A Bayesian Model to Forecast New Product Performance in Domestic and International Markets

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Abstract

This paper attempts to shed light on the following research questions: When a firm introduces a new product (or service) how can it effectively use the different information sources available to generate reliable new product performance forecasts? How can the firm account for varying information availability at different stages of the new product launch and generate forecasts at each stage? We address these questions in the context of the sequential launches of motion pictures in international markets.

Players in the motion picture industry require forecasts at different stages of the movie launch process to aid decision-making, and the information sets available to generate such forecasts vary at different stages. Despite the importance of such forecasts, the industry struggles to understand and predict sales of new movies in domestic and overseas markets.

We develop a Bayesian modeling framework that predicts first-week viewership for new movies in both domestic and several international markets. We focus on the first week because industry players involved in international markets (studios, distributors, and exhibitors) are most interested in these predictions. We draw on existing literature on forecasting performance of new movies to formulate our model. Specifically, we model the number of viewers of a movie in a given week using a Poisson count data model. The number of screens, distribution strategy, movie attributes such as genre, and presence/absence of stars are among the factors modeled to influence viewership. We employ a hierarchical Bayes formulation of the Poisson model that allows the determinants of viewership to vary across countries. We adopt the Bayesian approach for two reasons: First, it provides a convenient framework to model varying assumptions of information availability; specifically, it allows us to make forecasts by combining different sources of information such as domestic and international market-specific data. Second, this methodology provides us with the entire distribution of the new movie's performance forecast. Such a predictive distribution is more informative than a point estimate and provides a measure of the uncertainty in the forecasts.

We propose a Bayesian prediction procedure that provides viewership forecasts at different stages of the new movie release process. The methodology provides forecasts under a number of information availability scenarios. Thus, forecasts can be obtained with just information from a historical database containing data on previous new product launches in several international markets. As more information becomes available, the forecasting methodology allows us to combine historical information with data on the performance of the new product in the domestic market and thereby to make forecasts with less uncertainty and greater accuracy.

Our results indicate that for all the countries in the data set the number of screens on which a movie is released is the most important influence on viewership. Furthermore, we find that local distribution improves movie sales internationally in contrast to the domestic market. We also find evidence of similar genre preferences in geographically disparate countries. We find that the proposed model provides accurate forecasts at the movie-country level. Further, the model outperforms all the extant models in the marketing literature that could potentially be used for making these forecasts. A comparison of root mean square and mean absolute errors for movies in a hold out sample shows that the model that combines information available from the different sources generates the lowest errors. A Bayesian predictive model selection criterion corroborates the superior performance of this model. We demonstrate that the Bayesian model can be combined with industry rules of thumb to generate cumulative box office forecasts.

In summary, this research demonstrates a Bayesian modeling framework that allows the use of different information sources to make new product forecasts in domestic and international markets. Our results underscore the theme that each movie is unique as is each country—and viewership results from an interaction of the product and the market. Hence, the motion picture industry should use both product-specific and market-specific information to make new movie performance forecasts.

(*Hierarchical Bayes*; *New Products*; *Motion Pictures*; *International Markets*; *Forecasting*)

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1. Introduction

Companies that operate in global markets typically launch their products in new markets in several stages. At each stage in this sequential launch process, sales forecasts serve as critical inputs for a variety of marketing decisions. For example, initial forecasts serve as inputs for "go–no-go" decisions, and forecasts made later in the launch process aid in finalizing marketing mix decisions, formulating competitive strategies, etc. Because new products are launched sequentially in international markets, increasing amounts of information become available for generating sales forecasts as one moves from the initial stage to the later stages in the launch process. Thus, the forecasting challenge in international settings is generating a sequence of sales predictions that utilizes increasing amounts of prior information available from similar product categories and other markets where the new product has been launched.

The U.S. movie industry provides a powerful setting to develop and test a model that combines multiple information sources to generate a sequence of forecasts. Decision makers in the industry are required to make a series of decisions at different stages of the movie release process. Initially, in the *market evaluation stage,* movie studios have yet to pick a particular movie and have not decided which markets to enter. The only information available at this stage is the performance of previous movie releases in different markets. We refer to such data on previous releases as the "historical database." The historical database can be used to generate initial base forecasts. After *production of a specific movie,* decision-makers need sales forecasts in order to make market entry and mix decisions. Because the attributes of the new movie, such as genre and presence/absence of major stars, become known at this stage, they can be combined with the historical database to generate an updated forecast. Immediately *prior to domestic launch* of a new movie, the studios have determined the marketing mix for the domestic market.[1] Thus data on marketing mix variables, such as the number of screens in the domestic market, can be incorporated to generate a prelaunch forecast for the domestic market. These forecasts are inputs for marketing mix decisions for the entire life cycle of the movie. *Post domestic release,* forecasts of movie performance in international markets are required to finalize decisions such as distribution strategy and release schedule in these markets. At this stage, decision makers have an information set that consists of the historical database, movie attributes, and performance of the new movie in the domestic market. Just *prior to the international launch,* the studios have finalized the marketing mix variables for international markets for the initial week. Forecasts of first-week viewership are required to fine-tune strategic decisions, assess competition, and plan marketing activities for future weeks. The information set available to generate this final set of forecasts includes the historical database, new movie attributes, domestic performance data for the new movie, and marketing mix information on screens and distributors in international markets. In sum, the motion picture industry requires forecasts at different stages of the movie launch process to aid decision making and needs the information sets available to generate such forecasts vary at different stages.

In this paper, we present a Bayesian modeling framework to forecast new product performance. We apply our framework and estimation methodology to forecast the performance of U.S. movies released in overseas markets. To generate the requisite forecasts, we model the determinants of viewership for movies. Specifically, we relate the number of viewers per week to its determinants using a Poisson regression model (King 1988). The poisson parameter is modeled as a function of the number of screens (Jones and Ritz 1991), number of previous viewers as a proxy for word of mouth effects (Mahajan et al. 1984), a time trend (Squire 1992), movie attributes such as genre and presence/absence of stars (Sawhney and Eliashberg 1996), and distribution strategy. Because international markets differ significantly in market infrastructure, institutional arrangements, and consumer preferences, we expect the effects of the above variables to differ across countries. Accordingly, we model the effects of the independent variables as country-specific. In this manner, we document interesting cross-country differences

[1] As movies are typically released simultaneously in the United States and in Canada, our references to the domestic market include both these countries.

in the impact of marketing mix variables and movie attributes on movie viewership patterns.

We begin estimating our model using data from the historical database. Next, we generate first-week viewership predictions for movies in a hold-out sample at different stages of the movie launch process described above. In particular, we generate first-week forecasts at the post-movie production, pre- and post-domestic-launch, and pre-international-launch stages. We adopt a Bayesian prediction procedure that allows us (i) to make forecasts by combining different sources of information such as domestic and international market-specific data and (ii) to model the uncertainty in scenarios with less than complete information. Additionally, by employing the Bayesian methodology we are able to generate a predictive *distribution* of the first-week viewership of a new movie. Such a predictive distribution is more informative than a point estimate and provides a measure of the uncertainty in the forecasts (Gelman et al. 1995).[2] To evaluate the forecast performance of our model, we compare its predictive performance with those of several models in the extant marketing literature. In addition to generating first-week predictions we demonstrate how our formal model can be combined with industry rules of thumb to obtain cumulative viewership forecasts.

Our research contributes to the new products forecasting literature by developing a hierarchical Bayes model to forecast new product performances at different stages of product launch. In previous research, Lenk and Rao (1990) present a Bayesian model that uses information from previous product launches to make new product forecasts. In contrast, we pool information from both previously launched products and markets. Additionally, we also model the role of marketing activity at the level of each country. Rossi et al. (1996) use a Bayesian choice model to assess the information content of various information sets available for direct marketing purposes. They focus on the value of different information sets in making inferences about posterior parameters of individual consumers. In contrast, we use different information sets to generate out of sample forecasts and thereby assess the value of additional information available to managers at different stages of the new product launch process.

Our paper also adds to the modeling literature in international marketing that has primarily focused on understanding variations in intercountry sales diffusion patterns (Gatignon et al. 1989, Helson et al. 1993, Putsis et al. 1997). We add to this research by modeling the impact of marketing mix variables on product performance at the level of each country. Thus, our model outputs provide insights at the country level and can therefore be used to adapt marketing strategy to suit each country.

Finally, our work also contributes to the growing academic literature on motion pictures (Jones and Ritz 1991, Sawhney and Eliashberg 1996, Eliashberg and Shugan 1997, Krider and Weinberg 1998, Neelamegham and Jain 1999). In their study of motion pictures in the U.S. market, Sawhney and Eliashberg (1996) state, "*Our attempts to predict revenue patterns without any sales data meet with limited success.*" In this research, we propose a methodology to make first-week viewership forecasts in the domestic and several international markets with no data available on the movie's performance in these markets. Furthermore, we discuss how our model complements previous research (Sawhney and Eliashberg 1996) in generating managerially relevant cumulative box office forecasts.

From a managerial perspective, the domestic and international box office forecasts of the model should benefit decisions made by studios, distributors, and exhibitors. The international market for movies accounts for over half the box-office receipts of the U.S. motion picture industry and is a growing business area for this industry (*World Trade* 1996). In the past decade, revenues from foreign exhibition have doubled making the need for new product forecasts in each of the overseas markets very critical (*Variety* 1994b). The trade press and industry experts however, repeatedly emphasize the lack of a systematic methodology to predict box office performance (*Variety* 1994a, 1994b). By providing forecasts for new movies at the country level at different stages of the product launch process, our proposed Bayesian model can aid all three groups in the

[2]We treat the decision of whether or not to release a movie in a particular country as exogenous and focus on obtaining forecasts once such a decision has been made.

movie channel, i.e., studios, distributors, and exhibitors, in planning and finalizing their marketing activities and negotiating contracts.[3]

The remainder of the paper is organized as follows. The next section contains a detailed description of the data used in the analysis. This is followed by the proposed Bayesian model and forecasting procedure. Next, we describe the results. Finally, we discuss and conclude with some limitations and future research directions.

