A forecasting system for movie attendance

Article *in* Journal of Business Research · October 2013

DOI: 10.1016/j.jbusres.2013.01.013

3 authors, including:

Pablo Marshall
Pontifical Catholic University of Chile

Monika Dockendorff
Pontifical Catholic University of Chile

Journal of Business Research 66 (2013) 1800–1806

Contents lists available at SciVerse ScienceDirect

Journal of Business Research

A forecasting system for movie attendance☆

Pablo Marshall [a,*], Monika Dockendorff [b], Soledad Ibáñez [b]

[a] Pontificia Universidad Católica de Chile, Escuela de Administración, Chile
[b] Pontificia Universidad Católica de Chile, Chile

ARTICLE INFO

Available online 4 February 2013

Keywords:
Attendance prediction
Diffusion models
Dynamic prediction
New products

ABSTRACT

The main objective of this paper is to develop a system that uses historical data to forecast new movie attendance. In contrast to most models in the literature that consider aggregated prediction or the demand for a cross-section of movies, this paper analyzes the dynamic behavior of attendance at the movie level. The paper considers two alternative models for the weekly adoption or consumption of newly released movies. The Bass (1969) explains adoption through innovation and imitation effects. The Sawhney and Eliashberg (1996) model characterizes the adoption process through time-to-decide and time-to-act effects. The basis of the paper's results is a sample of 117 movies exhibited in Chile between 2001 and 2003. The two models present very similar results. For the Bass model, the innovation effect is greater than the imitation effect; but, in Sawhney and Eliashberg's model, the time-to-act is more significant than the time-to-decide. The sample prediction errors of these models present values between 2.7% and 17.1%, depending on the prediction horizon and the amount of historical data available.

1. Introduction

The recent economic literature pays significant attention to the movie industry because of the industry's unique characteristics. These characteristics confront academic researchers and practitioners with interesting and novel problems such as the complexity of the production process, a short product life cycle, and the uncertain nature of demand (Caves, 2000; Eliashberg, Elberse, & Leenders, 2006; Moul, 2005).

The movie industry believes that each film is unique, which makes forecasting demand very tricky especially early predictions. Forecasting demand is tricky because consumers have difficulty evaluating the quality of a movie before viewing the film. Because most of the screening income comes from new movies that have very short life cycles, the prediction of the performance of these movies is extremely important to the industry. In contrast to other products for which changes in distribution intensity are difficult to manage on short notice, movie theaters can easily adapt the allocation of screening capacity to a new movie on a weekly basis. They can either drop a movie from the theater, shift one to a smaller screening room, or reduce the number of copies. For this reason, an early demand forecast is extremely relevant for theater chains in their decision-making process regarding theater intensity. An early and accurate forecast of box-office demand in this industry is then a valuable tool.

In Chile, according to Cámara de Exhibidores Multisalas de Chile A.G. (CAEM, 2011), movie attendance has risen 10.7% annually in the last five years. In 2011, the industry reported earnings of US$ 96 million, or 0.04% of GDP. The average rate of movie attendance was approximately 0.86 times a year in 2010, whereas in developed countries this rate varies between 2 and 5 times per year. The CAEM reports that three major theater chains currently dominate the movie market in Chile: Cinemark with a 38% market share, Cine Hoyts with a 30% share, and Cinemundo with a 17% share. In Chile, the life cycle of a movie is usually shorter than 12 weeks.

The study here proposes a model to explain and forecast the demand for a movie at different stages of its life cycle. The authors propose using the Bass (1969) model to capture the evolution of the demand over the life cycle of a movie. Other industries have used the Bass (1969) model successfully. The model's main advantage is the explicit consideration of the word-of-mouth or imitation effect, a factor that determines the long-term success of movies and other experience goods according to De Vany and Walls (1999). The authors also compare the results of the Bass model with the results of another model proposed in the literature, Sawhney and Eliashberg (1996). The two models produce demand forecasts at different stages of the life cycle. These predictions have concrete uses in strategic film management and in the administration of movie theaters through the application of demand forecasting to the management of theater capacity and movie rotation throughout the different-size theaters of the cinema complex and the distribution and orientation of the marketing and media budget.

☆ We are grateful to a co-editor whose comments significantly improved the paper.
* Corresponding author at: Av. Vicuña Mackenna 4860, Macul, P.O. Box 76/17, Santiago, Chile.
E-mail addresses: pmarshall@uc.cl (P. Marshall), mdockend@uc.cl (M. Dockendorff), saibanez@uc.cl (S. Ibáñez).

0148-2963/$ – see front matter © 2013 Published by Elsevier Inc.
http://dx.doi.org/10.1016/j.jbusres.2013.01.013

Demand forecasting can also apply to the formalization of the potential demand estimate process for new movies as a support tool for the current anecdotal system based on experience and market wisdom. The potential for the demand forecast of movie performance can facilitate the risk distribution in the bargaining process between distributors (studios) and theaters that generates benefits for both parties that could imply potential market growth. Furthermore, forecasting can facilitate the estimate of the number of movie copies needed to satisfy the potential audience. Currently, most theaters in the movie industry use informal methods to predict demand.

