

*Business and Economics Scholars Workshop in Motion Picture Industry Studies  
Florida Atlantic University, 2002*

**The Drivers of Motion Picture Performance:  
The Need to Consider Dynamics, Endogeneity and Simultaneity**

**Anita Elberse**

Visiting Doctoral Fellow  
The Wharton School  
University of Pennsylvania  
1400 Steinberg Hall-Dietrich Hall  
Philadelphia, PA 19104, USA  
Email: [elberse@wharton.upenn.edu](mailto:elberse@wharton.upenn.edu)

**Jehoshua Eliashberg**

Sebastian S. Kresge Professor of Marketing  
The Wharton School  
University of Pennsylvania  
1400 Steinberg Hall-Dietrich Hall  
Philadelphia, PA 19104, USA  
Email: [eliashberg@wharton.upenn.edu](mailto:eliashberg@wharton.upenn.edu)

Current Draft: March 20, 2002

*Acknowledgements: We are indebted to Paddy Barwise, Bruce Hardie, Bill Putsis, Naufel Vilcassim, and participants of seminars at London Business School (London, UK) and the Erasmus University (Rotterdam, The Netherlands) for valuable comments. We also thank all motion picture executives and other industry experts who participated in a round of interviews. The study proposed here is part of the first author's dissertation; financial support from the Lloyd's of London Tercentenary Foundation is gratefully acknowledged.*

# **The Drivers of Motion Picture Performance: The Need to Consider Dynamics, Endogeneity and Simultaneity**

## **1. INTRODUCTION**

In the past two decades, academic researchers have made important advances in understanding the determinants of motion picture performance. However, many studies in this area are intrinsically demand-studies – they examine the relationship between (often cumulative) box office revenues and a set of determinants. A central premise underlying our current research project is that, in order to gain a thorough understanding of the determinants of motion picture performance, it is necessary to consider the determinants of both revenues and screens – i.e. the drivers of the behavior of both audiences and exhibitors. Our project will therefore involve the estimation of a simultaneous equations model – with one 'revenues' and one 'screens' equation – and specifically incorporate the intricate relationship between screens and revenues. In doing so, we address an important shortcoming in a wide range of previous studies that have studied the determinants of box office revenues as a function of a set of exogenous variables that includes the number of screens on which the movie played – the fact that they fail to account for the potential *endogeneity* of screens. We employ a *dynamic* simultaneous equations model, i.e. study the development of screens and revenues over the course of a movie's run. Importantly, in addition to addressing the interdependencies between screens and revenues by considering the endogeneity of screens in estimating revenues (and the endogeneity of revenues in estimating screens), we also account for the *simultaneity* of both processes.

From an econometric point of view, the concept 'endogeneity' is defined as the contemporaneous correlation between the regressor and the error term. In a simultaneous equations analysis as employed here, an endogenous variable can typically be described in terms of the exogenous variables and disturbance terms. Exogenous variables are determined from the 'outside', independently of the process described by the equation system (Theil, 1971). In more practical terms, and specified for this context, it refers to the possibility that screens and revenues have an overlapping set of predictors (of which some may not be included in the model). A change in one or more of those predictors leads to a change in revenues both directly (through the relationship between these predictors and revenues) and indirectly (through the relationship between these predictors and screens), which complicates the estimation. The concept of 'simultaneity' refers to the possibility that the disturbance terms associated with revenues and screens are related. That is, in more practical terms, they are likely to experience the same 'shocks' over time. Among other things, a failure to account for the endogeneity and simultaneity may lead to incorrect conclusions about the relative importance of predictors.

We note that the endogeneity problem is particularly relevant for studies that fall within what Litman (Litman & Ahn, 1998) has termed the '*economic approach*', i.e. those that explore factors that influence collective movie attendance decisions. Focusing on aggregate data, the economic approach seeks to

explore the variables that influence the financial performance of motion pictures. Prime examples are studies conducted by Litman himself over the past two decades (Litman 1983; Litman & Kohl 1989; Litman & Ahn 1998), as well as a study by Sochay (1994) who adopts a similar model and uses roughly the same variables. We refer to these four studies as the 'Litman studies'. Work by, among others, Prag and Casavant (1994) and Zufryden (2000) also belongs to this approach. The economic approach is often contrasted with the '*psychological approach*', which focuses on individual decisions to first attend movies from among the vast array of entertainment options and second, and more critical, to choose particular movies. Researchers adopting this approach generally try to relate such variables as opinions, needs, values, attitudes and personality traits to consumers' decision-making processes. Examples are Austin (1989), D'Astous and Touil (1999), De Silva (1998), Moller and Karppinen (1983), and Palmgreen and Lawrence (1991). Incidentally, several research efforts bridge the psychological and economic approaches by modeling aggregate patterns of motion picture diffusion based on assumptions about underlying decision-making processes on an individual level (e.g. Sawhney & Eliashberg, 1996). As researchers themselves have observed, such studies also face potential problems related to endogeneity and simultaneity.