2. Data Set

Our data are obtained from the domestic and overseas box office receipts reported in *Variety Magazine.* The *Variety* sample is a weekly report of worldwide box office performance covering the top 60 movies in the United States and the top 10 movies in international markets.[4] Data reported consist of the box office revenue, number of screens showing a film, number of weeks of the run on any prior release, the rank, the number of first-run engagements, and the name of each film's foreign rights holder and local distributor. Our particular sample of data covers the period January 1, 1994 to May 26, 1996. We obtained data for 35 movies for the United States and for the following 13 countries: Australia, Brazil, Canada, France, Germany, Italy, Japan, Mexico, Netherlands, Spain, South Africa, Sweden, and the United Kingdom.[5] These 13 countries represent over 80% of overseas box office (*Variety* 1994b). We tracked each film in the sample from its release in the domestic market to its international release and the time that it dropped out from the domestic and international charts. We also collected data on movie attributes such as genre, presence/absence of stars, critic reviews, and MPAA ratings from Cinemania Index (1996).[6] (See Table 1.)

The data set consists of 2,325 weekly observations that span 343 unique movie-country pairs. Table 1 provides selected descriptive statistics for the sample. The second column shows the number of movies from the sample released in each of the countries. Whereas 35 of the sampled movies are released in the United States and 28 movies in Canada (which constitute the domestic market), fewer numbers are released in other countries. Total movie viewership numbers reveal that the United States, United Kingdom, Germany, and France are the relatively larger markets. The mean weekly sales in these markets tend to be larger than the corresponding numbers in other countries. In most countries, the mean first-week viewership is almost double the mean weekly viewership, implying that the first-week viewership contributes to a significant proportion of total viewership. This underscores the importance of forecasting first-week viewership.

3. Model Development

The movie industry tracks weekly sales for each movie in several countries. Because the price per ticket for all first-run movies is constant across movies within a country, variation in the number or count of viewers is what drives variation in weekly sales. In this paper, we employ a hierarchical Bayes Poisson regression to model the number of viewers per week. Such a model is consistent with prior literature and conceptualization of the movie viewership process (Sawhney and Eliashberg 1996).[7]

[3]The studios in the United States produce movies and sell rights for foreign territories to distributors. These distributors contact exhibitors in different countries and arrange for the theatrical release of the movies. While studios and distributors work across many countries, exhibitors are often very fragmented and are more interested in forecasts for their own country and region as opposed to multi-country box office predictions.

[4]Because of this constraint in data availability, the movies included in our sample are not representative of all movies introduced in the international market. The methodology we employ for generating first-week forecasts, however, can be readily applied to any new movie.

[5]Data is reported jointly for the United Kingdom and Ireland.

[6]The criterion for inclusion of movies in the sample was their "long" runs in a number of countries. Consistent with prior research, we used data from only those countries where the movies had a run of greater than four weeks (Jones and Ritz 1991). Furthermore, movies included in the sample made it to the charts in at least two countries other than in the domestic market for greater than four weeks. This enabled us to assess the generalizability of the proposed procedure across different countries.

[7]Sawhney and Eliashberg (1996) model the time it takes for an individual consumer to adopt a movie and aggregate it to estimate the number of people who will view the movie. They obtain the CDF for the time to adopt for an individual as a Generalized Gamma distribution. It can be proved that when the length of time between

Table 1 Descriptive Statistics

Country	# of Movies	Viewership (in millions)	Mean Weekly Sales (in million dollars)	Mean First-Week Sales (in million dollars)	Mean Screens per Week	Mean Duration of Movie Run (in Weeks)	Longest Movie Run (in weeks)
Australia	26	11.14	0.7	1.4	104	8	12
Brazil	24	7.23	0.6	1.3	65	8	13
Canada	28	13.33	0.7	1.3	126	7	11
France	23	20.78	1.5	3.1	298	7	10
Germany	27	38.02	1.7	3.2	346	8	14
Holland	28	4.90	0.2	0.3	44	11	15
Italy	22	8.66	0.7	0.9	70	6	8
Japan	20	8.63	1.3	1.8	15	9	15
Mexico	22	2.11	0.2	0.3	37	7	9
South Africa	27	1.62	0.1	0.3	42	7	12
Spain	25	3.75	0.2	0.2	13	7	11
Sweden	23	2.76	0.2	0.5	50	10	15
U.K.	28	27.96	1.5	3.1	223	8	13
U.S.	35	273.02	4.0	18.4	995	18	30

Our hierarchical Bayes model consists of three stages. In the first stage, we model the distribution of the count of viewers for a movie in a specific country and week as following a Poisson distribution. In the second stage, we model the intensity of the count parameter of the poisson distribution as a function of covariates that include movie attributes and other marketing mix variables. We allow the effects of these covariates on the poisson intensity, i.e., the parameter estimates, to vary by country. In the third stage, we specify a distribution for each of the country-level parameters from the second stage. Additionally, diffuse priors are specified for parameters in the third stage. Below we explain each of these stages in detail.

First Stage: We begin by assuming that the count of viewers (V) for movie m in country c in week t, denoted by V_{mct} is poisson distributed. The parameter of the poisson distribution λ_{mct} is the mean count rate for movie m in country c in week t. The likelihood for the count intensity λ_{mct} is therefore defined as:

$$[V_{mct} \mid \lambda_{mct}] = [\exp(-\lambda_{mct})\ \lambda_{mct}^{V_{mct}}]/V_{mct}! \qquad (1)^{8}$$

Second Stage: Prior research using poisson models typically assume that λ_{mct} follows either a gamma or a log normal distribution (Clayton and Kaldor 1987). We follow the convention used in the poisson generalized linear models literature and assume that λ_{mct} follows a log normal distribution or equivalently that $\psi_{mct} = \log \lambda_{mct}$ is normally distributed. Models for ψ_{mct} can incorporate a number of covariates, main effects and interaction terms (Waller et al. 1997). Below we present the factors suggested by prior research on motion pictures and industry practice as influencing movie viewership.

The number of screens and theaters in which a movie is released affects the accessibility of a movie for viewers (Sawhney and Eliashberg 1996, Jones and Ritz 1991). Thus, we predict that increase in the number of screens employed for a movie is likely to have a positive effect on the count of viewers. We denote the weekly screens for each movie in each country by $\mathrm{SCREENS}_{mct}$. A related marketing mix variable that industry experts note as influencing movie viewership is the choice of the distributor (Vogel 1998). In the United

time 0 and the instant when the rth happening occurs follows a gamma function, the number of happenings in a fixed time interval is Poisson distributed (Mood et al. 1974). Hence, the count of viewers in a given time period is Poisson distributed.

[8]Throughout the paper, we use $[a \mid b]$ to denote the conditional distribution of a given b. Similarly, we use $[a]$ to denote the marginal distribution of a.

States, for example, prior work indicates that movies distributed by major studios (e.g., Warner Bros, Buena Vista) tend to have higher viewership than movies distributed by independent distributors (Ornstein 1998). If this holds internationally (in France, for example), the international branch of Buena Vista will generate higher weekly sales for a given movie than an independent French distributor. To measure the impact of a major distributor on movie viewership we define a dummy variable DIST_{mc}. Specifically, $\text{DIST}_{mc} = 1$ when the movie is distributed by an independent distributor and 0 otherwise.

Another factor influencing viewership count for a movie is the number of weeks since the initial release. Studios recognize the decline in size of movie viewership after the initial release week and closely monitor the ''drop off'' rate for each movie (Squire 1992). This drop off in viewership is a regular phenomenon for movies launched using a wide release strategy. A wide release begins with a large simultaneous release of the movie in many theaters and subsequent reduction in numbers of screens. Experts in the motion picture industry concur that films launched internationally tend to be big budget movies launched using the wide release strategy (Zetlin 1993). Thus, we expect to observe a drop off for international releases and we measure this using a trend variable (TREND_{mct}). This variable takes the value of the number of weeks the movie has been playing in a particular country since its initial release in that country. We expect TREND_{mct} to have a negative impact on viewership count.

A critical influence of a movie's viewership is the nature of word of mouth for the movie (Mahajan et al. 1984). The influence of word of mouth on movie adoption depends on three factors: valence of word of mouth (positive/negative/neutral), volume or amount of word of mouth discussion, and persuasiveness of the word of mouth generated (Mahajan et al. 1984, Neelamegham and Jain 1999, Mizerski 1982). Because we do not have access to individual survey data for each movie in each country, we use cumulative viewership as a proxy for word of mouth. Cumulative viewership for week t is measured from the week of initial release up to the week preceding week t and is denoted by $\text{CUMVIEWERS}_{mct-1}$.

Sawhney and Eliashberg (1996) identify a number of movie attributes that are relevant for prediction of movie viewership in the United States. Given the nature of our sample and availability of internationally comparable data, we include the following movie attributes: presence/absence of major stars and the genre of the movie. Following Sawhney and Eliashberg (1996), we use a dummy variable denoted by STARS_m to indicate the presence/absence of major stars. The classification was based on a list of major stars possessing "marquee value" (*Variety* 1994b). The genre classification and definitions are based on genre research by Austin and Gordon (1987). We use the Cinemania Index (1996) to classify movies in this study into THRILLER, ROMANCE, ACTION, DRAMA, and COMEDY genres. We use a dummy indicator for each genre with comedy as the base.

In addition to the systematic influence of the movie-specific variables outlined above, we anticipate that viewership is likely to be influenced by country-specific idiosyncrasies. In post-mortems of international movie sales, industry analysts discuss a number of reasons for movie performance ranging from unfavorable weather to national holidays (*Variety* 1994a). We use country-specific intercepts to capture these unobserved cross-country differences in movie viewership (Allenby and Rossi 1998).

