCREENS*) yet again emerge as the key predictor of box office revenues in all four markets. *WOM*, *SEASON*, and *COMP_REV* (all in three of the four markets) also rank among the key variables. The key predictor of screens is again expected revenues ($REVENUES^{**}$). The fact that elasticities for this variable are lower in the foreign markets than

Table 7 United States, Second Week and Beyond: OLS, 2SLS, and 3SLS

	OLS			2SLS			3SLS		
Variable	Coefficient	SE	*P*	Coefficient	SE	*P*	Coefficient	SE	*P*
U.S., Week 2—End of Run: Supply Equation, with LOG*(SCREENS) as Dependent Variable*									
CONSTANT	−0.41	0.44	0.36	−0.78	2.13	0.71	−0.59	0.38	0.12
LOG(*REVENUES***)	**0.81**	**0.03**	**0.00**	**1.08**	**0.05**	**0.00**	**1.08**	**0.05**	**0.00**
LOG(*COMP_SCR_NEW*)	**−0.07**	**0.03**	**0.01**	**−0.27**	**0.12**	**0.03**	**−0.26**	**0.02**	**0.00**
LOG(*COMP_SCR_ONG*)	0.09	0.06	0.18	0.08	0.06	0.17	0.06	0.05	0.27
LOG(*WOM*)	**0.25**	**0.05**	**0.00**	**0.36**	**0.10**	**0.00**	**0.35**	**0.09**	**0.00**
	$R^2 = 0.76$, Adj. $R^2 = 0.75$			$R^2 = 0.74$, Adj. $R^2 = 0.74$			$R^2 = 0.74$, Adj. $R^2 = 0.74$		
U.S., Week 2—End of Run: Demand Equation, with LOG*(REVENUES) as Dependent Variable*									
CONSTANT	0.24	0.16	0.13	0.25	0.24	0.288	0.29	0.24	0.22
LOG(*SCREENS*)	**0.95**	**0.01**	**0.00**	**1.01**	**0.02**	**0.00**	**1.01**	**0.02**	**0.00**
LOG(*COMP_REV*)	−0.02	0.01	0.15	−0.03	0.01	0.05	**−0.03**	**0.02**	**0.04**
LOG(*SEASON*)	**0.10**	**0.04**	**0.01**	0.02	0.06	0.75	0.02	0.06	0.70
LOG(*WOM*)	**0.87**	**0.01**	**0.00**	**1.04**	**0.04**	**0.00**	**1.05**	**0.04**	**0.00**
	$R^2 = 0.93$, Adj. $R^2 = 0.93$ $N = 2{,}489$, Missing $= 72$			$R^2 = 0.92$, Adj. $R^2 = 0.92$ $N = 2{,}489$, Missing $= 72$			$R^2 = 0.92$, Adj. $R^2 = 0.92$ $N = 2{,}489$, Missing $= 72$		

Note. Time dummies (for each week) used in estimating the model are not reported.

in the United States may reflect that exhibitors in the United States are more responsive to box office figures than their counterparts in foreign markets. *WOM* is significant in all four markets as well. Finally, *COMP_SCR_NEW* is significantly related to screens in Germany and the United Kingdom; *COMP_SCR_ONG* is significantly related to screens in Spain and the United Kingdom, all in the hypothesized direction.

Table 8 Foreign Markets, Second Week and Beyond: 3SLS

	France			Germany			Spain			United Kingdom		
Variable	Coefficient	SE	*P*	Coefficient	SE	*P*	Coefficient	SE	*P*	Coefficient	SE	*P*
Foreign Markets, Week 2—End of Run: Supply Equation, with LOG*(SCREENS) as Dependent Variable, 3SLS Estimates*												
CONSTANT	**1.83**	**0.21**	**0.00**	**2.94**	**0.23**	**0.00**	**−1.16**	**0.36**	**0.00**	**1.33**	**0.53**	**0.01**
LOG(*REVENUES***)	**0.37**	**0.02**	**0.00**	**0.09**	**0.01**	**0.00**	**0.08**	**0.010**	**0.00**	**0.59**	**0.04**	**0.00**
LOG(*COMP_SCR_NEW*)	−0.08	0.06	0.18	**−0.42**	**0.08**	**0.00**	−0.04	0.09	0.67	**−0.21**	**0.03**	**0.00**
LOG(*COMP_SCR_ONG*)	0.04	0.11	0.71	0.16	0.10	0.11	**−0.48**	**0.17**	**0.00**	**0.22**	**0.06**	**0.00**
LOG(*WOM*)	**0.28**	**0.07**	**0.00**	**0.32**	**0.16**	**0.05**	**0.88**	**0.05**	**0.00**	**0.82**	**0.16**	**0.00**
	$R^2 = 0.56$, Adj. $R^2 = 0.55$			$R^2 = 0.64$, Adj. $R^2 = 0.64$			$R^2 = 0.57$, Adj. $R^2 = 0.57$			$R^2 = 0.62$, Adj. $R^2 = 0.61$		
Foreign Markets, Week 2—End of Run: Demand Equation, with LOG*(REVENUES) as Dependent Variable, 3SLS Estimates*												
CONSTANT	**−1.50**	**0.20**	**0.00**	**−0.55**	**0.22**	**0.01**	−0.03	0.28	0.92	**1.08**	**0.23**	**0.00**
LOG(*SCREENS*)	**1.12**	**0.02**	**0.00**	**1.08**	**0.03**	**0.00**	**0.96**	**0.02**	**0.00**	**0.82**	**0.02**	**0.00**
LOG(*COMP_REV*)	**−0.15**	**0.04**	**0.00**	0.03	0.03	0.33	**−0.27**	**0.08**	**0.00**	**−0.16**	**0.04**	**0.00**
LOG(*SEASON*)	**0.15**	**0.04**	**0.00**	0.08	0.05	0.09	**0.27**	**0.08**	**0.00**	**0.48**	**0.13**	**0.00**
LOG(*WOM*)	**0.85**	**0.03**	**0.00**	**0.74**	**0.03**	**0.00**	**0.85**	**0.02**	**0.00**	0.24	0.15	0.11
	$R^2 = 0.84$, Adj. $R^2 = 0.84$ $N = 616$, Missing $= 54$			$R^2 = 0.88$, Adj. $R^2 = 0.88$ $N = 1{,}196$, Missing $= 159$			$R^2 = 0.83$, Adj. $R^2 = 0.83$ $N = 1{,}185$, Missing $= 125$			$R^2 = 0.76$, Adj. $R^2 = 0.76$ $N = 1{,}269$, Missing $= 123$		