Crucially, our model specification is based on recommendations made by Sawhney & Eliashberg (1996) in the concluding comments of a study published in *Marketing Science*:

*"It could be argued that the exhibition intensity (...) is likely to be a function of the box-office receipts, since movie exhibitors could determine the supply (number of screens) for a new movie endogenously based on the observed demand (box-office grosses) for the movie. The potential endogeneity could be addressed by an econometric model where the 'supply function' of exhibitors would be expressed as a box-office-receipts-dependent equation, and the 'demand function' of consumers would be expressed as a supply-dependent equation. The supply and demand equations could then be estimated simultaneously as a system of equations (...)"*

Three years later, Neelamegham and Chintagunta (1999) made a comment along the same lines:

*"The evolution of the number of screens over time will depend, in part, on the performance of the movie. A complete forecasting model (for long horizons) will entail modeling not just the number of viewers but also the number of screens, with some dependence across these measures over time"*

In this paper, we first review relevant literature that investigates the determinants of motion picture performance, particularly research that falls within the 'economic approach'. That is, we discuss the types of models employed by researchers in this area, describe the dependent variables used in those studies, and give an overview of insights regarding the role of various determinants. We then concentrate on three key observations that follow from our review of the literature – which in turn underlie our model specification – namely (1) the need for a dynamic modeling approach, i.e. to model the allocation of screens and the receipt of box office grosses over time as two interrelated processes, (2) the need to

consider revenues and screens as endogenous variables, and (3) the need to account for the possible simultaneity of both processes. Next, we discuss our proposed model in more detail. We conclude with an indication of the potential empirical contributions of our approach. Throughout our paper, we attempt to steer away from a pure econometric discussion and instead frame our discussion mostly in practical terms. Also, we focus on what is generally regarded as the 'domestic market' for the type of movies under consideration here, i.e. the US.

## **2. REVIEW OF RELEVANT LITERATURE**

Below, we discuss the types of models employed by researchers seeking to understand the determinants of motion picture performance, roughly divided into linear and non-linear modeling frameworks. We then detail the dependent variables used in these studies, which belong to one of three categories: cumulative rentals, cumulative revenues (both static approaches), and weekly revenues (dynamic approaches). We further note that studies that investigate the drivers of the screens allocated to a movie are virtually non-existent. Finally, we describe the insights that these studies have provided regarding the relative importance of various determinants of rentals or revenues, focusing on the number of screens, movie attributes, advertising, critical acclaim, distributor characteristics, word-of-mouth communication, competition, and seasonality, respectively.

### **2.1. Modeling frameworks**

#### **2.1.1. Linear Models**

Most studies seeking to understanding the determinants of motion pictures' theatrical performance have done so using a linear modeling framework. The 'Litman studies' are an obvious example: Litman (1983), Litman & Kohl (1989), Sochay (1994) and Litman & Ahn (1998) all use linear regression models to investigate the drivers of motion picture performance, which are estimated by means of ordinary least squares. The same holds true for Prag and Casavant (1994), Smith and Smith (1986), Eliashberg and Shugan (1997) (who focus on the role of critics), Ravid (1999) and Simonoff and Sparrow (2000), who each use a set of regression models to investigate the role of various determinants. Wallace et al (1993) employ a stepwise ordinary least squares regression model.

#### **2.1.2. Non-Linear Models**

Other researchers have used a non-linear modeling framework. For instance, Zufryden (1996) develops a three-step model to evaluate the market performance of new film releases as a function of advertising. He first estimates a regression model to construct a measure of the weekly awareness of movies, then fits a binomial logit model to capture the weekly intention to see movies using that measure of awareness, and finally estimates a log-linear model with the number of weekly tickets purchases as the dependent variable

and a set of independent variables that includes the 'intention' construct. In a later paper, Zufryden (2000) again uses a log-linear model to predict movies' weekly box office performance, with the latter expressed in dollar tickets sales. Neelamegham & Chintagunta (1999) develop a Bayesian modeling framework to predict first-week viewership for new movies. They model the number of weekly viewers using a Poisson count data model, and employ a hierarchical Bayes formulation of the Poisson model that allows various determinants of viewership – including the number of screens, distribution strategy, and movie attributes – to vary across countries. Sawhney and Eliashberg (1996) derive a non-linear expression for the weekly expected ticket sales, based on an individual's time to adopt a movie by combining two stochastic processes, representing (1) the time to decide to see a movie and (2) the time to act on that decision. The resulting three-parameter model for the cumulative number of 'adopters' of a movie at any given time during a movie's run is a generalized gamma distribution (which collapses to an Erlang-2 distribution or an exponential distribution if certain parameter conditions are met). Focusing his research effort on providing insights into seasonal patterns, Einav (2001) estimates a discrete choice model of weekly demand for movies. More specifically, he uses a multinomial logit model to predict weekly market shares for each movie. Directing his attention to saturation effects in demand, Moul (2001b; 2001a) also uses a discrete-choice modeling framework.

Although they do not focus on investigating a set of determinants of motion picture performance, two other studies are relevant as well. First, De Vany and Walls (1996) adopt a Bayesian framework and use a 'Bose-Einstein' distribution to model motion picture revenues. Second, Jones and Ritz (1991) incorporate the role of exhibition intensity in a motion picture diffusion model by constructing what they refer to as an 'interactive model'. The best-fitting model represents the exhibitor's adoption process with a modified Bass model and the consumer adoption process with a constant transfer rate. We return to key insights emerging from these studies in more detail in Section 4.