Finally, we hypothesize that product-market interactions are an important determinant of product performance in international markets. In other words, we expect the influence of each of the above covariates to vary across markets. Thus, the same number of screens may have a greater influence in Spain than in South Africa, or the thriller genre may be more appreciated in Japan than in Canada. Modeling such cross-country variations allows us to understand the differences in the relative impact of different marketing mix variables in each market. We model these variations by specifying country-specific parameters for each of the covariates.

Thus, we obtain the following specification for the count intensity parameter (λ_{mct}) in the second stage model. Recall that we set $\log(\lambda_{mct})$ to be equal to ψ_{mct}. Accordingly, we obtain:

$$\begin{aligned}\psi_{mct} &= \alpha_c + \beta_{1c}\ln(\text{SCREENS}_{mct}) + \gamma_{1c}(\text{DIST}_{mc}) \\ &+ \beta_{2c}(\text{TREND}_{mct}) + \beta_{3c}\ln(\text{CUMVIEWERS}_{mct-1}) \\ &+ \gamma_{2c}(\text{STARS}_m) + \gamma_{3c}(\text{THRILLER}_m) + \gamma_{4c}(\text{ACTION}_m) \\ &+ \gamma_{5c}(\text{ROMANCE}_m) + \gamma_{6c}(\text{DRAMA}_m), \qquad (2)\end{aligned}$$

where α_c is the country-specific intercept;

$\beta_{1c}, \beta_{2c}, \beta_{3c}$ are the country-specific parameters for SCREENS, TREND and CUMVIEWERS, respectively;

$\gamma_{1c}, \gamma_{2c}, \gamma_{3c}, \gamma_{4c}, \gamma_{5c}, \gamma_{6c}$ are the country-specific parameters for DIST, STARS, THRILLER, ACTION, ROMANCE, and DRAMA, respectively.

Note that we use β for parameters associated with covariates that vary across movies, countries, and time. The γ parameters are for covariates that vary at the movie or the movie-country level alone.

Third Stage: To complete the Bayesian model specification, it is necessary to incorporate variability in the parameters in Equation (2) above by specifying distributions for them. Following previous Bayesian analysis of Poisson-log link models (see for example, Ghosh et al. 1998), we assume that the parameters for the intercept and covariates are mutually independent. Furthermore, we specify the country-specific intercept to be drawn from a normal distribution with mean 0 and variance σ^2_α, i.e., $\alpha_c \sim N(0, \sigma^2_\alpha)$. σ^2_α provides us with a measure of the dispersion of the unobserved heterogeneity across countries. We specify the other country-specific parameters as being normally and independently distributed. The country-specific parameters are thus distributed as follows:

$$\begin{aligned}\beta_{jc} &\overset{\text{ind}}{\sim} N(\mu_{\beta j}, \sigma^2_{\beta j}), \quad j = 1, 2, 3, \\ \gamma_{ic} &\overset{\text{ind}}{\sim} N(\mu_{\gamma i}, \sigma^2_{\gamma i}), \quad i = 1, 2, \ldots, 6. \qquad (3)\end{aligned}$$

The above means and variances provide us insights on the relative effects of the covariates included in this model across countries. For example, $\mu_{\beta 1}$ represents the mean effect of SCREENS across all countries and $\sigma^2_{\beta 1}$ provides a measure of the cross-country dispersion of the effects of screens. In the following discussion, for the sake of brevity, we define $\beta_c = \{\beta_{1c}, \beta_{2c}, \beta_{3c}\}$, $\gamma_c = \{\gamma_{1c}, \gamma_{2c}, \gamma_{3c}, \gamma_{4c}, \gamma_{5c}, \gamma_{6c}\}$, $\mu_\beta = (\mu_{\beta 1}, \mu_{\beta 2}, \mu_{\beta 3})$ and $\mu_\gamma = (\mu_{\gamma 1}, \mu_{\gamma 2}, \mu_{\gamma 3}, \mu_{\gamma 4}, \mu_{\gamma 5}, \mu_{\gamma 6})$ and $\sigma^2_\beta = (\sigma^2_{\beta 1}, \sigma^2_{\beta 2}, \sigma^2_{\beta 3})$ and $\sigma^2_\gamma = (\sigma^2_{\gamma 1}, \sigma^2_{\gamma 2}, \sigma^2_{\gamma 3}, \sigma^2_{\gamma 4}, \sigma^2_{\gamma 5}, \sigma^2_{\gamma 6})$.

Next, we specify noninformative (but proper) distributions for the set of hyperpriors μ_β, μ_γ, σ^2_α, σ^2_β, and σ^2_γ. We assume a diffuse normal prior for each element of μ_β and μ_γ. In case of the variance terms σ^2_α, σ^2_β, and σ^2_γ, we follow the convention of specifying a gamma prior for the inverse of the variance of each parameter. For example, let the inverse of the variance (precision) of $\sigma^2_{\beta 1}$ be $\tau_{\beta 1}$. A conjugate gamma distribution Ga(a,b) is specified for $\tau_{\beta 1}$.

In summary, the three stages of the hierarchical model specified above, give us the following series of conditional distributions:

$$\begin{aligned}&\text{Stage 1} \quad V_{mct} \mid \lambda_{mct}, && (4a)\\ &\text{Stage 2} \quad \lambda_{mct} \mid \alpha_c, \beta_c, \gamma_c, \text{ movie- and country-specific covariates}, && (4b)\\ &\text{Stage 3} \quad \alpha_c \mid \psi^2_\alpha \\ &\qquad\qquad\ \beta_c \mid \mu_\beta, \sigma^2_\beta \\ &\qquad\qquad\ \gamma_c \mid \mu_\gamma\ \sigma^2_\gamma. && (4c)\end{aligned}$$

Diffuse priors are specified for the hyperparameters in the third stage.

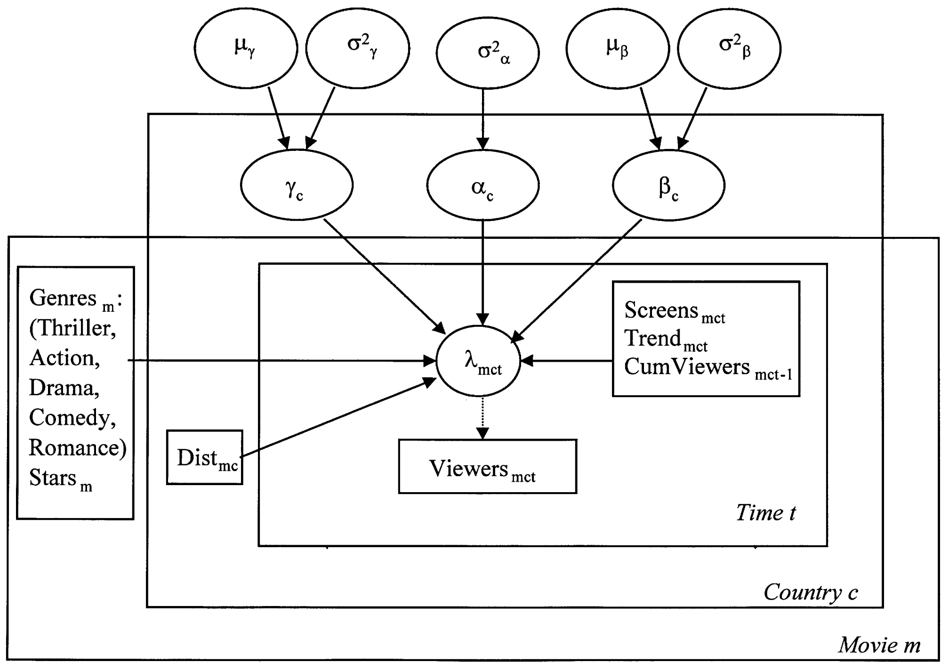
A graphical representation of the proposed three Bayesian hierarchical model is given in Figure 1 by the use of a Directed Acyclic Graph (DAG) (Lauritzen and Spiegelhalter 1988). This representation enables us to lay out the structure of our model in a simple and clear manner. In Figure 1, the circles represent the unknown quantities while the squares represent the known quantities (data and priors). The full arrows show the deterministic relationships while the dashed arrow indicates a stochastic link to which a probability distribution is attached. Absence of an arrow implies independence between those quantities in the model specification. The three stages as well as the interrelationships between the stages are displayed in the figure.

Next, we discuss the procedures adopted to estimate the parameters of the model specified above.

Model Estimation

Bayesian estimators combine prior information about model parameters with information contained in the data to arrive at the posterior distributions for the parameters. In particular, we wish to obtain the marginal

Figure 1 Model Specification



posterior distributions of the model parameters. However, obtaining the marginal posteriors for parameters of interest in hierarchical Bayesian models such as the one proposed above is complicated by the intractability of these distributions.

Recent advances in statistics known as Markov Chain Monte Carlo methods permit samples to be drawn from the joint posteriors of the parameters and thereby from the marginal posteriors. The key idea here is to sample each parameter in turn from its distribution conditional upon data and current values of all other parameters (its full conditional distribution). Gibbs sampling thus expoits the hierarchical nature of the model to estimate the parameters (Tanner and Wong 1989, Gelfand and Smith 1990; for marketing applications see Allenby and Ginter 1995, Lenk et al. 1996, Rossi et al. 1996).

We fit the proposed model via Gibbs sampling using BUGS (Spiegelhuter et al. 1995), aided by the CODA S + function (Best et al. 1995) for assessing convergence and computing posterior summaries. BUGS uses S-like syntax, for specifying fairly complex hierarchical models (Ghosh et al. 1998). The program converts this syntax into a directed acyclic graph (see Figure 1). The nodes of the graph correspond to the complete conditional distributions necessary for the Gibbs algorithm. See Gilks et al. (1996) for details and examples of models estimated using the BUGS syntax.

