An experience product’s quality is difficult to assess prior to purchase, largely due to the limited availability of information before consumption. In the absence of perfect information, firms routinely use certain market signals to provide product quality information to consumers. Accordingly, drawing from signaling theory, this research aims to identify a collection of product core attributes in the form of signals and brand extension features to successfully manage experience product franchises. In doing so, we make use of Bayesian models with both deterministic effects via the use of predictor variables and probabilistic effects via the use of brand extension properties. Such models allow us to explore specifically the relative performance effects of the parent product of a franchise and of its extensions given the same level of product core attributes. The results of this study, based on the motion picture franchise data, indicate that there are critical product core attributes such as continuity, timing, and prior perception that collectively lead to successful successive generations. Furthermore, our study shows that brand features measured by the relationships between the parent product and its subsequent extensions at the infancy of the franchise are essential for the continuation of experience products. Similarly, our results indicate that the parent product’s success on later extensions’ performance starts to diminish, implying that the established “brand name” is what carries the franchise forward.

Introduction

Consumers often have incomplete information about product attributes, quality, and benefits. Such imperfect information steers consumers to rely more on brand names as quality signals to reduce uncertainty and to increase perceived quality (Erdem and Keane, 1996) because brands represent valuable sources of information for consumers to make decisions (Aaker, 1991; Keller, 1993). Accordingly, understanding the way consumers perceive quality and lessen uncertainty has been an important topic in both economics and marketing literatures at least since Akerlof (1970) argued that poor quality would prevail over high quality products if there were no signaling mediums in the marketplace. Firms therefore often use various signals to convey credible messages to the market regarding the future prospects of the products prior to launch. In the absence of such signals, consumers faced with greater uncertainty might delay their decision to adopt a new product. Thus, examining how and/or what type of potential signals can be used by managers to communicate product quality to consumers, consequently reducing uncertainty and enforcing product adoption, may provide important managerial insights for the successful introduction of new products to markets.

Despite this strongly supported managerial importance, little is known about the signals that firms use to convey directly unobservable product quality information to consumers. Signaling theory (Spence, 1973) highlights the importance of credible signals and explains why firms are likely to focus their attention on cues that mitigate consumers’ perceived uncertainties regarding the quality of products. Accordingly, by using signaling theory as our theoretical base, the purpose of this paper is to investigate two main streams of research questions in the context of experience products and their brand extensions. First, the study attempts to identify the brand extension signals or core attributes that affect an experience product’s (e.g., a motion picture) performance. Second, the paper will shed light on the performance relationship between the parent product (e.g., first movie of a franchise) and its several extensions (i.e., multiple sequels) with special emphasis on the length of the franchise, product continuity, timing, prior perception, and how they are linked together. In doing so, the study proposes to explore specifically the relative performance
effect of a first extension as opposed to a second, third, or fourth of a franchise given the same level of signals or core attributes.

In answering the previously raised questions, the paper proposes a novel Bayesian hierarchical model with two core components: one to account for the deterministic effects of product attributes or signals and one to account for multiple extension specific random effects. As a result, once the product attributes in the form of signals are identified or controlled for, our proposed model will be able to account for many other unobserved factors (i.e., unobserved heterogeneity) one would naturally encounter in various extensions of a parent product unlike traditional methods such as the least squares regression. For instance, it is possible that the uncertainty (measured by variance) of a first extension is higher than that of a parent given their individual core attributes or signals. In addition, the study aims to provide findings that are easily interpretable by practitioners and thus adopts a Bayesian inference point of view which gives us results interpretable in terms of probabilities. For instance, as a by-product of our proposed model, one would be able to exactly compute the probability that a second extension will perform better than a first extension given their respective core attributes which is very valuable from a practical perspective. The use of Bayesian methods in the experience products literature is scarce with the exception of Neelamegham and Chintagunta (1999) where a Bayesian Poisson model is considered to model/forecast the attendance counts at different stages of the new product launch process in the context of motion pictures.

The current study, unlike the rest of the literature, is able to capture the effects of several brand extensions of experience products instead of just one due to the introduction of the random extension effects structure of our model that could give us further insights about a franchise, thus making it more appealing and interesting from a brand extension point of view. In fact, correlations between the performance of a parent and its extensions given similar core attributes can be calculated. To the best of our knowledge, such a feature had not been considered previously in the literature. As a result, the findings can show roughly when the performance of a parent in a franchise starts to lose its importance after a certain number of extensions. In addition, the findings show decisive support in favor of using the extension effects in assessing market success by using fit/predictive performance measures commonly used in Bayesian analysis. Another point is on the common belief in the literature that first extensions do worse than their parents (Basuroy and Chatterjee, 2008; Moon, Bergey, and Iacobucci, 2010; Ravid, 1999) for experience products such as motion picture franchises. Our findings show that first extensions do worse than their parents consistent with what is suggested in the literature but also found that second extensions do better than first ones on average given core attributes, thus making the second extension a critical turning point in the life of a brand.