## **2.2. Dependent variables: Rentals, Revenues and Screens**

### **2.2.1. Cumulative Rentals and Revenues (Static Frameworks)**

Models featured in early studies on motion picture performance predominantly use *cumulative theatrical rentals* (i.e. that portion of the revenues accruing to the distributor) as the dependent variable. Litman (1983) set the tone by investigating the predictors of theatrical rentals, adjusted for inflation. In later years, Smith and Smith (1986), Wallace et al (1993), Sochay (1994), and Prag and Casavant (1994) all operationalized performance in terms of theatrical rentals. More recently, perhaps motivated by the wide availability of such data, the attention is mostly directed to *cumulative box office revenues*. For example, Litman & Ahn (1998) estimate regression models with both domestic and worldwide revenues as the dependent variable, while Ravid (1999) investigates the predictors of, among other things, domestic box office receipts and total revenues across all sources.

### 2.2.2. Weekly Rentals, Revenues, and Screens (Dynamic Frameworks)

Jones and Ritz were conceivably the first researchers to use *weekly box office revenues* as the dependent variable, i.e. consider each week of a movie's run. More recently, De Vany and Walls (1996; 1997; 1999) and Moul (2001b; 2001a) have followed their example by using weekly box office revenues, starting from the opening week and ending when the movie drops off the Top 50 list, as the dependent variable in their analyses. Zufryden (1996) directs his attention to the number of weekly *tickets* bought for a given film rather than its revenues. Incidentally, Neelamegham and Chintagunta (1999) also use weekly revenues data, but focus their analyses on opening week revenues in the domestic and a set of foreign markets. Their modeling framework can only be characterized as 'dynamic' in the sense that it captures dynamics *across* markets; they do not investigate dynamics *within* a movie's run in each market.

Jones and Ritz (1991) considered the *weekly number of screens* on which a film is showing as a second dependent variable. To the best of our knowledge, their study is alone in this respect – other studies include the weekly number of screens (De Vany & Walls, 1996; De Vany & Walls, 1997; De Vany & Walls, 1999; Neelamegham & Chintagunta, 1999; Zufryden, 2000; Moul, 2001b; Moul, 2001a), the number of theaters (Zufryden, 1996), the maximum number of screens in any week of its run (Jedidi, Krider, & Weinberg, 1998), or the mean number of screens for the first two weeks of a movie's run (Sochay, 1994; Litman & Ahn, 1998) only as *independent* variables.

Because of the lack of research on the predictors of screens (recall that Jones and Ritz (1991) did not include any other predictors of either revenues or screens in their analyses), our discussion below only deals with insights regarding the determinants of rentals or revenues. That is, we only discuss knowledge about the drivers of the behavior of audiences, not that of exhibitors.

### 2.3. Independent variables: Determinants of Rentals and Revenues

Research to-date has consistently shown that the number of *screens* allocated to a movie is a key predictor of revenues. All 'Litman studies' (Litman, 1983; Litman & Kohl, 1989; Sochay, 1994; Litman & Ahn, 1998) find the mean number of screens for the first two weeks of a movie's run to be a significant predictor of either cumulative rentals or cumulative revenues. The significant role of screens is generally even more apparent in studies that consider weekly revenues (e.g. Jones & Ritz, 1991; De Vany & Walls, 1996; De Vany & Walls, 1997; Zufryden, 2000). Neelamegham & Chintagunta (1999), who focus on opening week revenues, conclude that amidst a range of other variables, "for all countries in the data set the number of screens on which a movie is released is the most important influence on viewership".

Previous research (Litman, 1983; Litman & Kohl, 1989; Litman & Ahn, 1998; Prag & Casavant, 1994; Wallace et al., 1993; Zufryden, 2000) that has studied the relationship between *budgets* and (weekly or

cumulative) revenues or rentals has generally found overwhelming evidence for a positive association. Contradictory evidence exists on the influence of stars on revenues. Whereas some have found evidence for a positive relationship between *stars* and (weekly or cumulative) revenues (De Silva, 1998; Levin & Levin, 1997; Litman & Kohl, 1989; Sochay, 1994; Neelamegham & Chintagunta, 1999; Ravid, 1999; Sawhney & Eliashberg, 1996; Wallace et al., 1993), others have raised doubts about the strength of this relationship (Austin, 1989; De Vany & Walls, 1999; Litman, 1983; Litman & Ahn, 1998; Ravid, 1999). Furthermore, whereas all 'Litman studies' (Litman, 1983; Litman & Kohl, 1989; Sochay, 1994; Litman & Ahn, 1998) fail to find evidence for an association between the presence of a high-profile *director* and a movie's financial success, that may be explained by the limited manner in which the concept has been measured. The involvement of a well-known director in itself, his or her ability to combine all creative aspects of a movie into an attractive mix, his or her capacity to generate publicity, and his or her ability to secure sufficient funding for a movie all make a relationship between a movie's director power and its revenues likely (e.g. Shugan, 1998).