In our model estimation we ran five parallel, initially overdispersed MCMC chains. Convergence of the Gibbs sampler was assessed according to three criteria. First, we graphically monitored the chains and plotted the traces from each chain for each parameter as a separate time series. Second, we calculated sample autocorrelations. Third, we monitored the Gelman and Rubin (1992) diagnostic measure. This measure is based on a comparison of within and between chain variances for each variable. These criteria enabled us to detect the iteration at which an acceptable degree of convergence is achieved. A large number of iterations after the convergence were used to generate parameter estimates and standard deviations. As a byproduct of the Gibbs sampling procedure we obtain the distribution of the posterior coefficients. In the following, we discuss the use of the distribution of these posterior parameters (ψ_{mct}, α_c, β_c, γ_c, σ^2_α, μ_β, μ_γ, σ^2_β, σ^2_γ) to make first-week predictions for new movies in domestic and international markets.

Prediction Procedure

Below we describe the procedure used for predicting the first-week performance of movies in a hold-out sample. For a certain country, c, suppose V_{mct} denotes the unobserved first week viewership of a new movie (m'). We follow Bayesian modeling convention (Gelman et al. 1995) and use the observed data (for example, performance of previous movie releases) and posterior parameters obtained from our model estimation to make inferences about V_{mct}. Recall from Equation (1) that movie viewership (V_{mct}) is assumed to follow a Poisson distribution with an intensity parameter λ_{mct}. Hence, we can obtain the distribution of $V_{m'ct}$ conditional on the observed data and the model parameter $\lambda_{m'ct}$ (i.e., the posterior predictive distribution of $V_{m'ct}$) as:

$$p(V_{m'ct} \mid \text{Data}) = \int p(V_{m'ct} \mid \lambda_{m'ct}) p(\lambda_{m'ct} \mid \text{Data}) d\lambda_{m'ct}. \quad (5)$$

The first of the two factors in the integral is just the poisson distribution for the future observation given the value of $\lambda_{m'ct}$ (Equation (1)). The second factor is the posterior distribution of $\lambda_{m'ct}$ given the observed data. The posterior predictive distribution of $V_{m'ct}$ can thus be thought of as an average of the conditional predictions over the posterior distribution of λ. The key challenge in generating forecasts of viewership is determining the predictive distribution of λ (i.e. $p(\lambda_{m'ct} \mid \text{Data})$). Once $p(\lambda_{m'ct} \mid \text{Data})$ is obtained, the distribution of $V_{m'ct}$ can be generated using the relation specified in Equation (1).

We now discuss how to obtain $p\ (\lambda_{m'ct} \mid \text{Data})$ at different stages of new movie launch process. Figure 2 presents (a) the different stages in the movie launch process and the nature of information available at each stage, and (b) how it is possible to use such information to infer the distribution of $p(\psi_{m'ct} \mid \text{data})$ where $\psi_{m'ct} = \log \lambda_{m'ct}$. In Figure 2, we present differences in the extent of movie-specific covariate information (denoted by b, c, d, e, g, h, gl, and hl) and data (denoted by a and f) available to estimate posterior parameters at different stages of the movie launch process. We derive below the predictive distributions for $\psi_{m'ct}$ at each stage in the movie launch process, beginning with the initial stage with the least amount of information. We use these predictive distributions to generate new movie first-week forecasts following the computational steps laid out in panels 1 to 5 in the bottom half of Figure 2.

(a) **Market Evaluation:** This is the beginning of the decision process for movie releases. Base forecasts of average movie performances in different markets are necessary to make market prioritization decisions. At this stage, the forecaster has access to information in the "historical database," i.e., the performances of previous releases in the different markets contained in our sample. Because we are interested in the first week forecast, the value for $\text{TREND}_{m'ct}$ is one, and the value for $\text{CUMVIEWERS}_{m'ct\text{-}t}$ is zero because there are no previous viewers.

Let $X_{m'ct}$ denote the set all unknown covariates for the new movie, θ denote the set of country-specific parameters, and ζ denote the set of hyperparameters. Thus $X_{m'ct} = \{\text{SCREENS}_{m'ct}, \text{DIST}_{m'c}, \text{GENRE}_{m'}, \text{STARS}_{m'}\}$, $\theta = \{\alpha_c, \beta_c, \gamma_c\}$, $\zeta = \{\sigma^2_\alpha, \mu_\beta, \sigma^2_\beta, \mu_\gamma, \sigma^2_\gamma\}$. If we knew the exact values of both $X_{m'ct}$ and θ we could use the relation in Equation (2) to obtain the distribution of $\psi_{m'ct}$. However, we do not know the exact values of the covariates. Hence, we must integrate out $X_{m'ct}$ using a distribution of $X_{m'ct}$ that represents our beliefs about the likely values of $X_{m'ct}$, i.e.,

$$p(\psi_{m'ct} \mid \theta, \zeta) = \int p(\psi_{m'ct} \mid \theta, \zeta, X_{m'ct}) p(X_{m'ct}) dX_{m'ct}. \quad (6)$$

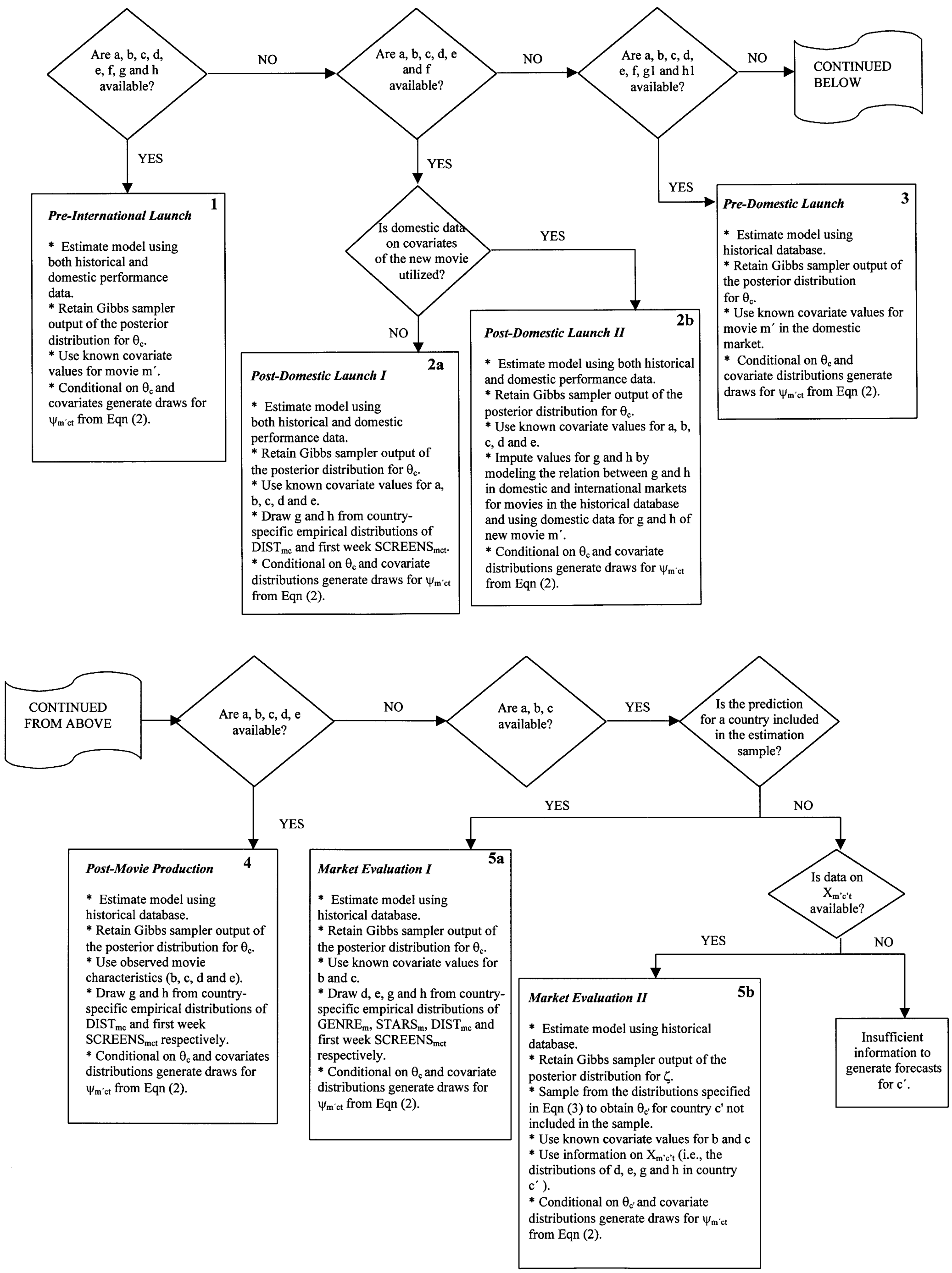
In the absence of any other information, we use the empirical distribution of the covariates from the historical database to generate random draws of $X_{m'ct}$ (Rossi et al. 1996). We use the empirical distribution of first-week screens for country c and generate random draws from this distribution to obtain $\text{SCREENS}_{m'ct}$.[9] Similarly, we draw from the country-specific empirical distributions for movie characteristics ($\text{DIST}_{m'c}$ $\text{GENRES}_{m'}$, and $\text{STARS}_{m'}$).

Additionally, we also need to account for uncertainty in our knowledge of θ. The nature of uncertainty about θ depends upon the type of prediction we wish to make. If we wish to make a prediction for a country already included in our sample (for example, France),

[9]We use *country-specific* empirical distributions for screens because of the large variations in market infrastructure across the countries. Furthermore, because there is a significant difference in the number of screens in the first and subsequent weeks, we use *first-week* screens data for generating draws to be used in first-week predictions.