The Bass (1969) and Sawhney and Eliashberg (1996) models use three parameters to characterize the behavior of consumers that allow for the possibility to generate forecasts based on past values with only three weeks of data. This paper uses movie attendance that measures the number of people frequenting a particular movie rather than the box-office income, as in some previous studies. This parameter fulfills the paper's goal of determining the potential demand and then using the forecast as a decision tool for theater intensity.

The results of the study come from a sample of 117 movies played in Chile during the 2001 to 2003 period. The two models yield similar results. For the Bass (1969) model, the innovation effect is greater than the imitation effect, whereas in the Sawhney and Eliashberg (1996) model, the time-to-act is more significant than the time-to-decide. The sample prediction errors of these models present values between 2.7% and 17.1%, depending on the prediction horizon and the amount of historical data available.

Aside from this introduction, the organization of the paper is as follows. Section 2 introduces and describes the two models. Section 3 describes and explains the database. Section 4 shows the forecast of both models based on different data groups, and Section 5 provides the results of these forecasts separately for each model. Section 6 contains general conclusions and further applications. The Appendix A contains a detailed definition of the variables.

2. Models for demand in the movie industry

The marketing models in the movie industry rely on distinct approaches. One approach uses demand models with cross-sectional movie data. These models consider total box-office performance as the dependent variable and various factors like the production budget and the number of screens as independent variables. Litman (1983) was one of the first to develop a multiple regression model in an attempt to predict the financial success of films. Litman's model provides evidence that the independent variables of production costs, critics' ratings, science fiction genre, major distributor, Christmas release, Academy Award nomination, and Academy Award win are all significant determinants for the success of a theatrical movie. Litman and Kohl (1989) and Litman and Ahn (1998) replicate and expand on the initial work by Litman (1983), while Cameron (1999) and Dewenter and Westermann (2005) investigate cinema demand in the UK and Germany. In a slightly different venue, Terry, Butler, and De'Armond (2004) examine the determinants of foreign box-office õrevenue for English language movies using U.S. domestic box-office revenue, action movies, children's movies, sequels, Academy Award wins, and the production budget.

Stimpert, Laux, Marino, and Gleason (2008) investigate the variables associated with the success of creative products and services by focusing specifically on movies. Their study offers a comprehensive examination of the factors that influence a movie's box-office success: quality, other product attributes, advertising expenditures, and the distribution pattern. Based on a review of the literature, the authors develop and test a model using a sample of 439 movies. All of these preceding models use cross-sectional data that fail to account for the dynamicity of demand and hence are unable to predict the life cycle of a particular movie.

A second approach to modeling attendance focuses on the aggregate prediction and time-series analysis of attendance; for example, Hand (2002) proposes a time-series model for cinema admissions in the UK, and Hand and Judge (2012) investigate whether Google Trends' search information can improve the forecasts of movie attendance. These models do not take into account either the information for particular movies or the dynamic of a movie's life cycle. These models are useful for the analysis of the industry as a whole but not for the managerial decisions at the theater level.

This paper uses a third approach that models both total demand and the dynamic behavior of movie attendance. This type of model allows for the analysis and prediction of the life cycle of individual movies. One of these studies is by Sawhney and Eliashberg (1996). The authors consider a behavioral model in which the average consumer goes through two stages in executing his or her decision to attend a movie: the time-to-decide to attend and the time-to-act upon the decision. Usually, advertising and word-of-mouth are the most important factors behind the long-term success of movies and other experience goods (De Vany & Walls, 1999). In this context, this paper uses the Bass (1969) model that explicitly considers advertising, word-of-mouth, and other independent variables in order to explain and predict the life cycle of individual movies.

In a related line of research, McKenzie (2009) proposes a duration model to consider the longevity of films in Australia, and Dellarocas, Zhang, and Awad (2007) study the impact of online word-of-mouth communities on revenue. Other studies use additional models to forecast demand in the movie industry, such as the Jones and Ritz (1991) model that embodies the effects of distribution screening on the diffusion of movies. These models conceptualize the diffusion into two parallel processes: the theater (screens) and the consumer adoption processes. Both processes have a relation to the assumption that each retailer that adopts a new movie increases its pool of potential consumers by a fixed amount. Another model is the Jones and Mason (1990) model that has a more complex conceptualization that can accommodate additional distribution-related phenomena.

When comparing these three approaches, the first one produces results for the total attendance to a film without considering its life cycle, although this approach can deliver predictions at the individual level. The second approach produces results at the aggregate level and is not useful for managerial decisions at the exhibition stage. The third approach is more complete because this model predicts both the dynamic and the total behavior of movie attendance at the individual level.

2.1. The Bass (1969) model

Over a large number of applications, the Bass (1969) model successfully describes the empirical adoption of a new product. The basic assumption underlying the model is that the probability of adoption of a new product depends linearly on two forces: one that is independent of the number of previous adopters, called the innovation effect; and one with a relation to previous adopters, called the imitation effect. For modeling movie attendance, the Bass model is attractive because the model explicitly considers the worth-of-mouth or imitation effect in the adoption of a product or service, both online and off-line.

The Bass (1969) model conceptualizes the adoption of a new movie as an event in which two different factors influence the decision. These factors can be external forces like advertising, prices, and promotions characterized by the innovation effect; or internal forces like the imitation of previous consumers. The study of one of these effects' prevalence in a given movie, or type of movie, allows for the efficient orientation of marketing efforts. If external forces are more significant in the adoption process of certain movies, one should highlight the attributes of the movie itself such as awards, nominations, featured movie stars, plot, special effects and the like.