In addition to budgets and talent, *genre* has been shown to be related to the financial success of motion pictures (e.g. Litman, 1983; Litman & Kohl, 1989; Prag & Casavant, 1994; De Silva, 1998). However, research findings are not conclusive (e.g. Jedidi et al., 1998). Whether a movie is a *sequel* (or is based on a known story) also appears to play a role (e.g. Prag & Casavant, 1994; Sawhney & Eliashberg, 1996; Litman & Ahn, 1998; Jedidi et al., 1998). Finally, a movie's *ratings* have been shown to affect its financial performance. Ratings not only have the ability to directly restrict the potential audience for a movie, they also have consequences for exhibition and marketing strategies. As a result, several studies find that restrictive ratings weaken a movie's cumulative rentals or revenues (e.g. Litman, 1983; Sawhney & Eliashberg, 1996). However, other studies fail to find a significant relationship between ratings and revenues (e.g. Prag & Casavant, 1994). De Silva (1998) shows that the importance of ratings significantly differs across demographic groups. Age and marital status emerge as key predictors: younger and non-married audiences are more likely to attend movies.

Lehmann and Weinberg (2000) note that there appears to be little published empirical research relating *advertising* levels to opening strength, decay rate, total revenue, or other measures of a movie's performance, despite advertising's obvious importance in building an audience for a movie. Among the exceptions are Prag and Casavant (1994), Zufryden (1996; 2000), De Silva (1998), and Moul (2001b), who all argue for or find evidence of a positive relationship. Lehmann & Weinberg's (2000) study, which directly relates advertising levels to movie performance, shows that the level of advertising for a movie is positively correlated with opening strength. However, they indicate, the direction of causality is unclear: it is plausible that movies that are expected to be popular receive more advertising.

A range of studies have provided evidence for a positive relationship between *critical reviews* and (cumulative or weekly) theatrical rentals or revenues (Litman, 1983; Litman & Kohl, 1989; Litman & Ahn, 1998; Sochay, 1994; Prag & Casavant, 1994; Ravid, 1999; Sawhney & Eliashberg, 1996; Zufryden,

2000). Wallace, Seigerman and Holbrook (1993) find that the relationship between critics' reviews and cumulative rental income is U-shaped. Eliashberg and Shugan (1997), who present a detailed review of work in this area, show empirically that critical reviews correlate with late and cumulative box office receipts but do not have a significant correlation with early (i.e. opening) box office receipts. In a wider context, several authors have debated the differences in tastes of ordinary consumers and professional critics (e.g. Austin, 1983; Cameron, 1995; Holbrook, 1999).

Several researchers have studied the impact of *distributor characteristics* on (cumulative or weekly) box office rentals or revenues – particularly whether the involvement of a major distributor makes a difference – but a clear picture does not emerge. Litman (1983) and Litman and Kohl (1989) find the presence of a major distributor to have a significant impact on cumulative rentals or revenues, while Sochay (1994) and Litman and Ahn (1998) show the opposite. Neelamegham and Chintagunta (1999) find that the power and financial muscle of major studios boosts viewership of movies distributed by them in the domestic market, but internationally the reverse holds.

To our knowledge, only Neelamegham & Chintagunta (1999) have attempted to empirically assess the relationship between *word-of-mouth communication* and weekly revenues. They used cumulative viewership as a proxy for word-of-mouth effects, but failed to show any significant results. Given the apparent key role of word-of-mouth effects, they attribute that to the shortcomings of their measure. The lack of attention for word-of-mouth communication is surprising, particularly given that industry experts appear to agree that this is a critical factor underlying a movie's 'legs' or 'staying power', i.e. its continuing appeal to audiences and exhibitors, and therefore its ultimate financial success.

Movies are not released in a vacuum – they compete with other movies for the attention of audiences and for shelf space in theaters. Despite the apparent importance, most previous research is only scratching the surface when it comes to investigating the role of a movie's *competitive environment* in the initial and ultimate success or failure of movies. By and large, although mostly implicitly, these efforts are focused on competition for the attention of audiences, rather than competition for shelf space allocated by exhibitors. Sochay (1994) and Litman & Ahn (1998) use 'concentration ratios' to measure the impact of competition on the ultimate financial performance of motion pictures. Sochay's 'top 10' concentration ratio for a given movie is derived by taking the revenues accruing to the top 10 movies in a movie's opening week (excluding the revenues for the movie under consideration, if it appeared in the top 10), as a percentage of total film revenues for that week. He found it to be negatively related to both the length of a movie's run and theatrical rentals. Jedidi et al (1998) and Zufryden (2000) employ the number of new releases introduced at each week of a movie's run as a proxy for the competition for revenues it experiences. Krider and Weinberg (1998) use a game-theoretic model to analyze the high-season release timing of two motion pictures with different drawing power that are competing directly for the same target audience. They empirically show that a primary concern in timing releases is 'to stay away from movies that have the same target audience'.