Figure 2 Prediction Procedure

Informational Inputs: a: Historical Database b: $TREND_{m'ct}$ c: $CUMVIEWERS_{m'ct-1}$ d: $GENRE_{m'}$ e: $STARS_{m'}$ f: Domestic performance of m' g: $SCREENS_{m'ct}$ h: $DIST_{m'c}$ g1: $SCREENS_{m'}$ for domestic market h1: $DIST_{mc'}$ for domestic market



it is reasonable to use the posterior distribution of θ for that particular country (e.g., θ_{FRANCE}) in making our predictions. Thus, we obtain the predictive distribution for $\psi_{m'ct}$ based on observed historical data to be:

$$p(\psi_{m'ct} \mid \text{Historical Data}) = \iiint p(\psi_{m'ct} \mid \theta, \zeta, X_{m'ct})$$
$$p(\theta, \zeta \mid \text{Historical Data}) p(X_{m'ct}) d\theta d\zeta dX_{m'ct}. \tag{7}$$

The steps required to compute the integrals in Equation (7) are specified in Panel 5a of Figure 2. To make predictions for countries not included in our sample (for example, South Korea) we need to infer the country-specific parameters based on the distribution for the hyper parameters (i.e., ζ). Thus, we can account for our lack of specific knowledge of South Korean parameters. Let θ' denote the posterior parameters for a country c' not included in our estimation sample. The predictive distribution for $\psi_{m'ct}$ given historical data for the countries in the sample and information on the covariate distribution in c' is given by:

$$p(\psi_{m'c't} \mid \text{Data}) = \iiint p(\psi_{m'c't} \mid \theta', \zeta, X_{m'c't}) p(\theta' \mid \zeta)$$
$$p(\zeta \mid \text{Hist. Data}) p(X_{m'c't}) d\theta' d\zeta dX_{m'c't}. \tag{8}$$

Panel 5b in Figure 2 specifies the steps required to compute the integral in (8). Because of the paucity of readily available data on $X_{m'c't}$ we do not present empirical results for countries not included in our sample.

(b) **Post-Movie-Production:** At this stage of the decision process, the information set expands to include the movie characteristics (i.e., genre and absence/presence of stars). The movie has however not been launched in any market and the managers require prelaunch forecasts for both domestic and international markets.

We generate forecasts for the international markets at the post movie-production stage by conditioning our inferences about $\psi_{m'ct}$ on the observed movie characteristics. Let $M_{m'}$ denote the known movie characteristics ($\text{TREND}_{m'ct} = 1$, $\text{CUMVIEWER}_{m'ct\text{-}l} = 0$, $\text{STARS}_{m'}$, $\text{GENRE}_{m'}$) and $\text{D}_{m'ct}$ denote the unobserved $\text{DIST}_{m'c}$ and $\text{SCREENS}_{m'ct}$. In contrast to the market-evaluation stage, in the post-movie-production stage, we only average over the empirical distributions for $\text{SCREENS}_{m'ct}$ and $\text{DIST}_{m'c}$ and not all the other covariates. Hence we obtain the distribution of $\psi_{m'ct}$ to be:

$$p(\psi_{m'ct} \mid \text{Hist.Data}) = \iiint p(\psi_{m'ct} \mid \theta, \zeta, M_{\text{m}'}, D_{\text{m}'\text{ct}})$$
$$p(\theta, \zeta \mid \text{Historical Data}) p(D_{m'ct}) d\theta d\zeta dD_{m'ct}. \tag{9}$$

To generate forecasts for international markets, we use the country-specific empirical distributions to obtain random draws from $\text{SCREENS}_{m'ct}$ and $\text{DIST}_{m'c}$. We use these draws, observed movie characteristics, and proceed as per steps described in Panel 4 of Figure 2.

(c) **Pre-Domestic-Launch:** New movies are typically first launched in the domestic markets (United States and Canada). Prelaunch forecasts in the domestic markets are required to plan marketing activity over the movie's life cycle and make decisions regarding the international launch (Sawhney and Eliashberg 1996). In addition to information from the historical database and movie characteristics, information on the distribution strategy ($\text{DIST}_{m'c}$) and $\text{SCREENS}_{m'ct}$ for the domestic market is typically available to make pre-domestic-launch launch forecasts (Squire 1992). Thus, we have access to all the information in movie-specific covariates for the domestic markets. Hence, we obtain the distribution of $\psi_{m'}$ for the domestic market (the United States) to be as follows:

$$p(\psi_{m'\text{USA}t} \mid \text{Historical Data}, X_{m'\text{USA}}) = \iint p(\psi_{m\text{USA}t}$$
$$\mid X_{m'\text{USA}t}, \theta, \zeta) p(\theta, \zeta \mid \text{Historical Data}) d\theta d\zeta. \tag{10}$$

To compute the above integral and generate the pre-domestic-launch forecasts, we follow steps delineated in Panel 3 of Figure 2.

(d) **Post-Domestic-Launch I and II:** Once the movie is released in the domestic market, forecasts in international markets are required to finalize marketing mix decisions in each market. The information set at this stage expands to include domestic performance data for the new movie. At this stage, therefore, we augment the data in the historical data set with data on the new movie's domestic performance. Estimation of the proposed model with this new data set provides us with a distribution of posterior parameters.

We use two methods to generate the distribution of covariates for which the values are unknown ($\text{SCREENS}_{m'ct}$ and $\text{DIST}_{m'c}$). Forecasts from the *Post-Domestic-Launch I* model are obtained by using the country-specific empirical distributions of

$\text{SCREENS}_{m'ct}$ and $\text{DIST}_{m'c}$ along with the observed movie characteristics as covariates. Panel 2a describes the steps in the prediction procedure for this model.

We also generate forecasts from a model called *Post-Domestic-Launch II* model that utilizes the observed domestic data on $\text{SCREENS}_{m'ct}$ and $\text{DIST}_{m'c}$. Specifically, we generate these forecasts by treating the lack of information on SCREENS and DIST in the international markets as a missing data problem (Gelman et al. 1995). To impute values for this "missing" data (i.e., SCREENS and DIST in international markets), we model the relation between the SCREENS and DIST in the domestic and international markets for movies in the historical database. First, we calculate the ratio of the SCREENS in each of the international markets to the SCREENS in the domestic market. We also calculate the number of times there was a match in the distribution strategy used in the domestic market and each of the international markets. Making these calculations for each country and movie in the historical database provides us with a distribution of the SCREENS proportions and DIST matches for each international market. For example, the average SCREENS proportion in Germany is 1.17 and 78% of the time there is a match in the DIST variable in the domestic and German market.

Next, we multiply the country-specific empirical distributions of SCREENS proportions and DIST matches with the number of SCREENS and DIST in the domestic market for the new movie. This provides us with a distribution for SCREENS and DIST for each international market. Thus, if the number of screens for the new movie is 93 in the domestic market, the average of the distribution of SCREENS for Germany for the new movie is 93*1.17 = 109 screens. We use these distributions for $\text{SCREENS}_{m'ct}$ and $\text{DIST}_{m'c}$ and generate first-week viewership forecasts following the steps outlined in Panel 2b of Figure 2.

(e) **Pre-International-Launch:** Managers require first-week international market forecasts at this stage to fine-tune strategic decisions, assess competition, and plan marketing activities for future weeks. At this stage, the decisions regarding market choice and number of screens for release have already been finalized for each of the international markets. Hence, exact values for all the covariates are available, as well as both the historical database and domestic market data. We estimate the proposed model with a data set that consists of both the historical and domestic new movie performance data, and we obtain the distribution of posterior parameters. These are used along with the exact covariate values to generate $\psi_{m'ct}$ (Figure 2, Panel 1).

In summary, first-week viewership forecasts are required for managerial decisions in all five stages. The information available increases as we move from stage (a) to stage (e), and the methodology we have described above allows us to make predictions while accounting for the varying information availability. In the empirical section, we make predictions for new movies in all five stages and compare the relative value of additional information at each stage.

4. Results

In this section, we first discuss the substantive results we obtain from our model estimation. Next, we assess the fit of our model by conducting in-sample model comparisons and presenting first-week forecasts for hold-out sample generated with different information sets. Finally, we illustrate how the model outputs can be combined with industry rules of thumb to generate managerially relevant forecasts.

Model Estimation

Tables 2 and 3 report descriptive statistics of the posterior coefficients for the proposed model. In Table 2, we summarize the posterior distributions of the third-stage parameters of the model by reporting their means, standard deviations, and percentiles. Recall that these parameters measure the impact of the independent variables on viewership and are estimated by pooling the data across countries (see Equation (3)). The posterior mean for coefficient SCREENS ($\mu_{\beta 1}$) equals 1.65 and is almost nine standard deviations greater than zero. Jones and Ritz (1991) present evidence that retailer's adoption of screens is an important determinant of movie viewership in the U.S. market. Our findings confirm this result and suggest that the critical importance of screens for movie viewership extends to international markets. Consistent with our expectations we find that the posterior mean for TREND is negative and statistically significant. We