However, if internal forces are more influential, then the allocation of resources should go toward creating notoriety for the movie to enhance the word-of-mouth effect. Organizing movie release events, media advertising, movie-related contests, and merchandising can help achieve this allocation.

According to the Bass (1969) model, the expected number of cumulative adopters by time t is

$$N(t) = N\frac{1-e^{-(p+q)t}}{1+(p/q)e^{-(p+q)t}} \tag{1}$$

where p (>0) is the innovation parameter, q (≥ 0) is the imitation parameter, and N (>0) is the parameter representing the total number of potential adopters of a new movie. The assumption is that $N(0)=0$. That is, the number of adopters at time $t=0$. Starting from Eq. (1) the instantaneous adoption rate by time t can be determined and takes the form:

$$\frac{dN(t)}{dt} = (p+qN(t)/N)(N-N(t)). \tag{2}$$

According to Eq. (2), the new adopters at time t are a proportion of the difference between the total potential number of adopters and the observed number of adopters up to time t. The first pair of parentheses in Eq. (2) defines the adoption parameters: the innovation parameter defined as p and the imitation parameter defined as q. The parameters p, q, and N are unknown and can be estimated based on the historical data of the number of adopters of the innovation or from other innovation processes or historical data. Srinivasan and Mason (1986) propose a nonlinear least squares procedure that reports good results for the estimation of the parameters.

In the case of a dominant innovation effect relative to the imitation effect, attendance tends to concentrate in the early weeks because of the heavy exposure of the potential viewers to influential advertising. Once a movie release occurs, viewers rush to theaters, and a very low proportion of the potential audience defers consumption to the following weeks. In this scenario, advertising should highlight the technical elements and characteristics of the movie to influence the adoption process of movies. Therefore, a mass-release should take place in several theaters with multiple film copies supported by varied advertising efforts. Conversely, if the imitation effect has a higher relative impact than the innovation effect, fewer viewers attend movie theaters during the initial weeks of screening, and the majority attends in the following weeks. If this scenario exists, marketing efforts should concentrate on inspiring discussion, controversy, or notoriety, thus fostering the transmission of the movie experience through word of mouth from early attendees to the mass audience and finally to the laggards. A platform release is more suitable for this situation in which fewer theaters and film copies have screenings in the early weeks of release, but their number progressively rises as demand increases.

2.2. The Sawhney and Eliashberg (1996) model

Sawhney and Eliashberg's (1996) model conceptualizes the adoption of a new movie as a two-stage process. In the first stage, the person receives influential information about a new movie. In the second phase, the consumer takes time before acting to see the movie. Thus, the possibility exists to model the adoption rate (or time to see the movie) of a particular person as the added amount of time he or she takes to decide to see the movie plus the time necessary to act on the decision (i.e., to actually watch the movie).

The recognition of the variable time-to-act is an extension of the assumption that individuals act immediately after receiving motivational information (Chatterjee and Eliashberg, 1990; Roberts & Urban, 1988). Sawhney and Eliashberg (1996) model the processes of time to decide and time to act as two stochastic, independent processes. The independence assumption underlying these processes implies that the time an individual takes to hear or see influential information in relation to a certain movie does not impact the time that the person takes to act on his or her previous decision.

The time-to-decide has a relation to the individual's media exposure and propensity to be persuaded by word of mouth, whereas a different set of factors influences the time-to-act: movie-going habits, free time, and the willingness to go to a suitable movie theater (distance, theater comfort, screening quality, parking lots, and others). The stochastic structure allows the model to estimate the dynamic uncertainty of the adoption pattern in addition to the average expected value of the pattern.

The assumption is that any individual in the potential adopter population can have exposure, independently of other members of the population, to a piece of influential advertising. The probability that the time-to-decide process takes place before time t for any member of the population has an exponential distribution with a parameter λ. The expected time for advertising exposure for any individual is then $1/\lambda$. When λ is extremely high, the average time to decide to watch a movie tends toward zero. The expectation is that λ will be particularly large for blockbuster movies for which the intensity of publicity and media advertisement is very high.

Once the individual has made a decision, the assumption is that he or she will take some time-to-act to see the movie. Another assumption is that the distribution of this time-to-act process is in accordance with an exponential model with parameter γ. The assumption of γ being constant is a restrictive assumption, but the model considers γ for the sake of the parsimony. Sawhney and Eliashberg's (1996) model relaxes this assumption to allow γ to be an explicit time-varying function of screening intensity.

The model measures the screening intensity as the number of movie theaters playing a certain film that changes with time. The time changes influence the time-to-act parameter γ. Therefore, screening intensity can have a relation to parameter γ either by making a proportion in absolute terms of movie theaters or by calculating the percentage of the total number of theaters in the market playing a certain movie.

The release strategy determines the function that relates parameter γ with screening intensity. These strategies are either a wide-mass release-taking place in an important percentage of movie theaters in the market, or a platform release in which the number of theaters playing the movie increases as a positive word-of-mouth effect nurtures the audience. These types of release strategies establish the evolution in the number of theaters for a certain movie during its life cycle.