Finally, *seasonal variations* result from differences in the number and strength of movies on release and differences in demand: in high-season periods the competition is generally more intense, but the total audience is larger as well. Litman (1983), Litman and Kohl (1989) and Sochay (1994) find movies released in peak-seasons (e.g. Summer and Christmas) to have significantly higher cumulative theatrical rentals and revenues. Radas and Shugan (1998) estimate the seasonal pattern for the motion picture industry, and find that the average box office is higher for movies released in the high season. Ravid (1999) and Zufryden (2000) both use a measure based on weekly revenues in previous years but generate contrasting results: while Ravid (1999) fails to find a significant relationship, Zufryden (2000) does. Noteworthy is also a recent contribution by Einav (2001) who breaks seasonality down into seasonality in underlying demand and in the quality of movies released, and finds that observed release patterns are not closely related to the former.

### **3. SOME KEY OBSERVATIONS**

Three key observations emerge from our review of the literature. Below, we describe how they have shaped our proposed modeling approach. We start by elaborating on the need for a dynamic modeling approach. We then move to an explanation of why it is crucial to account for the endogeneity of screens in estimating revenues. Next, building on the previous two points, we discuss the need to account for the simultaneity of developments in screens and revenues. This leads us to a description, albeit in very general terms, of our proposed modeling approach.

#### **3.1. A Dynamic Approach**

Movies collect revenues over a period of time, and the distribution of both revenues and screens over time is often markedly different across movies – the contrast between so-called 'sleepers' and 'platformers' is the popular example in this case. Furthermore, it is well established that the role of determinants can vary for different stages of a movie's run. Recall, for example, that Eliashberg & Shugan (1997) found that critical reviews correlate with late and cumulative box office receipts but do not have a significant correlation with early box office receipts. In addition, it seems safe to assume that the role of word-of-mouth communication changes once a possible pre-release 'buzz' created by advertising and critical reviews is overshadowed by first-hand accounts from moviegoers who have had a chance to see the movie. As far as exhibitors' decisions regarding exhibition levels are concerned, it is also likely that the role of determinants varies over time. In fact, it may well be that the importance of exogenous variables decreases over the course of a movie's run, as more information about box office performance becomes available and exhibitors are better able to assess a movie's 'true' market potential.

Perhaps surprisingly, we observe that research that takes a time series approach and allows the influence of determinants of movie performance to vary over time is limited. As noted, a large number of studies

that study the determinants of motion picture performance either focus on *cumulative* revenues or rentals (e.g. Litman, 1983; Litman & Kohl, 1989; Sochay, 1994; Litman & Ahn, 1998; Prag & Casavant, 1994) or *opening* week revenues (e.g. Neelamegham & Chintagunta, 1999) – both static approaches. Even when time series data is used, the impact of determinants over time is often modeled in a restrictive way, or only one determinant is considered in isolation (e.g. Radas & Shugan, 1998; Sawhney & Eliashberg, 1996).

### 3.2. Endogeneity of Screens

Recall that it is likely that screens and revenues have an overlapping set of predictors. A change in one or more of those predictors leads to a change in revenues both directly (through the relationship between these predictors and revenues) and indirectly (through the relationship between these predictors and screens). A good example of a study that fails to account for the endogeneity of screens when estimating revenues is Litman (1983). Litman investigated the relationship between the financial performance of motion pictures and three categories of factors: those related to 'creative sphere' (e.g. genre, stars, director, budget, ratings, and critical reviews), 'scheduling and release pattern' (e.g. distributor, release timing, and release strategy), and 'marketing effort' (e.g. competitive forces and advertising intensity). It was the front runner of a series of similar studies, each using more recent data, conducted by Litman and Kohl (1989), Sochay (1994), and Litman and Ahn (1998). As indicated, all use simple linear regressions estimated by means of ordinary least squares, with cumulative theatrical rentals or box office grosses as the dependent variable, and with the mean number of screens allocated over the first two weeks of a movie's run as one of the independent variables. All studies also find screens to be a highly significant predictor of revenues.

We again stress that the 'Litman studies' are not alone in this respect – there are many other studies that estimate revenues as a function of screens in a linear or non-linear framework without accounting for the endogeneity of screens (e.g. Prag & Casavant, 1994; Sawhney & Eliashberg, 1996; Neelamegham & Chintagunta, 1999; Zufryden, 2000). Nevertheless, the 'Litman studies' serve as a particularly useful benchmark here.

Crucially, such straightforward regression analyses may lead to misleading results if they fail to account for, in econometric terms, the likely contemporaneous correlation between the regressor and the error term. This endogeneity problem is particularly significant here because screens account for a large part of the variation in revenues. We can illustrate this with a (simplified) example involving only a movie's opening week. Assume exhibitors allocate screens to a movie in its opening week based on its 'revenue potential', which they in turn assess using a combination of objective characteristics, such as its budget, stars, and director, and subjective criteria, such as the market 'buzz' surrounding the movie and signals about the distributor's commitment to the movie – not an unrealistic set of assumptions. Further, suppose there is a high positive correlation between screens and revenues in the opening week – a relationship that, as indicated, is confirmed by a number of studies (e.g. Neelamegham & Chintagunta, 1999). It should now be obvious that running a simple regression analysis with revenues as the dependent variable, and screens,

budget, stars, director as independent variables violates basic assumptions of the classical linear regression model. For example, suppose the positive 'buzz' surrounding a movie increases. This is likely to lead to an increase in revenues both directly (audiences are more likely to want to see the movie) and indirectly (studios are more likely to demand more screens and exhibitors are more likely to want to allocate more screens, which in turn affects revenues). Thus, the regressor (screens) and error term (belonging to revenues) are likely to be correlated, which makes the ordinary least-squares estimator biased and inconsistent.