Table 2 Proposed Model Stage 3 Parameter Estimates

		Estimated Posterior Summaries			
Stage 2 Parameter	Stage 3 Parameter	Mean	SD	Mean/SD	Percentiles (2.5, 97.5)
Country-Specific Intercept	Precision (τ_a)	0.06	0.02	3.000	(0.03, 0.11)
Screens	Mean ($\mu_{\beta 1}$)	1.65	0.19	8.658	(1.270, 2.04)
	Precision ($\tau_{\beta 1}$)	2.48	0.98	2.542	(0.968, 4.78)
Trend	Mean ($\mu_{\beta 2}$)	−0.63	0.06	−10.376	(−0.755, −0.513)
	Precision ($\tau_{\beta 2}$)	24.30	10.23	2.375	(8.64, 47.4)
Cumulative Viewers	Mean ($\mu_{\beta 3}$)	−0.10	0.04	−2.715	(−0.164, −0.025)
	Precision ($\tau_{\beta 3}$)	70.54	30.13	2.341	(25.8, 141)
Distribution	Mean ($\mu_{\gamma 6}$)	0.07	0.03	2.293	(0.009, 0.123)
	Precision ($\tau_{\gamma 6}$)	140.10	72.14	1.942	(41.4, 315)
Stars	Mean ($\mu_{\gamma 5}$)	0.09	0.03	3.128	(0.031, 0.141)
	Precision ($\tau_{\gamma 5}$)	115.30	47.23	2.441	(42.9, 224)
Thriller	Mean ($\mu_{\gamma 1}$)	0.13	0.04	3.369	(0.054, 0.214)
	Precision ($\tau_{\gamma 1}$)	63.61	28.50	2.232	(22.1, 136)
Action	Mean ($\mu_{\gamma 2}$)	0.10	0.04	2.537	(0.021, 0.176)
	Precision ($\tau_{\gamma 2}$)	72.81	38.33	1.900	(23.7, 170)
Romance	Mean ($\mu_{\gamma 3}$)	0.10	0.05	1.971	(−0.003, 0.204)
	Precision ($\tau_{\gamma 3}$)	36.52	15.11	2.417	(13.4, 71.9)
Drama	Mean ($\mu_{\gamma 4}$)	−0.02	0.04	−0.540	(−0.094, 0.053)
	Precision ($\tau_{\gamma 4}$)	70.69	29.88	2.366	(26.4, 142)

also find that the posterior mean for CUMVIEWERS is negative, suggesting that the word-of-mouth generated across countries for the movies in the sample is negative. This, however, does not have face validity given the superior box office performance of the movies in the sample. We conclude, therefore, that CUMVIEWERS is not a good proxy for word-of-mouth effects. Instead, the sign of the posterior coefficient suggests that this measure may be capturing market saturation effects.

The table indicates that the impact of big-name stars on viewership, as measured by the STARS variable, is positive and statistically significant, thus adding to the evidence on this variable presented by Sawhney and Eliashberg (1996). Similarly, the use of local distributors, as measured by the DIST variable, is associated with significant increase in viewership. The means of the posterior distributions of the indicator variables for the various genres suggest that, across countries, THRILLER is the most popular genre. In terms of variability across countries, among the five genres, the precision of the ROMANCE genre is the lowest (standard deviation = 15.11), suggesting that intercountry differences in viewership are most pronounced for this genre.

Whereas we report distributions of the posterior parameters across countries in Table 2, in Table 3 we show how these estimates vary for the countries in our sample. Specifically, we report the country-specific coefficients β_c and γ_c. Recall from Equation (2) that these coefficients relate the movie and country-level covariates to the log of the Poisson model intensity parameter (ψ_{mct}). To facilitate interpretation of the intercept term as being unique to each country and to make comparisons of the relative effects of the other parameters, we standardized the covariates included in the model (Montgomery 1997).

While the posterior means for the country-specific intercepts are positive for all the countries, the size of this effect varies across countries. In particular, Japan and Brazil display the largest intercepts, whereas the United States has the smallest intercept. This implies

Table 3 Proposed Model Stage 2 Posterior Parameter Estimates

	Intercept	SCREENS	TREND	CUM VIEWERS	STARS	DIST	THRILL	ACTION	ROM	DRAMA
Australia	3.80	2.61	−0.49	−0.18	0.01*	0.10	0.01*	0.08	−0.02*	0.03†
	(0.02)	(0.07)	(0.03)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Brazil	4.17	1.69	−0.61	−0.09	0.03†	0.19	0.03*	0.03*	0.07*	−0.01*
	(0.03)	(0.05)	(0.04)	(0.02)	(0.01)	(0.07)	(0.08)	(0.07)	(0.06)	(0.05)
Canada	3.87	1.18	−0.67	−0.04	0.09	−0.05*	0.14†	0.26	0.03*	−0.003*
	(0.03)	(0.04)	(0.03)	(0.01)	(0.01)	(0.07)	(0.08)	(0.07)	(0.06)	(0.05)
France	3.42	1.59	−1.11	−0.06	0.08	0.04	0.36	0.25	0.30	0.18
	(0.04)	(0.05)	(0.03)	(0.01)	(0.01)	(0.01)	(0.03)	(0.02)	(0.02)	(0.02)
Germany	3.64	1.79	−0.70	−0.13	0.02	0.07	0.23	0.09	0.27	0.06
	(0.03)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Holland	3.67	1.15	−0.61	−0.01*	0.02*	−0.03*	0.14	−0.05*	0.08	−0.20
	(0.04)	(0.06)	(0.03)	(0.03)	(0.02)	(0.02)	(0.04)	(0.04)	(0.03)	(0.05)
Italy	4.60	1.42	−0.64	0.03*	−0.01*	0.10	0.09	0.12	−0.06	−0.21
	(0.04)	(0.07)	(0.07)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Japan	7.74	2.94	−0.33	−0.12	0.20	0.23	0.27	−0.14*	0.16†	−0.02
	(0.10)	(0.08)	(0.02)	(0.01)	(0.02)	(0.02)	(0.10)	(0.09)	(0.08)	(0.05)
Mexico	3.18	0.97	−0.94	0.02*	−0.05*	0.02*	0.23	0.08†	−0.11†	−0.05*
	(0.07)	(0.06)	(0.11)	(0.05)	(0.03)	(0.03)	(0.05)	(0.05)	(0.06)	(0.06)
Spain	2.99	1.89	−0.55	−0.27	0.09	0.10	−0.03*	0.02*	−0.05*	0.004*
	(0.13)	(0.18)	(0.08)	(0.05)	(0.04)	(0.03)	(0.05)	(0.05)	(0.07)	(0.04)
South Africa	3.70	0.43	−0.72	0.14	0.20	0.03*	0.25	0.24	0.39	−0.07*
	(0.06)	(0.03)	(0.05)	(0.03)	(0.02)	(0.02)	(0.05)	(0.05)	(0.04)	(0.05)
Sweden	3.25	1.63	−0.50	−0.26	0.17	0.03*	0.09†	0.11	0.27	0.16
	(0.08)	(0.13)	(0.03)	(0.03)	(0.02)	(0.03)	(0.05)	(0.05)	(0.04)	(0.03)
U.K.	3.81	1.76	−0.60	−0.18	0.09	0.01†	0.03	0.18	−0.08	0.03*
	(0.02)	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.07)
U.S.	1.72	1.88	−0.43	−0.19	0.25	—	0.02	0.12	0.16	−0.1
	(0.02)	(0.01)	(0.004)	(0.002)	(0.002)		(0.004)	(0.004)	(0.00)	(0.01)

†Significant at the 10% level.
*Not significantly different from zero.

that the observed covariates (screens, trend, cumulative viewers, movie attributes) play a larger role in determining viewership in the United States as compared to the international markets. Consistent with results in Table 2, the number of screens on which a movie is released is the most critical element of the marketing mix in *all* countries. Screens have the largest impact on viewership in Japan and Australia and the least in South Africa and Mexico. These findings have face validity in that while the Japanese market is one of the largest international markets, it lags substantially behind the European and North American markets in the number of screens and theatrical infrastructure development (Jaeger II 1997). In the mid-1990s, increased market development activities in Australia boosted the theatrical market in that region (Jaeger II 1997). This provides an explanation for the relative importance of screens in that country. Both South Africa and Mexico are developing countries with very poor market infrastructure for movies (Squire 1992).

Means of the coefficients for TREND and CUMVIEWERS are negative for most countries. The coefficient for TREND is most negative for France, suggesting that the drop off rates are sharpest in that country. In contrast, movie releases in Japan tend to have the most gradual drop off. The posterior means for the presence of stars is either positive or zero for the countries in our sample. The United States has the largest posterior mean for the presence of stars, followed by Japan and South Africa. The lack of effect of this variable in some of the other countries might be due to the lack of recognition of all the stars in these markets (*Variety* 1996). The positive posterior means for the DIST variable highlights an interesting institutional detail in international movie marketing. All the movies included in the sample had a major distributor in the United States. Industry experts note that the power and financial muscle of major studios boosts viewership of movies distributed by them in the domestic market (Ornstein 1998). Internationally, however, we find that the reverse holds. Local distributors, by providing greater attention and support, ensure increased viewership in their own markets.

In terms of genre preference, we find that countries in the British Commonwealth (U.K., Canada, and Australia) and Italy prefer action movies the most. Consistent with industry wisdom, Japanese and Mexican audiences are partial to thrillers (*Variety* 1994a). By contrast, romance is the most preferred genre in the United States, Sweden, Germany, and South Africa. These results suggest that it is possible to create nongeographic groupings of countries for movie marketing based on their relative genre preferences.

In summary, we find that screens are the most important influence on movie viewership in international markets. Local distribution improves movie sales internationally in contrast to the domestic market. We also find evidence of similar genre preferences in geographically disparate countries.

Model Assessment

To assess the fit of the model we calculate the mean predictions of viewership made by the model for each of the countries. This prediction along with actual viewership is presented in Figure 3 for several movie–country pairs. The figure indicates that predicted and actual values are very close. These results generalize to all movie–country pairs in the estimation sample.

In-Sample Fit Measures. While existing models in the marketing literature have been proposed at the movie-country level (i.e., these models are estimated separately for each movie in each country), the proposed model uses the complete estimation sample (i.e., merges data across movies and countries). Hence, we conduct model comparisons with just movie–country data (separate-data analysis) as well as with the entire estimation sample data (merge-data analysis). We compare the following models with a comparable formulation of the proposed hierarchical Bayes model: (a) the early sales forecasting model for motion pictures developed by Sawhney and Eliashberg (1996); (b) the Fourt and Woodlock (1960) model for predicting sales of new products (Figure 3 shows that the pattern of movie sales tend to follow the patterns used in the development of this model, hence making this model a natural alternative to the proposed Bayesian model); (c) naive (logged) OLS model, which is an ordinary least-squares formulation of the proposed model; and (d) a Poisson maximum likelihood model that has the same set of exogenous variables as the proposed Bayesian model.