The time-to-act should approach zero as the time-to-act parameter γ approaches infinity. In practical terms, an intensive screening strategy could reduce the expected time-to-act to a very small number but not to zero, considering that individuals always take a finite time-to-act after adopting the decision to see a film for reasons that have no relation to the movie itself, such as the availability of leisure time. Accordingly, the expected cumulative number of new adopters by time t is

$$N(t) = \frac{N}{\lambda-\gamma}\left[(\lambda-\gamma)+\gamma e^{-\lambda t}-\lambda e^{-\gamma t}\right] \tag{4}$$

where $N>0$ is the potential population size, $N(t)>0$ is the cumulative number of adopters by time t that represents both the time to decide and the time to act, $\lambda>0$ is the time-to-decide parameter, and $\gamma>0$ is the time-to-act parameter.

3. Data

The Cinematographic Chamber of Commerce provides the data for the study. The data comes from a sample of 117 movies released in commercial movie theaters, mainly Cine Hoyts, Cinemark, NAI, Chile films and Cinemundo, in Chile between 2001 and 2003 that played for three weeks or longer. The studios of Columbia, Universal, Paramount, Disney, MGM, Fox, Warner, New Line, Angel Films and Nu Visión distributed all of the films.

The variables for each movie are the total and weekly movie attendance as well as the following movie characteristics: genre, country of origin, age rating, competitors, director, actors/actresses, advertising spending, number of copies at release time, reviews, sequel existence, and the date of release or seasonality. The Appendix A provides the definitions of the variables and their sources. These variables agree with the variables in Stimpert et al. (2008). Stimpert et al. propose dividing the variables into four meaningful categories: quality, other product attributes (e.g., genre, casting, ratings and sequels), advertising, and distribution. Two of the variables are particularly important to the model. Advertising spending determines the final inclusion of the movie in the database. This information is confidential and had to come directly from the distributors of each movie. In order to estimate the three parameters of the model, each movie has to have a box-office period of three weeks or more.

The mean of the total attendance for the 117 movies in the sample is 169,406 with a standard deviation of 208.954. The quartiles of the distribution are 35,444; 79,633; and 204,956 respectively. However, the mean of the life cycle is 12 weeks with a standard deviation of 6, and quartiles of 8, 11, and 15 weeks respectively.

4. Box-office demand models

This section presents the estimation of the demand models in Section 3. These models use traditional econometric tools for the potential market and dynamic elements in the diffusion process. Specifically, a regression model that uses independent variables to provide information from the database, while both the Bass (1969) and the Sawhney and Eliashberg (1996) models estimate the diffusion process.

4.1. Total box-office model

To generate a model that explains total demand for a certain movie, this paper considers a regression of the total accumulated demand as the dependent variable on the movie characteristics described in Section 3.

Table 1 presents the results from the model. The variables that explain total demand (N) are: advertising spending (AS); number of film copies (NC); reviews (R) from the local El Mercurio newspaper; genre (G), particularly drama (D); and age rating (AR). The t-statistics show that the most significant variables are the number of film copies and advertising spending. Table 1 presents the values of the standard deviations in the regression in parentheses, and the R^2, standard deviation, and number of data points are in the bottom row. The model uses the natural logarithm for the total-demand and advertising spending variables in the regression. The study also uses base levels for the qualitative variables. Age rating starts at older than 18, and reviews use 5 stars.

Advertising spending and the number of copies have positive coefficients and are highly correlated with total movie attendance. The review (R) is also important in the regression coefficients, even though some of the t-statistics are not particularly strong. The results for the review variable disclose that attendees distinguish between a good movie (4 or 5 stars) and a bad movie (1, 2, or 3 stars), but do not make a distinction for each of the five categories.

4.2. Diffusion models

To estimate the dynamic behavior of movie attendance, the paper uses both the Bass (1969) and Sawhney and Eliashberg (1996) models. These two diffusion models consider only the shape of the diffusion process. The estimations of the Bass model for each movie

Table 1
Econometric model for the potential audience.[a]

Variable	Coefficient	Standard error	Standardized coefficient	p-value
Constant	−0.812	1.727	−0.470	0.639
Log (advertising spending)	0.679	0.112	0.256	0.000
Number of copies	0.032	0.009	0.106	0.001
1-star review	−0.493	0.188	−0.060	0.010
2-star review	−0.462	0.134	−0.100	0.001
3-star review	−0.319	0.115	−0.067	0.007
4-star review	0.170	0.136	0.014	0.214
Drama	0.121	0.082	0.020	0.143
All ages	0.077	0.111	0.004	0.485
Older than 14	−0.026	0.108	−0.001	0.811
$n=117$; $s=0.657$; $R^2=0.761$				

[a] Coefficients, standard errors, and p-values for independent variables in the regression with the total audience that has a log-transformation as the dependent variable.