### **3.3. Simultaneity of Fluctuations in Revenues and Screens**

Having established the need to model both revenues and screens and their interdependencies over the course of a movie's run, and the need to account for the endogeneity of screens, we are left with one, related, key consideration: that of a possible simultaneity of both processes. That is, we need to account for the fact that the errors of both equations may be correlated. This implies that exogenous factors not included in the model could simultaneously 'shock' both revenues and screens. Again, a simple example may help to underline the importance. Building on the previous example, suppose that during the course of a movie's run, the 'buzz' that surrounds a movie suddenly increases. A possible Oscar nomination is one likely explanation for such a phenomenon. If strong enough, such a 'buzz' may lead to an increase in audience demand for a movie and, because exhibitors *expect* this to be the case, an increase in the number of screens allocated to the movie (which in turn could lead to an increase in revenues). The result, at any given week of a movie's run, is a likely correlation between the disturbances of the screens and revenues equation.

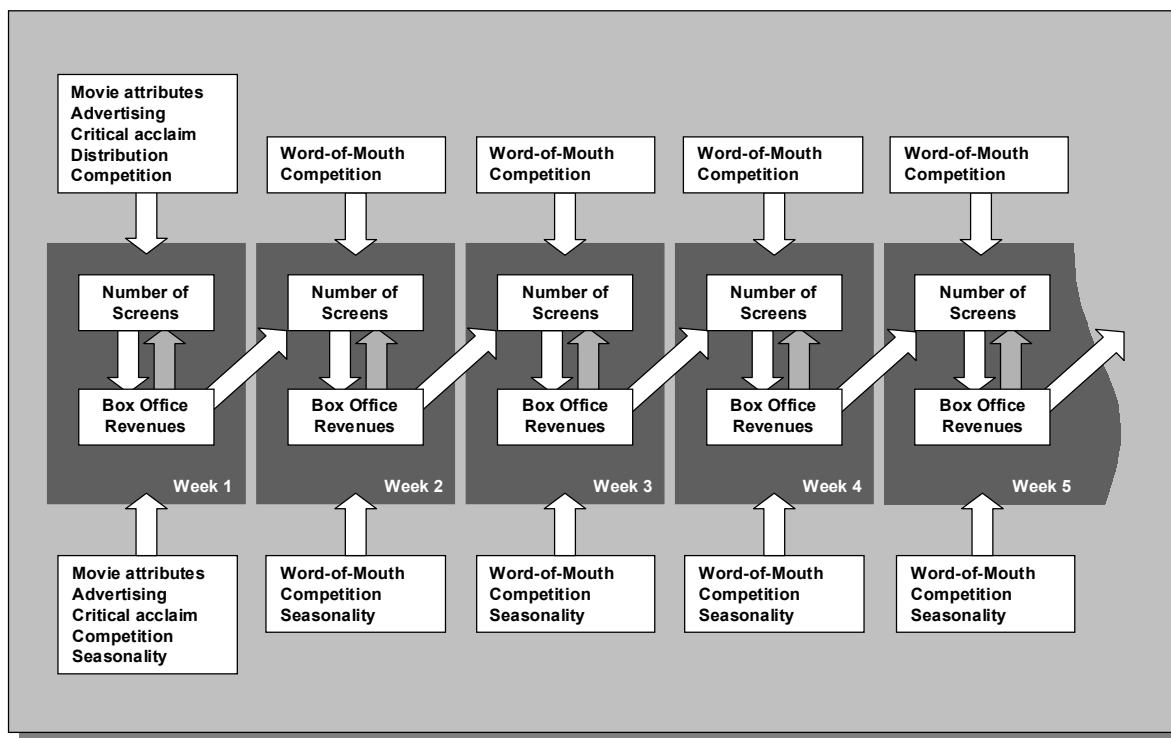
## **4. PROPOSED NEW MODELING APPROACH**

Before we move to the model specification, we point in more detail to two particularly relevant studies. First, regarding the interplay between screens and revenues, a study conducted by Jones and Ritz (1991) is highly relevant. Jones and Ritz set out to incorporate the effect of distribution into new product diffusion models, and propose a dynamic model based on the assumption that there are two parallel adoption processes occurring for any new product – one for retailers, and one for consumers. They apply their model to data from the motion picture industry, taking the number of screens as a measure of retailers' behavior, and box office revenues as a measure of consumers' behavior. Jones and Ritz empirically show that the retailer's allocation of screens is an important determinant of movie viewership in the US market. Although they generate important insights into the interplay between revenues and screens, and offer support for some key assumptions underlying our approach, we note that their approach differs significantly from ours in a number of respects. Crucially, their modeling framework does not incorporate any other determinants of motion picture performance, and it is difficult to envision how their model can be adjusted or extended to overcome that disadvantage. We note that a simultaneous equations modeling approach as proposed here appears to be the most suitable method to analyze the interplay between

revenues and screens, as well as the role played by a range of determinants hypothesized to influence this process. Second, De Vany and Walls (De Vany & Walls, 1996; also see De Vany & Walls, 1997) model what they refer to as the 'adaptive' and 'self-organizing' nature of demand dynamics. They assume that movie-goers act in a 'Bayesian' manner in the sense that they rely on information revealed during a film's run to refine their initial expectations about its quality, which leads to a 'Bose-Einstein' distribution for motion picture revenues. The supply of theatrical engagements (i.e. screens), they argue, matches this pattern, and adapts to capture the increasing returns. However, their model does not explicitly incorporate exhibition levels.