In Table 4 Panel A, we compare the performance of the different models on two criteria: Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). The table reveals that on both criteria the hierarchical Bayes model has the smallest errors, followed by the Poisson Maximum Likelihood model and the Sawhney and Eliashberg (1996) specification. The naïve OLS model displays the poorest performance.

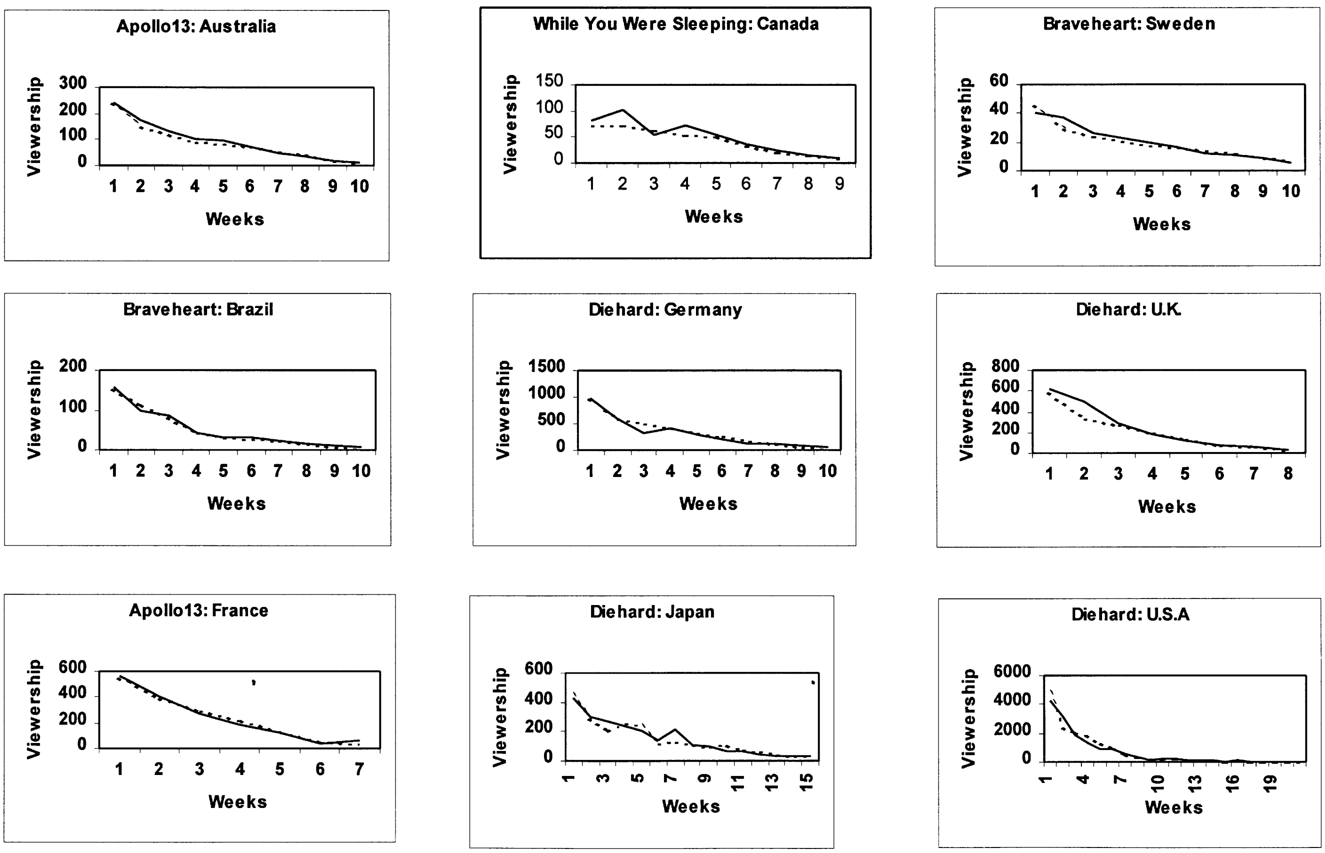
In Table 4, Panel B, we compare the proposed hierarchical Bayes model with two other models estimated with all the data available in the estimation sample. These models are the Poisson maximum likelihood and naïve OLS models. The covariates included in these models were identical to those included in the hierarchical Bayes model. We also included country-level dummies in both the comparison models. Both criteria of RMSE and MAE provide evidence of the superior in-sample fit of the proposed model.

Table 4, Panel C shows the root mean square error for each country across the 25 movies in the estimation database. This panel reiterates the superior performance of the hierarchical Bayes model at the level of each country. We find that the errors in model fit are the largest for the United States, in contrast to low errors for Canada. Given the better fit of the hierarchical Bayes model to the Canadian data, as compared to the fit for the U.S. market, and the early release of movies

Figure 3 Actual Viewership and Model Predictions

Actual Viewership ————

Predicted Viewership-------



in Canada, we treat the Canadian market as the "domestic" market in the subsequent predictions.[10]

Overall, the in-sample fit of the Bayesian model is superior to the other comparison models. It is important to keep in mind that this superior performance comes at the cost of longer computation time and more parameters. Given the criticality of accurate forecasts and the easy access to computational time, this seems to be a reasonable tradeoff to make.

Hold-Out Sample: First-Week Viewership Predictions. We estimate the hierarchical Bayes model for a set of 25 movies and make first-week predictions using different information sets for 10 movies (*The Net, Water World, Dangerous Minds, Twelve Monkeys, Heat, Get Shorty, Seven, Toy Story, Jumanji, and Nine Months*). We generate first-week performance forecasts for both domestic and overseas markets at different stages of the movie launch process.

We begin by making prelaunch first-week predictions for the new movies in the domestic markets (United States and Canada). In particular, we present predictions made at the post-movie-production stage and pre-domestic-launch stages. The information set in the post-movie-production stage consists of the historical database and movie characteristics (Figure 2, Panel 4). In the pre-domestic-launch stage, we add

[10]We also carried out the predictions treating the U.S. market as the domestic market. However, the Canadian assumption led to smaller prediction errors.

Table 4 In-Sample Fit

Panel A: Separate-Data Analysis: Model Comparisons

Models	Sawhney and Eliashberg (1996)	Fourt and Woodlock (1960)	Naïve OLS	Poisson Maximum Likelihood	Separate-data Hierarchical Bayes Model
Root Mean Square Error	33.33	35.98	41.21	27.87	27.05
Mean Absolute Error	22.52	23.82	29.47	16.70	16.20

Panel B: Merged-Data Analysis: Model Comparisons

Models	Naïve OLS	Poisson Maximum Likelihood	Proposed Hierarchical Bayes Model
Root Mean Square Error	460.83	345.10	339.10
Mean Absolute Error	193.01	79.60	72.30

Panel C: Model Comparisons of RMSE by Country

Country	Naïve OLS	Poisson Maximum Likelihood	Proposed Hierarchical Bayes Model
Australia	33.68	11.11	6.90
Brazil	52.51	6.60	5.44
Canada	34.19	29.81	12.66
France	22.88	17.79	13.71
Germany	34.90	27.01	21.80
Holland	52.87	3.42	2.66
Italy	30.57	10.58	5.48
Japan	33.47	11.93	6.21
Mexico	55.57	2.71	1.47
South Africa	34.95	1.31	1.16
Spain	51.60	43.98	3.19
Sweden	40.56	2.67	2.58
U.K.	40.92	31.08	24.10
U.S.	436.37	337.30	336.73

information on SCREENS and DIST in the domestic market to the information set (Figure 2, Panel 3). Table 5 presents the aggregate results from 10 predictions made for the United States and Canada. The error measures reported in the table indicate that for both countries, there is a reduction in error when information about SCREENS and DIST is added. Furthermore, this information is relatively more relevant to the U.S. market. Later in this section we compare our model's performance to prelaunch predictions reported for the U.S. market in the extant literature.

In Table 6 we show the aggregate results from predictions made to forecast first-week sales in each of the international markets. Because all 10 movies were not launched in all 12 international markets (giving 10*12 = 120 predictions), we make 103 first-week predictions. In addition to comparing the performance of the hierarchical Bayes models using different information sets, we also compare the performance of these models with a Pre-International-Launch II model. This model employs only domestic market performance data and information on movie attributes, distribution, and screens in international markets (i.e., without information from the historical database).[11] We conduct this comparison because this model utilizes only the data available at the movie–country level and hence is simpler to estimate. Furthermore, comparison of the fit of this model with that of the model using both domestic and historical database allows us to assess the infor-

[11]For the International Launch II model we make 101 instead of 103 predictions, because in two cases we had access to only one data point for the domestic market making the estimation of this model infeasible.

Table 5 First-Week Predictions for Domestic Markets

	U.S.		CANADA	
Decision Process Stage	Post-Movie-Production	Pre-Domestic-Launch	Post-Movie-Production	Pre-Domestic-Launch
Information Set	Historical Data, Movie Attributes	Historical Data, Movie Attributes, SCREENS, DIST	Historical Data, Movie Attributes	Historical Data, Movie Attributes, SCREENS, DIST
Root Mean Square Error	1174.40	892.01	81.16	80.74
Mean Absolute Error	1003.80	680.30	71.80	68.70

Table 6 First-Week Predictions: Comparisons of Distribution of Error Squared and Absolute Error Across Stages

Decision Process Stage	Post-Movie-Production	Post-Domestic-Launch I*	Post-Domestic-Launch II*	Pre-International-Launch I*	Pre-International-Launch II**
Information Set	Historical Data, Movie Attributes	Historical and Domestic Data, Movie Attributes	Historical and Domestic Data, Movie Attributes	Historical and Domestic Data, Movie Attributes, SCREENS and DIST	Domestic Data, Movie Attributes, SCREENS and DIST
Error Squared					
Mean	26886.70	25183.69	19668.69	17116.05	22210.79
Maximum	388129.00	356409.00	264196.00	324900.00	442225.00
RMSE	163.97	158.69	140.25	130.83	149.03
Absolute Error					
Maximum	623.00	597.00	514.00	570.00	665.00
Mean	87.38	84.74	82.49	69.50	80.19

*Number of predictions made using each of the models is 103.