Table 2
Descriptive statistics for the p and q parameters in the Bass model.[a]

	Mean	Std. dev.	Min.	Percentile			Max.
				25%	50%	75%	
p parameter							
3 data points[b]	0.439	0.185	0.072	0.267	0.394	0.536	0.955
6 data points[c]	0.379	0.152	0.049	0.264	0.348	0.459	0.742
9 data points	0.319	0.148	0.040	0.213	0.312	0.406	0.701
12 data points	0.292	0.138	0.097	0.177	0.279	0.350	0.688
Total	0.402	0.184	0.097	0.276	0.364	0.522	0.928
q parameter							
3 data points[d]	0.209	0.302	0.000	0.000	0.000	0.439	1.365
6 data points[e]	0.134	0.198	0.000	0.000	0.022	0.220	0.971
9 data points	0.120	0.199	0.000	0.000	0.035	0.160	0.939
12 data points	0.120	0.188	0.000	0.000	0.076	0.161	0.938
Total	0.162	0.219	0.000	0.000	0.076	0.228	0.938

[a] The mean; standard deviation; minimum value; percentiles 25%, 50%, 75%; and the maximum value for parameters p and q use 3, 6, 9, and 12 data points.
[b] For the estimate with 3 data points, 9 movies with outlier values are excluded for mean and standard deviation computations.
[c] For the estimate with 6 data points, 5 movies with outlier values are excluded for mean and standard deviation computations.
[d] For the estimate with 3 data points, 9 movies with outlier values are excluded for mean and standard deviation computations.
[e] For the estimate with 6 data points, 5 movies with outlier values are excluded for mean and standard deviation computations.

Table 3
Descriptive statistics for the $1/\lambda$ and $1/\gamma$ parameters in the Sawhney and Eliashberg (1996) model.[a]

	Mean	Std. dev.	Min.	Percentile			Max.
				25%	50%	75%	
$1/\lambda$ parameter							
3 data points[d]	2.216	1.251	0.406	1.406	1.864	2.868	6.702
6 data points[e]	2.695	1.284	1.247	1.837	2.259	3.331	6.982
9 data points	3.047	1.342	1.287	1.987	2.544	3.744	7.411
12 data points	3.319	1.395	1.429	2.155	3.088	4.527	7.102
Total	2.537	1.437	0.362	1.584	2.209	3.045	8.105
$1/\gamma$ parameter							
3 data points[b]	0.114	0.155	0.000	0.000	0.059	0.193	0.688
6 data points[c]	0.095	0.136	0.000	0.000	0.024	0.187	0.726
9 data points	0.096	0.139	0.000	0.000	0.045	0.191	0.628
12 data points	0.118	0.143	0.000	0.000	0.066	0.202	0.545
Total	0.102	0.132	0.000	0.000	0.053	0.183	0.534

[a] The mean; standard deviation; minimum value; percentiles 25%, 50%, 75%; and the maximum value for the parameters $1/\lambda$ and $1/\gamma$ use 3, 6, 9, and 12 data points.
[b] For estimates using 3 data points, 7 outlier movies are excluded.
[c] For estimates using 6 data points, 2 outlier movies are excluded.
[d] For estimates using 3 data points, 7 outlier movies are excluded.
[e] For estimates using 6 data points, 2 outlier movies are excluded.

use 3, 6, 9, and 12 data points. Table 2 presents these estimates and the statistics for the innovation and imitation parameters p and q for the 117 movies in the database. The estimation procedure minimizes the difference between the model estimates and the data points corresponding to each week's attendance. The mean value of parameter p that uses all of the available data is 0.402. As more data points are added to the estimate, p decreases. The fact that word of mouth, or the imitation effect, has relatively more of an effect on movies with longer life cycles than the innovation effect could explain this decrease.

The second panel of Table 2 presents the estimates for the imitation parameter q. The average value of this parameter is 0.162. The estimates for the q parameters become smaller as more data points are added to the estimation procedure, but this change is less significant than the one observed for the p parameter in the first panel. There is a total of 39 cases in which q has a value of zero.

The R^2 statistics reach highly significant values in most of the Bass model estimations, and these indicators do not decrease from a statistical point of view with a reduced number of data points. On average, R^2 equals 0.972.

The innovation effect is, on average, higher than the imitation effect. A possible conclusion from these estimates is that advertising, price, and promotions are more influential in the adoption process than word of mouth. In other words, the innovation effect is more influential when the distributer highlights the attributes and characteristics of the movie by discussing or sharing positive movie experiences with potential audiences. The results further indicate that the innovation effect is higher for movies with shorter life cycles and lower movie attendance than for blockbusters. This finding might suggest the existence of an additional effect that has a positive correlation with this type of movie. No differences exist for the imitation effect in this type of movie. However, a relative analysis indicates that the imitation effect is more important for movies that have longer life cycles and are more popular.

Advertising efforts should be mainly oriented towards an emphasis on the movie's characteristics and attributes and launching promotions and emphasizing movie theaters' comfort and convenience, as opposed to creating notoriety for the movie (e.g., release events, merchandising, and contests). Thus, in this scenario a wide-mass release is the most effective strategy. This strategy involves playing the movie in several theaters simultaneously and supporting the release with intensive advertising.

The second dynamic model that represents the behavior of demand through time is the Sawhney and Eliashberg (1996) model. The results for the parameters $1/\lambda$ and $1/\gamma$ are in the two panels of Table 3. The estimates use 3, 6, 9, and 12 data points for each movie. The definition of time is weeks.