Now, moving to the description of our proposed model, Figure 1 illustrates our conceptual framework. The figure reflects our hypotheses concerning the relationship (depicted by the arrows) between endogenous and exogenous variables, i.e. screens, (expected) revenues, movie attributes, advertising, critical acclaim, distributor characteristics, word-of-mouth communication, competition, and seasonality, which are mostly based on findings from previous research. In the absence of more detailed information, three comments may help clarify our approach.

*Figure 1: Conceptual Framework*



First, regarding the role of exogenous variables, 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 box office performance data become available – i.e. after the first week. For example, on the 'screens' side, rather than hold on to a priori predictions of demand, exhibitors adapt exhibition levels to demand as it

unfolds. Other factors – time-variant factors – play a role for the full duration of a movie's run. Also note that some factors are only hypothesized to influence revenues, some are only hypothesized to influence screens, and some are hypothesized to influence both revenues and screens. Furthermore, not obvious from Figure 1, some variables are operationalized differently in the 'screens' equation than they are in the 'revenues' equation. Competition is the best example in this regard – we use fairly different measures of competition in both equations.

Second, as far as the interaction between revenues and screens 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. The revenues in the first week, in turn, influence the number of screens allocated to the movie in its second week, which again influences the box office revenues, and so on (e.g. De Vany & Walls, 1996). More specifically, we hypothesize that exhibitors allocate screens based on expectations of revenues (indicated in the above figure by means of gray arrows). Expected revenues are updated each week, on the basis of earlier expectations and realized revenues in previous weeks, with most recent realized revenues given the highest weight. 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. We note that this 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 the revenues are satisfactory. Exhibitors are known to 'pull' movies despite contractual agreements with a distributor if they perform much worse than expected.

Third, as mentioned, we use a simultaneous equations model with one 'revenues' equation and one 'screens' equation to test the hypotheses depicted in the figure. We opt for a multiplicative or, more specifically, a log-linear formulation. This mostly follows from our aim to incorporate that, by definition, when a movie has not been allocated any screens, 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 (e.g. Jones & Ritz, 1991). 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.

## **5. CONCLUSION**

We have described three shortcomings in the literature addressing the drivers of motion picture performance: a prevalence of static approaches, a failure to address the potential endogeneity of screens in estimating revenues, and a failure to account for the possible simultaneity of developments in screens and revenues. Particularly the treatment of screens as an exogenous variable may have led to a distorted picture about the determinants of a motion picture's financial performance. Our project promises to generate relevant new insights into a wide range of potential determinants of motion picture performance, and into the interplay between revenues and screens, across a movie's run. Our research project will reveal

which factors are predominantly related to the behavior exhibitors, which factors are predominantly related to the behavior of audiences, and which factors are related to the behavior of both exhibitors and audiences. Furthermore, by comparing our findings to results we generate when we employ a traditional regression model estimated by means of ordinary least squares – in line with, for example, the 'Litman studies' – we anticipate that we can draw new conclusions about the relative importance of drivers of motion pictures' financial performance. These insights will help distributors and exhibitors in adequately predicting and adapting to demand for a motion picture as it is revealed during its entire theatrical run. The findings therefore can aid in the development of more accurate forecasting models and screen management tools.

## REFERENCES

- Austin, B. A. (1983). Critics' and Consumers' Evaluation of Motion Pictures: A Longitudinal Test of the Taste Culture and Elitist Hypotheses. Journal of Popular Film and Television, 10, 156-167.
- Austin, B. A. (1989). Immediate Seating: A Look at Movie Audiences. Belmont, CA: Wadsworth.
- Cameron, S. (1995). On the Role of Critics in the Cultural Industry. Journal of Cultural Economics, 19(4), 321-331.
- D'Astous, A., & Touil, N. (1999). Consumer Evaluations of Movies on the Basis of Critics' Judgments. Psychology & Marketing, 16(8), 677-694.
- De Silva, I. (1998). Consumer Selection of Motion Pictures. B. R. Litman (Editor), The Motion Picture Mega-Industry. Needham Heights, MA: Allyn & Bacon.
- De Vany, A., & Walls, W. D. (1996). Bose-Einstein Dynamics and Adaptive Contracting in the Motion Picture Industry. The Economic Journal, 106(November), 1493-1514.
- De Vany, A., & Walls, W. D. (1997). The Market for Motion Pictures: Rank, Revenue, and Survival. Economic Inquiry, 35(4), 783-797.
- De Vany, A., & Walls, W. D. (1999). Uncertainty in the Movie Industry: Does Star Power Reduce the Terror of the Box Office? Journal of Cultural Economics, 23(4), 285-318.
- Einav, L. (2001). Seasonality and Competition in Time: An Empirical Analysis of Release Date Decisions in the US Motion Picture Industry. Working Paper, Harvard University.
- Eliashberg, J., & Shugan, S. M. (1997). Film critics: Influencers or predictors? Journal of Marketing, 61(April), 68-78.