Note. Time dummies (for each week) used in estimating the model are not reported.

5. Summary, Managerial Implications, and Research Opportunities

Summary

Our findings provide strong evidence for the importance of considering endogeneity and simultaneity of audience and exhibitor behavior in studies aimed at better understanding the drivers of box office performance. For the data at hand, results obtained using the statistically preferred estimation method, SLS, are often markedly different from those obtained using ordinary least squares, which suggests that previous research employing simple regression techniques may have drawn incorrect conclusions about the significance and role of certain determinants of revenues. Here, we find that several variables usually assumed to influence revenues directly, also—or even predominantly—influence such revenues indirectly, namely, through their impact on the allocation of screens. Advertising expenditures emerge as a particularly good example in this respect.

Our study provides important new insights regarding the drivers of the behavior of audiences and exhibitors, and their interdependencies. Main findings can be summarized as follows:

- Within the United States and each foreign market under consideration, screens and (expected) revenues are highly interrelated: the number of screens is the key determinant of revenues, and expected revenues in turn are the key determinant of screens. Whereas the relationship between opening screens and revenues is concave in the United States, it is convex in each foreign market.
- Advertising support is a key predictor of opening week revenues and screens (i.e., a movie's marketability), while word-of-mouth communication is an important predictor of revenues and screens in subsequent weeks (i.e., a movie's playability).
- In the United States and United Kingdom, critical acclaim plays a surprising role—it is positively related to opening week revenues but negatively related to opening week screens. The latter may reflect distributors' power to negotiate a wider opening for critically unacclaimed movies, or their confidence in the ability of critically acclaimed movies to gain momentum after a more limited opening.
- The variable measuring competition for *revenues*—based on the idea that movies experience particularly strong competition from new releases with similar characteristics—is a strong predictor in virtually every market under consideration. Also, it appears valuable to distinguish two components of competition for *screens*—competition from new releases versus competition from ongoing movies—as they capture two different dimensions of the competitive environment.
- We find some support for hypothesized relationships between a movie's budget and star power and the behavior of exhibitors and, to a lesser extent, audiences. However, particularly compared with previous empirical research, our study assigns a relatively small role to these determinants.
- Our findings provide some support for the view that the demand for movies is seasonal. Seasonality mostly affects audience demand in the later stages of a movie's run.
- In line with our hypotheses, we find strong support for a relationship between performance in the United States and performance in foreign markets—generally both in terms of opening week revenues and opening week screens. In addition, consistent with the idea that the buzz for a movie is perishable, our findings support the hypothesis that the time lag between releases negatively moderates this relationship (i.e., the longer the time lag, the weaker the relationship)—an effect that is mostly driven by foreign exhibitors' screen allocations.

Managerial Implications

What are the implications of these findings for motion picture exhibitors and studios/distributors? First, our study offers overwhelming evidence suggesting that exhibitors control the main predictor of a movie's box office revenues throughout its run: screen space. For distributors, the key to securing large audiences for their movies therefore is to find a marketing mix that appeals to audiences (pull) as well as exhibitors (push). Allocating resources to a push marketing strategy is particularly important in foreign markets, where additional opening screens go hand in hand with increasing returns. Advertising is a crucial instrument of such a strategy. In fact, there is anecdotal evidence suggesting that distributors tend to overspend on advertising, which may well be explained by the need to convince exhibitors of their commitment to a movie. Producing expensive movies with well-known stars is another means by which high opening week screens and revenues can be achieved. Of course, these actions drive up the production and marketing costs of movies and therefore increase the stakes for distributors. As a possible way out of this spiral, our study also draws attention to the effects of a movie's attributes relative to those of other movies on release, rather than its absolute characteristics. A careful planning of the timing of a movie's release, with attention for the likely competitive environment over the course of its run, is crucial.