Parameter $1/\lambda$ presents an average value of 0.102, while parameter $1/\gamma$ has an average value of 2.537. The value of $1/\gamma$ increases as more data points become available. This increase might be because all of the movies in the sample have three or more observations. However, when using 12 data points to compute the mean, the sample only represents movies whose life cycles are 12 weeks or more.

It follows that the average time to decide to see a $1/\lambda$ movie is closer to zero because λ is very high. The average time to act, $1/\gamma$, as expected is significantly larger and consistent with the impossibility of instantaneously acting and seeing the movie according to the previously adopted decision. This impossibility exists because external factors such as the availability of free time, theater location, the willingness to go to the theater, and the screening schedule play major roles in this process. Movies with long life cycles and high attendance tend to have lower values for the parameter γ, and thus a higher value for time-to-act, $1/\gamma$. The R^2 statistic reaches large values and does not statistically decrease in partial estimates. The mean value for both models under study equals 0.971.

4.3. Preliminary estimates

According to the estimates, the demand's dynamics as characterized by parameters p and q for the Bass (1969) model and by parameters $1/\lambda$ and $1/\gamma$ in the Sawhney and Eliashberg (1996) model are only possible to estimate after the movie's release.

To obtain models that predict the values of p and q before the release of the movie and that use only movie attributes, the study regresses the values of p and q with the Bass model. The data indicates that models for p and $(p+q)$ yield better results than models for the original innovation and imitation parameters. A similar exercise can be done for the parameters in the Sawhney and Eliashberg (1996) model, although the results for the parameters λ and γ are not satisfactory in our sample. This finding implies that, prior to a movie's release, predictions of the parameters of the Sawhney and Eliashberg model must be based on the mean values from Table 3. Table 4 presents the results of the models for the Bass model parameters p and $(p+q)$.

In the model for the p parameter, advertising spending (AS), number of copies (NC), reviews (R) and genre (G) are significant. The model for the $(p+q)$ parameter uses the same variables, although they are less significant. The R^2 statistics in these models are 0.280 and 0.161 respectively.

Table 4
Regression model for the preliminary estimates.[a]

Model for the p Parameter

$$p = 1.574 - 0.083 \log AS + 0.007\, NC + 0.095R_1 + 0.108R_2 + 0.023R_3 - 0.043R_4 + 0.074F_0$$

(0.437) (0.028) (0.002) (0.045) (0.032) (0.028) (0.033) (0.021)

R^2	Std. dev.	N
28.0%	0.162	116

Model for the p+q Parameter

$$p + q = 0.144 - 0.022 \log AS + 0.001NC + 0.146R_1 + 0.119R_2 + 0.0454R_3 - 0.097R_4 - 0.006F_0$$

(0.619) (0.040) (0.003) (0.065) (0.046) (0.039) (0.046) (0.029)

R^2	Std. Dev.	N
16.1%	0.224	113

[a] Coefficients, standard errors, and statistics for the preliminary regression models.

5. Prediction

For measuring the forecasting gains of the models, this study uses an ad hoc forecasting system that might be similar to the one used by the theater. The authors assume that experience allows the theater to know the average attendance rate across movies for each copy of the movie, and how the distribution of this audience is proportional to the movies' life cycle. This assumption makes obtaining a theater's forecast possible in order to compare this forecast to the results in the models. Table 5 presents the average relative error for the 117 movies in the sample. Because the forecasting method for this benchmark has a relation to the number of attendees per copy, the error is larger in the first weeks. This result comes from the forecast including poorly performing movies. The average prediction error is 118% for the first week and 48% for the twelfth week.

The comparison of the proposed models calculates the relative mean error for each movie. The definition of the relative mean error is the difference between the real and the predicted cumulative attendance divided by the real cumulative attendance. The study performs this procedure for the estimation of the total box office take as well as for the intermediate cumulative attendance after 3, 6, 9, and 12 weeks of screening. The computation of the errors uses

Table 5
Ad-hoc exhibitor's average relative forecast error.[a]

1st week	3rd week	6th week	9th week	12th week	Total
117.62%	126.80%	105.46%	60.99%	47.71%	191.62%

[a] Exhibitor's average relative forecast error for the cumulated box-office attendance by the 1st, 3rd, 6th, 9th, and 12th week of screening.

the estimates from 0, 3, 6, 9, and 12 observations. Table 6 presents the results. For the Bass (1969) model, the average prediction error before the release is about 50% for the different horizons and that prediction error drops to about 10% when three weeks of data are available, and to about 3% when more than three weeks of data are available. Very little difference seems to exist in the prediction errors of the different time horizons given the information available for the prediction. Very little difference also seems to exist between the prediction errors using six or more data points. Therefore, the prediction of the demand has three important points in time: before the release, after three weeks, and after six weeks. The prediction error for the Sawhney and Eliashberg (1996) model presents similar results.

Table 7 presents the proportion of cases where the Bass model outperforms the Sawhney and Eliashberg model. As Table 7 shows, the diffusion model that more accurately predicts the movie attendance in terms of potential audience is the Sawhney and Eliashberg model. However, the difference with the Bass model is not significant and when the number of observations available is 9 or 12, the Bass model has smaller errors in the current sample. A second advantage to the Bass model is that the model allows for a preliminary estimate analysis. Another potential prediction of these models is the longevity of a movie; that is, the number of weeks a certain movie will be screened in theaters.