- Hettema, J., Leidelmeijer, K. C., & Geenen, R. (2001). Dimensions of Information Processing: Physiological Reactions to Motion Pictures. European Journal of Personality, 14, 39-63.
- Holbrook, M. B. (1999). Popular Appeal versus Expert Judgements of Motion Pictures. Journal of Consumer Research, 26(September), 144-155.
- Jedidi, K., Krider, R. E., & Weinberg, C. B. (1998). Clustering at the Movies. Marketing Letters, 9(4), 393-405.
- Jones, J. M., & Ritz, C. J. (1991). Incorporating Distribution into New Product Diffusion Models. International Journal of Research in Marketing, 8(June), 91-112.
- Krider, R. E., & Weinberg, C. B. (1998). Competitive Dynamics and the Introduction of New Products: The Motion Picture Timing Game. Journal of Marketing Research, 35 (February), 1-15.
- Lehmann, D. R., & Weinberg, C. B. (2000). Sales Through Sequential Distribution Channels: An Application to Movies and Videos. Journal of Marketing, 64(3), 18-33.
- Levin, A. M., & Levin, I. P. (1997). Movie Stars and Authors as Brand Names: Measuring Brand Equity in Experiential Products. Advances in Consumer Research, 24, 175-181.
- Litman, B. R. (1983). Predicting Success of Theatrical Movies: An Empirical Study. Journal of Popular Culture, 16, 159-175.
- Litman, B. R., & Ahn, H. (1998). Predicting Financial Success of Motion Pictures. B. R. Litman (Editor), The Motion Picture Mega-Industry. Needham Heights, MA: Allyn & Bacon.
- Litman, B. R., & Kohl, L. S. (1989). Predicting Financial Success of Motion Pictures: The '80s Experience. Journal of Media Economics, 2, 35-50.
- Moller, K., & Karppinen, P. (1983). Role of Motives and Attributes in Consumer Motion Picture Choice. Journal of Economic Psychology, November, 239-262.
- Moul, C. C. (2001a). Saturation and the Demand for Motion Pictures. Working Paper, Department of Economics, Washington University, September 2001.
- Moul, C. C. (2001b). Word-of-Mouth and Saturation: Why Movie Demands Evolve the Way They Do. Working Paper, Department of Economics, Washington University, September 2001.
- Neelamegham, R., & Chintagunta, P. (1999). A Bayesian Model to Forecast New Product Performance in Domestic and International Markets. Marketing Science, 18(2), 115-136.
- Palmgreen, P., & Lawrence, P. (1991). Avoidances, Gratifications, and Consumption of Theatrical Films:

- The Rest of the Story. B. A. Austin (Editor), Current Research in Film: Audiences, Economics, and Law (Volume 5) (pp. 39-55). Norwood, NJ: Ablex.
- Prag, J., & Casavant, J. (1994). An Empirical Study of the Determinants of Revenues and Marketing Expenditures in the Motion Picture Industry. Journal of Cultural Economics, 18, 217-235.
- Radas, S., & Shugan, S. M. (1998). Seasonal Marketing and Timing New Product Introductions. Journal of Marketing Research, 35(3), 296-315.
- Ravid, S. A. (1999). Information, Blockbusters, and Stars: A Study of the Film Industry. Journal of Business, 72(4), 463-492.
- Sawhney, M. S., & Eliashberg, J. (1996). A Parsimonious Model for Forecasting Gross Box-Office Revenues of Motion Pictures. Marketing Science, 15(2), 113-131.
- Shugan, S. M. (1998). Forecasting Failure and Success of New Films. Working Paper, The University of Florida.
- Simonoff, J. S., & Sparrow, I. R. (2000). Predicting Movie Grosses: Winners and Losers, Blockbusters and Sleepers. Chance, 13(3), 15-24.
- Smith, S. P., & Smith, V. K. (1986). Successful Movies: A Preliminary Empirical Analysis. Applied Economics, 18, 501-507.
- Sochay, S. (1994). Predicting the Performance of Motion Pictures. Journal of Media Economics, 7(4), 1-20.
- Theil, H. (1971). Principles of Econometrics. New York: John Wiley & Sons.
- Wallace, W. T., Seigerman, A., & Holbrook, M. B. (1993). The Role of Actors and Actresses in the Success of Films: How Much is a Movie Star Worth? Journal of Cultural Economics, 17(1), 1-27.
- Zufryden, F. S. (1996). Linking Advertising to Box Office Performance of New Film Releases: A Marketing Planning Model. Journal of Advertising Research, (July-August), 29-41.
- Zufryden, F. S. (2000). New Film Website Promotion and Box-Office Performance. Journal of Advertising Research, (January-April), 55-64.

-----