To empirically support the research questions, the study makes use of motion picture franchise data as an example of an experience product. A number of unique characteristics make the motion picture industry an ideal case for this study. First, motion pictures have a relatively short product life cycle which would be of interest to managers as these products are characterized by unpredictable demand, frequent market entries, and rapid market exits. Second, the motion picture industry is increasingly relying on sequels, namely brand extensions of a parent product. Movie sequels comprise a growing portion of box office revenues. According to Box Office Mojo, all top ten-grossing movies in 2012, nine of the top ten-grossing movies in 2011, and eight of the top ten-grossing movies in 2010 were sequels (Anderton, 2010; Evers, 2013; Kurtzleben, 2012), providing an ideal setting to test our model. Furthermore, a large academic literature exists on motion pictures, serving as a useful benchmark for assessing and comparing the importance of sequels as brand extensions. The proposed model with the random effects structure of brand extensions is also

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**BIOGRAPHICAL SKETCHES**

Dr. Goksel Yalcinkaya is an associate professor of the Marketing Department at the Paul College of Business and Economics at the University of New Hampshire. His current research interests include new product launch, diffusion of innovations, and international marketing. Within these broad areas, his major research areas are the emergence of aggregate level diffusion patterns from individual level adoption decisions, the relative impact of exploitation and exploration capabilities on product innovation and market performance, and the new product launch strategies. His work has previously been published in various academic journals including *Journal of the Academy of Marketing Science*, *Journal of International Marketing*, *Journal of World Business*, *International Marketing Review*, and *Journal of Product Innovation Management*. Currently, he serves on the Editorial Boards of *Journal of International Marketing* and *Journal of Global Academy of Marketing Science*.

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applicable to other experiential products such as video games and books that are franchises where similar relationships between the parent and its extensions exist. For instance, in the video game industry, several developers prefer building sequels to games which did well in sales rather than pursing a new franchise due to the risks involved in development and to the lack of potential fan base. In fact, even sequels of video games from previous generations of consoles dominate the video game marketplace. In addition, core attributes considered for motion picture franchises such as product continuity, franchise length, and timing would also be relevant and influential attributes in other experiential products that are franchises.

The remainder of the paper is organized as follows. The next section introduces theoretical background and support. Next is a description of the data followed by the proposed models. We then present and discuss the results, followed by managerial implications. Finally, our paper concludes with a quick summary, limitations, and future research directions.

**Conceptual Framework**

Two main bodies of literature indicate the importance of product quality signaling to consumers and provide theoretical foundations linking it to business performance. First, the new product literature posits that a high product-to-product attribute fit positively relates to consumer evaluations of a newly introduced product (Bouten, Snelders, and Hultink, 2011; Simonin and Ruth, 1998). As the fit between two products increases, consumers perceive the products to be comparable and transfer their positive attitudes more easily from the existing product to the subsequent product. Consistent with this reasoning, greater similarity between the parent and the extended product creates easier associations for consumers (Aaker and Keller, 1990). One common marketing practice is to introduce brand extensions as a function of parent brand characteristics to capitalize on brand equity (Aaker and Keller, 1990; Park, Milberg, and Lawson, 1991). For firms developing new products, failing to take core brand attributes into consideration may lead to poor performance (Beverland, Napoli, and Farrelly, 2010). As categorization theorists noted, consumers categorize a brand extension as a function of the established brand to form their evaluations (Boush et al., 1987; Park, Jun, and Shocker, 1996). Once consumers more closely relate a brand extension to the parent brand, the two will be categorized more closely in the minds of consumers and the associations will be more readily transferred (Aaker and Keller, 1990; Bouten et al., 2011; Kane, 1987; Keller, 1993). The continuity of core product attributes serves as a quality cue and likely enhances brand recognition, thereby reducing risk and uncertainty associated with the new product (Klink and Athaide, 2010). The need for quality cues becomes even more pronounced with an experience product (e.g., entertainment goods) since the quality of experience products (e.g., entertainment goods) are difficult to assess prior to purchase and are readily apparent only after consumption (Nelson, 1970). The limitations of experience products are accentuated by the life of a product as these typically have short life cycles and uncertain demands (Calantone, Yeniyurt, Townsend, and Schmidt, 2010; Luan and Sudhir, 2010). Therefore, marketing managers in the entertainment industry often only get one chance to make their offerings appealing to consumers. This requirement consequently necessitates an important need to brand new product offerings accurately right from the start.