6. Conclusions and limitations

This study contributes to a better understanding and prediction of the demand for movies in different stages of their life cycle. From an academic point of view, our study proposes a novel approach for modeling the demand that combines a Bass (1969) model for the modeling of the life cycle with an econometric model for the estimation of the potential market. In this context, our results show that the Bass model fits the data very well and hence this model, used extensively in the marketing literature for the adoption of technological products, can also prove useful for the adoption or consumption of movies. The advantage of using the Bass model is that the model is widely studied in the marketing literature and its parameters have an appealing interpretation. Specifically, the model explicitly considers the imitation effect, which has gained recognition as an important determinant for the demand in movie attendance (De Vany & Walls, 1999). The results suggest that the movie market is not completely uncertain. In line with the literature, the authors of this study show that advertising spending and quality are the two most important variables for explaining the demand.

Table 6
Relative mean error, Bass (1969) model and Sawhney and Eliashberg (1996) model preliminary estimate, Bass model.[a]

	Screening weeks				
	3	6	9	12	Total
Bass model					
Preliminary estimate	48.94%	46.25%	40.28%	48.66%	55.65%
3 observations	*	10.25%	16.12%	20.34%	16.72%
6 observations	*	*	3.84%	5.50%	5.63%
9 observations	*	*	*	3.47%	4.27%
12 observations	*	*	*	*	2.72%
Sawhney and Eliashberg model					
3 observations	*	10.04%	15.21%	18.53%	17.07%
6 observations	*	*	3.82%	5.22%	6.19%
9 observations	*	*	*	2.69%	3.80%
12 observations	*	*	*	*	3.44%

[a] Relative mean error values for the box-office estimates for the 3rd, 6th, 9th and 12th weeks of screening and total life cycle by using 3, 6, 9, and 12 observations for each one of the models and the error for the preliminary estimates for Bass model.

Table 7
Model comparison, Sawhney and Eliashberg (1996) model vs. Bass (1969) model.[a]

Bass model vs. Sawhney and Eliashberg model	6th week	9th week	12th week	Total box-office
3 observations	47.6%	38.1%	38.4%	46.0%
6 observations	*	48.0%	44.2%	47.4%
9 observations	*	*	55.7%	52.3%
12 observations	*	*	*	63.8%

[a] Percentage of instances in which the estimated errors for the Bass model are smaller than the resulting estimated errors for the Sawhney and Eliashberg model.

This study also contrasts the modeling strategy to the Sawhney and Eliashberg (1996) model. The forecasting exercise that uses the Bass model yields results that are similar to the Sawhney and Eliashberg model. The average prediction error before the release is about 50% and declines to about 3% when more than three weeks of data are available. However, very little difference seems to exist between the prediction errors using six or more data points. Therefore, the prediction of demand has three important points in time: before the release but with known characteristics of the movie, after three weeks, and then after six weeks.

From a practitioner's point of view, the predictions derived from these models are a useful tool for the movie industry and for theaters when deciding on screening intensity: the screening time frame, the movie rotation shift to smaller screening rooms, and the licensing negotiations with distributors. The predictive power of the models in the Chilean market is slightly weaker than in the North American market in comparison to Sawhney and Eliashberg (1996). The small size of the Chilean market might explain this phenomenon. In Chile, the release of a movie has a maximum of 60 screens, while in North America approximately 2000 screens exist.

The models in this study do not include all potential competitive factors. Some competition effects not included in the estimated models are the number of films released simultaneously and the advertising expenditures of all movies released at the same time. Another limitation to this study regards the sample selection. Because of the sample's reliance on the availability of advertising spending obtained from big distributor chains, the results might infer that the movies in the sample incurred particularly high marketing expenses and thus the movies launch occurred with wide and massive release strategies.

Therefore, the sample could contain a disproportionately high number of movies from big distribution chains. The Bass (1969) model's p and q parameters might overestimate the value of p, related to the innovation effect, or underestimate the value of q, related to the imitation effect. Similarly, the Sawhney and Eliashberg (1996) model's results could be misleading — particularly the value of its parameter λ, advertising intensity — that could alter the relative importance of both parameters.

The movie industry today is experiencing some important changes such as new media and cultural practices, digital rollouts, alternative content, and the shortening of release windows. From the perspective of this study, and considering the sample data from the years 2001 to 2003, these changes might affect the life cycle of a movie, the relative importance of the innovation and imitation effects in the Bass (1969) model, and the impact of the independent variables in the model. However, people in most countries are demanding more entertainment and hence the focus of the method in this study can still apply to a different country, a different time, or a different channel.

Appendix A. Variables

Variable definitions and source.