Furthermore, in an international context, our findings have implications for the suitability of simultaneous (i.e., so-called day-and-date releases) versus sequential release strategies—a much debated issue in the motion picture industry (e.g., Variety 2001). Proponents of day-and-date releasing have become more vocal in recent years, and some executives have observed "a general inclination among studios to shrink worldwide releasing" (Variety 2001). In the early stages of our study, we conducted a number of interviews with motion picture executives involved in the production, distribution, and exhibition of motion pictures. Among other things, these interviews led to detailed insights into the array of factors underlying motion picture distributors' choices on international release strategies. Our study mostly provides relevant insights into the appropriateness of simultaneous versus sequential releases in fostering the buzz that surrounds movies. Our finding that there is an association between a movie's performance in the United States and in major European markets may not be surprising, but it is relevant to consider that this is not just a consequence of the sheer availability of the movie in theaters. This is not to say that a movie's U.S. performance is always the best available indicator of its foreign performance, but on average, it is worthwhile for distributors and foreign exhibitors to closely monitor a movie's performance in the United States.

The finding that the time lag between releases moderates this relationship also has important implications for distributors and exhibitors. It suggests that the buzz (e.g., in the form of word-of-mouth communication or media exposure) that a movie is able to generate in the domestic market may quickly fade or wear out over time. This implies that, provided a movie performs reasonably well in its domestic market, it deserves recommendation to schedule the movie's foreign releases reasonable close to its domestic release. The longer distributors delay a movie's release in foreign markets, the less they will be able to hold on to the momentum that the movie created in the domestic market.

Interestingly, our findings suggest that foreign exhibitors—not foreign audiences—mostly fuel this time-lag effect. An emphasis on shorter release time lags can thus be an important element of a distributor's *push* marketing strategy in foreign markets, even though, ironically, shortening time lags appears to have little value as a *pull* strategy. At the same time, our findings can help distributors who prefer a sequential release strategy (for example because it allows them to adjust foreign marketing strategies based on the movie's performance in the United States) to counter potential negative effects of such a strategy. Just like distributors need to manage other aspects of the marketing mix that signal the movie's quality or their commitment to support the movie in each of its foreign territories, they are advised to attempt to take away any potential fears of a reduction in revenues associated with longer release time lags among exhibitors. Our study comes to their aid in that we find only limited support for the common perception among industry executives that moviegoing audiences in foreign markets are only affected by the momentum or buzz that a movie has generated in the United States if the foreign release is slotted near the United States release. If distributors can convince exhibitors to not let release time lags impact their allocation decisions, day-and-date release strategies are not necessarily preferred.

Research Opportunities

We think five future research opportunities are particularly worthwhile.

• First, as a direct extension, our model could be applied to industries or products that share key characteristics with motion picture markets—particularly (a) a strong interrelationship between performance and availability and (b) a sequential international release pattern. Prime candidates are other media and entertainment products (e.g., books, videogames), fashion goods (e.g., clothing, toys), and other industries with highly volatile demand where novelty wears out quickly. In specifying the model, context-specific drivers of demand and/or supply and, in some cases, context-specific time intervals (e.g., months instead of weeks) will have to be considered.

• Second, we observe that advances in digital technology bring speed to market issues to the forefront in the motion picture industry because they allow for faster and easier word-of-communication about motion pictures on a global scale, may lead to substantial savings in print costs associated with simultaneous releases, and introduce the possibility of an instantaneous worldwide distribution (of legal and *il*legal copies). Our study may have not yet picked up the influence of these developments, but the landscape is changing rapidly. In due time, a replication may be desirable.

• Third, this study's main findings on the role of a movie's competitive environment, along with earlier work such as that by Krider and Weinberg (1998) and Einav (2001), could be utilized in the development of normative models of the optimal timing of releases. Such models could be employed to determine a release timing that maximizes a movie's expected profitability throughout its run. For foreign markets, one interesting avenue is to explicitly model the trade-off between the costs and benefits of shorter release time lags.

• Fourth, research could focus on determining the adequate screen capacity in a particular market, given the demand for motion pictures. As indicated, our findings provide some support for a claim often made by motion picture experts at the end of 1990s, namely that the United States was overscreened and foreign markets were largely underscreened. The issue has high managerial relevance in the United States (where many theater chains have faced bankruptcy in recent years) and in foreign markets (where many multiplexes are being built).

• Finally, a fundamental issue in understanding demand dynamics, future empirical research could consider the relationship between a movie's prerelease expectations or buzz and its actual—initial and/or ultimate—market performance. For instance, again in the context of motion pictures, many industry experts claim that when a movie is very strongly hyped or buzzed but it is initially not well received among audiences, this may exert a negative influence on the movie's later box office performance.

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