**Number of predictions made using each of the models is 101.

mation value in the historical database. Similarly, comparing the performance of the model using both historical and domestic data with the model using historical data allows us to assess the informational content in the domestic data.

The key finding from this table is that predictive performance of the proposed model improves as additional information is included in the modeling and prediction process. Comparing the results on the rows showing RMSE and MAE, we find that the model using both movie-specific performance data from the domestic market (i.e., Canada) and the country-specific historical data outperforms all the other models. The RMSE value for this combined information model is 130.83, and the MAE for this model is 69.5. Both these numbers are smaller than the prediction error measures reported for all the other models. Furthermore, we find that the distribution of these error measures also attest to the superior performance of this model.

The RMSE and MAE results reported in Table 6 focus on the accuracy of the prediction without taking into account the dispersion in the prediction distributions. We therefore compare the models—using a Bayesian predictive model selection criterion (*L-criterion*) that accounts for both aspects of a prediction, forecast accuracy, and size of the predictive distributions. This criterion is similar to the mean square error criterion and considers both the mean and the variance of the prediction (Laud and Ibrahim 1995). It is based on a Bayesian predictive density and is free of asymptotic definitions. For a given model M, let P_{mc} represent an element from the first week predictive distribution for movie m in country c. The actual first-week viewership is denoted by V_{mc}. The L-criterion is given by:

$$L_M^2 = E(P_{mc} - V_{mc})'(P_{mc} - V_{mc}) = \sum_{mc=1}^{103} [\{E(P_{mc}) - V_{mc}\}^2 + \mathrm{var}(P_{mc})].$$

This criterion therefore implies that a performance of a model is measured by a combination of how close its predictions are to the observed data and the variability of the predictions. Typically, the square root of $L^2{}_M$ is employed, and this is denoted by L_M. We found the values for L_M for the four models post-movie-production, post-domestic-launch I and II, and pre-international-launch I to be 1917.49, 1900.90, 1420.63, and 1325.44, respectively. For the pre-international-launch II model (i.e., the domestic-data model), we found the value of this measure to be 1340.68. The model using both domestic and historical data (pre-international-launch I) thus has the lowest L_M measure and hence is superior to all the other models.

Comparison of the models in Table 6 provides the following insights. First, consider the relative performance of the pre-international-launch I model and the post-domestic-launch I model. We find that the lack of exact information on SCREENS and DIST creates additional uncertainty in the latter model. This uncertainty increases both the variance of the predictive distribution as well as the accuracy to the extent that the SCREENS and DIST selected for the new movies differ from the past empirical distributions. Next, compare the two models estimated with the *same* information availability at the post-domestic launch stage. We find that there is a decrease in both prediction errors and L-criterion when we use the post-domestic launch II model. This result clearly demonstrates the benefits of using available information more intensively within the proposed Bayesian framework. Finally, comparisons of the results of the Post-Domestic-Launch I and Post-Movie-Production models indicate that with the addition of domestic data the percentage reduction in RMSE and MAE are 3.2% and 3%, respectively. Analogously, when we compare the Pre-International-Launch models II and I, we find that the percentage reduction in RMSE and MAE are 12.2% and 13.3%, respectively, with the addition of historical data. These comparisons suggest that while both movie-specific domestic data and country-specific historical information are important, the historical information is relatively more valuable.

In sum, all these results underscore the theme that each movie and each country are unique—and viewership results from an interaction of the product and the market. Hence, while making forecasts it is important to use both historical data about the market and data on product performance in the domestic market.

Combining Proposed Model with a Rule of Thumb

Movie producers typically employ a number of rules of thumb to make forecast predictions (Squire 1992). Below, we illustrate how one such rule of thumb can be combined with the formal Bayesian model to make predictions of cumulative viewership for new unlaunched movies.

In interviews with managers in the motion picture industry, we were told that managers used the following rule-of-thumb to obtain cumulative movie performance forecasts. Managers used their understanding of the movie market and the strengths of a particular movie, to estimate the proportion of total box office that will be accounted for by the first-week box office. For the U.S. market, this proportion tended to be between 30% and 50%. We use a variant of this rule-of-thumb to generate cumulative viewership forecasts for our hold-out sample in domestic and international markets.

Because we do not have access to market-specific estimates made by managers for the movies in our hold-out sample, we calculate the average proportion of first-week viewership to total viewership for the movies in the historical database in each of the countries in our sample. We use this measure as a "managerial estimate" for the movies in our hold-out sample. Specifically, we use this proportion and the first-week forecasts estimated at the pre-international-launch stage to calculate cumulative viewership for each movie in the hold-out sample in the international markets. For example, the mean proportion for Germany is 0.25 and the first-week forecast for *The Net* (in thousands) in Germany is 337, giving us a cumulative viewership forecast (in thousands) of 1348.

We compare our forecasts of cumulative viewership to actual viewership for 88 movie–country combinations for which we had complete data. We find the mean absolute percentage error (MAPE) for the domestic markets to be 45.2% for the United States and 44.5% for Canada. We find the MAPE across all the international markets to be 43.3%. We find that the markets with the largest errors are Brazil (69%) and the United Kingdom (64.5%), and markets with the smallest errors are Japan (21%) and Germany (22.4%). These results compare favorably with previous "no data" forecasts for new movies reported by Sawhney and Eliashberg (1996). In particular, those authors find an MAPE of 71% for 10 unlaunched movies in the U.S. market. They find that this error drops dramatically with the addition of actual movie performance data. Thus, while the proposed model (combined with a rule of thumb) provides relatively better prelaunch forecasts than the Sawhney and Eliashberg (1996) model, the latter model provides excellent postlaunch predictions. This suggests that it might be worthwhile to use the proposed Bayesian methodology to make prelaunch forecasts and use these in combination with the postlaunch forecasts obtained from Sawhney and Eliashberg (1996).

5. Discussion and Conclusions

This paper attempts to shed light on the following research questions: When a firm introduces a new product (or service), how can it effectively use the different information sources available to generate reliable new product performance forecasts? How can the firm account for varying information availability at different stages of the new product launch and generate forecasts at each stage? To address these questions, we do the following.

We propose a Bayesian model and prediction procedure that provides viewership forecast at different stages of the new product launch process. The methodology provides forecasts under a number of information-availability scenarios. Thus, forecasts can be obtained with just information from a historical database containing data on previous new product launches in domestic and several international markets. As more information becomes available, the forecasting methodology allows us to combine historical information with information on the performance of the new product in the domestic market and thereby make forecasts with less uncertainty and greater accuracy. Furthermore, it is possible to combine this formal model with industry rules of thumb to generate managerially relevant forecasts.

We apply the proposed methodology to forecasting movie performances in domestic and international markets. For all the countries in the data set, we find that the number of screens on which a movie is to be released is the most important influence on viewership. Further, we find that local distribution improves movie sales internationally in contrast to the domestic market. Our results indicate that the proposed model provides accurate forecasts at the movie–country level. The model outperforms all the extant models in the marketing literature that could potentially be used for making these forecasts.

The results across the movies in a hold-out sample demonstrate the usefulness of both information from the domestic market on the performance of the new movie and information contained in the historical database. A comparison of root mean square and mean absolute errors across models shows that the lowest errors are made by the model that combines information available from the different sources. A Bayesian predictive model selection criterion *L*-criterion corroborates the superior performance of this model. The results, thus, demonstrate the value of a formal model using all available information for making viewership forecasts. The results suggest that movie studios, distributors, and exhibitors should use both product-specific and market-specific information to make new movie forecasts internationally.

In terms of the contribution of the paper, we see it as addressing an important issue in the new products forecasting literature. Furthermore, we tackle a managerial problem in the motion picture industry by proposing a procedure to make first-week forecasts. While both count data models and hierarchical Bayes procedures are familiar in the marketing literature, this is one of the first attempts, in marketing, to combine the two to address a managerial problem.

The modeling framework proposed in readily generalizable to other settings—both international and domestic. In the international context, this methodology can be used in any product category where there is a sequential launch. Such a product introduction strategy is very common in international markets. Some examples of such a product introduction strategy are Citibank's sequential launch of credit cards in Asia Pacific, the launch of the nicotine patch first in Ireland and subsequently in the United States, and Toshiba's introduction of the Libretto subnotebook computer first in Asia and then in the U.S. market. In the domestic context, the proposed methodology can be used to predict both sequential launches in different states/ areas and also different types of markets. For example, this methodology can be used to predict video sales of a movie using data from the theatrical performance.

Clearly, there is still room for improvement in the model forecasts obtained. One of the reasons for the current performance levels is that we do not have access to information on other variables influencing movie viewership, such as advertising, production budgets, and release schedule (Krider and Weinberg 1998, Eliashberg and Shugan 1997). Furthermore, numerous other factors impact international adoption, and it is impossible to account for all of them—by using a distribution for the intercept parameter in the count data model, we are capturing some of these variables such as weather, local cinema activities, etc.

One avenue for future research is to extend the forecasting horizon and generate week-by-week forecasts. While the motion picture industry is most interested in first-week forecasts, it may be useful to forecast performance over time when assessing launch profitability in a particular country. This brings up the issue of the number of screens. The evolution of the number of screens over time will depend, in part, on the performance of the movie. Consequently, 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.[12]

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