Variable	Definition	Source
Box-office	Weekly attendees for a particular movie	Cinematographic Chamber of Commerce
Genre	Genres include: comedy, romance, sci-fi, drama, musical, terror, mystery, thriller, adventure, Western, action, crime, warfare, family, animation, among others. To reduce the number of categories, those genres that respond in a similar way are combined to form a new category	Internet Movie Database
Country of origin	Three parallel categories were tested to see which responded better to the models. First, the movies were divided into three regions or country categories: USA, Latin-America, and others. Secondly, movies were selected in four categories, including Chile as the fourth group, allowing the registration of possible special behaviors for national films. Groups: USA, Latin-America, Chile, and others. Third, movies were separated using spoken language as the differentiation criterion.	Internet Movie Database
Age rating	Three groups are considered: all spectators, older than 14, and older than 18	"El Mercurio" newspaper, Culture & Entertainment; National Library Archives
Competition	Number of movies released simultaneously as well as the total amount of copies of these released films.	Cinematographic Chamber of Commerce
Director	Number of Oscar nominations and awards obtained by the film director, previously and during the movie's life cycle.	Internet Movie Database and the Official Academy Awards web site
Actors/ actresses	Number of nominations and awards obtained by each actor in the following categories: Best actor/actress and best supporting actor/actress	Internet Movie Database and the Official Academy Awards web site
Advertising spending	Total media expenditures incurred for promoting and publicizing a given movie in Chile	Individual distributors
Film reviews	"El Mercurio" newspaper film review. Movie quality is assessed by assigning a certain number of "stars" in a scale from 1 to 5, where 1 star means very bad and 5 stars means excellent	"El Mercurio" newspaper
Number of film copies	Number of films copies playing a particular movie at release time	Cinematographic Chamber of Commerce
Sequel	Continuation of prior movies, based on a TV show, or a remake or re-release of an old movie.	Own generation
Seasonality	Defined as a continuous and discrete variable. The first one considers standardized values between 1 and 0 as a result of the average monthly attendance during the three years of evaluation. The latter considers three scenarios: high, medium, and low attendance	Own generation

References

Bass, F. M. (1969). A new product growth model for consumer durables. *Management Science*, *15*(1), 215–227.

Cámara de Exhibidores Multisalas de Chile A.G. (2011). *El Cine en Chile*. Santiago: CAEM.

Cameron, S. (1999). Rational addiction and the demand for cinema. *Applied Economic Letters*, *6*, 617–620.

Caves, R. E. (2000). *Creative industries: Contracts between art and commerce*. Cambridge, MA: Harvard University Press.

Chatterjee, R., & Eliasberg, J. (1990). The innovation diffusion process in a heterogeneous population: A micro modelling approach. *Management Science*, *36*, 1057–1079.

De Vany, A., & Walls, D. (1999). Uncertainty in the movie industry: Does star power reduce the terror of the box office? *Journal of Cultural Economics*, *23*, 285–318.

Dellarocas, C., Zhang, X., & Awad, N. F. (2007). Online product reviews in forecasting sales: The case of motion pictures. *Journal of Interactive Marketing*, *21*(4), 23–45.

Dewenter, R., & Westermann, M. (2005). Cinema demand in Germany. *Journal of Cultural Economics*, *29*, 213–231.

Eliashberg, J., Elberse, A., & Leenders, M. A. A. M. (2006). The motion picture industry: Critical issues in practice, current research and new research directions. *Marketing Science*, *25*(6), 638–661.

Hand, C. (2002). The distribution and predictability of cinema admissions. *Journal of Cultural Economics*, *26*, 53–64.

Hand, C., & Judge, G. (2012). Searching for the picture: Forecasting UK cinema admissions using Google Trends data. *Applied Economics Letters*, *19*, 1051–1055.

Jones, M. J., & Mason, C. H. (1990). The role of distribution in the diffusion of new durable consumer products. *Report No.90-110*. Cambridge MA: Marketing Science Institute.

Jones, M. J., & Ritz, C. J. (1991). Incorporating distribution into new products diffusion models. *International Journal of Research in Marketing*, *8*, 91–112.

Litman, B. R. (1983). Predicting success of theatrical movies: An empirical study. *The Journal of Popular Culture*, *16*, 159–175.

Litman, B. R., & Ahn, H. (1998). Predicting financial success of motion pictures. In B. R. Litman (Ed.), *The motion picture mega-industry*. Boston, MA: Allyn & Bacon Publishing, Inc.

Litman, B. R., & Kohl, A. (1989). Predicting financial success of motion pictures: The '80s experience. *The Journal of Media Economics*, *2*(1), 35–50.

McKenzie, J. (2009). Revealed word-of-mouth demand and adaptive supply: Survival of motion pictures at the Australian box office. *Journal of Cultural Economics*, *33*, 279–299.

Moul, C. C. (2005). *A concise handbook of movie industry economics*. Cambridge, UK: Cambridge University Press.

Roberts, J. H., & Urban, G. L. (1988). Modeling multiattribute utility risk, and belief dynamics for new consumer durable brand choice. *Management Science*, *34*(2), 167–185.

Sawhney, M. J., & Eliashberg, J. (1996). A parsimonious model for forecasting gross box-office revenues of motion picture. *Marketing Science*, *15*(2), 113–131.

Srinivasan, V., & Mason, C. (1986). Nonlinear least squares estimation of new product diffusion models. *Marketing Science*, *5*(2), 169–178.

Stimpert, J. L., Laux, J. A., Marino, C., & Gleason, G. (2008). Factors influencing motion picture success: Empirical review and update. *Journal of Business & Economics Research*, *6*, 39–52.

Terry, N., Butler, M., & De'Armond, D. A. (2004). The economic impact of movie critics on box office performance. *Academy of Marketing Studies Journal*, *8*(1), 61–73.