Second, drawing on the consumer behavior applications of the signaling perspective (Kirmani and Rao, 2000; Rao, Qu, and Ruckert, 1999), signaling theory focuses on how potential cues can be used to signal quality when key product attributes are not readily identified. Signaling theory has been used as a framework for understanding how two parties (e.g., buyer and seller) cope with unobservable information in a pre-consumption context (Spence, 1973). A signal is a cue that a seller can utilize “to convey information credibly about unobservable product quality to the buyer” (Rao et al., 1999, p. 259). A key concept in signaling theory is asymmetric information. Asymmetric information refers to “limited access of information for at least one of the entities involved in the decision process” since some information is private. In the context of marketing signals, although firms know their own true product quality, customers do not, so information asymmetry and imperfect information are present. This information asymmetry is resolved if firms signal quality to consumers through various mechanisms, such as continuity of core product attributes. The signaling perspective of a brand argues that when faced with uncertainty due to imperfect and asymmetric information about a product, consumers utilize what they already know about the brand in terms of brand credibility and consistency to decrease perceptions of risk and to boost quality perceptions (Erdem and Swait, 1998; Wernerfelt, 1988). As a result, signaling theory indicates that firms that better identify and understand the signals consumers use to evaluate quality when faced with incomplete information.
about product attributes should have superior customer knowledge and be able to develop new offerings that better fit with customer needs (Kirmani and Rao, 2000). Theoretically, the signaling perspective contributes to the new product launch literature by providing a lens and a methodology to assess the success of managerial strategies, such as “sequels” as brand extensions, in influencing the way consumers perceive a product quality. The research stream has examined a variety of marketing cues as product quality and competitive signals, including brand (Erdem and Swait, 1998), product innovation reputation (Henard and Dacin, 2010), price (Dawar and Parker, 1994), promotional incentives (Song and Parry, 2009), warranties (Boulding and Kirmani, 1993), product pre-announcement (Su and Rao, 2010), and advertising intensity (Hultink and Langerak, 2002). Our study extends this marketing cue stream by applying signaling theory in the context of motion picture sequels as brand extensions of experience goods.

Although some researchers have examined the fit between parent and extension in the context of an entertainment product (Basuroy and Chatterjee, 2008; Hennig-Thurau, Houston, and Heitjans, 2009; Sood and Drèze, 2006), decisions about what contributes to a sequel’s success and/or how much attention should be given to various potential signaling factors has been limited. Similarly, a few marketing researchers have examined sequels as brand extensions of an experience product. Based on the survey data collected from university students, Sood and Drèze (2006) find that dissimilar extensions are preferred over similar ones when it comes to movies because consumers tend to prefer different themes and/or new story lines. The authors primarily focus on consumer reactions to the title and suggest that sequels with descriptive titles are rated higher than those with numbered titles. Basuroy and Chatterjee (2008) demonstrate that sequels tend to perform worse at the box office compared to their parents. The authors also find that sequels that follow their parents quickly are more likely to do better than those with longer time lags. The sequel effects found in these studies are related to a short time period or a small sample size. Furthermore, among various potential signals the firm can use, these studies focus only on selective ones, thus hampering a holistic understanding of the interconnected relationships among various signals. In contrast, our focus is on much broader market signals based on a longer and larger data set. More recently, Hennig-Thurau et al. (2009) measured the monetary value of movie sequels. Although they examined sequel effects over a longer time period by incorporating a larger body of extension product attributes, their focus was only on initial sequels and cannot extend beyond the parent and its sequel. Our study overcomes this important limitation by modeling the relationships among multiple sequels.

Data and Modeling of Successive Experience Product Releases

Our data set covers all movie sequels released in the United States between November 21, 1976 (i.e., “Rocky”) to August 19, 2011 (i.e., “Spy Kids: All the Time in the World”). The data are primarily obtained from the popular movie online database site, The Numbers, and are complemented and cross-validated by other popular online movie data sources such as Box Office Mojo, IMDb, and the Movieinsider. Our data set consists of 677 movie titles from 263 unique franchises with 263 sequels, 85 2nd sequels, 34 3rd sequels, 14 4th sequels, 7 5th sequels, 5 6th sequels, 3 7th sequels, 2 8th sequels, and 1 9-10-11th sequels (an average of 1.77 sequels). For each movie, the data set includes the following box office variables: number of screens, total domestic (i.e., U.S.) box office revenues, time lag between each sequel, official release date, an estimate of production budget, title continuity, star continuity, director continuity, and critical reviews. Because of the long sample period, all monetary data (e.g., revenues and budgets) were deflated (inflated prior to 1983) using the CPI (Consumer Price Index, All Urban Consumers, All items, 1982–1984 = 100) data from the Bureau of Labor Statistics to ensure comparability across years.

Our dependent variable is the total amount of gross that the movie generated in the United States. The production budget data are drawn from The Numbers. Time lag is calculated as the time between a parent and a sequel or two subsequent sequels in years. Consistent with previous studies, the paper incorporates the distribution intensity as the number of screens the movie was released on (Elberse and Eliashberg, 2003; Sawhney and Eliashberg, 1996). To capture the effects of core product continuity, the study uses three continuity measures of title, director, and star that are coded as dummy variables. Title continuity takes a value of 1 when sequels use a numbering title strategy as in “Hangover 2,” and 0 when sequels use a naming title strategy as in “Transformers: Dark of the Moon.” Star continuity takes a value of 1 if the main actor(s) from a parent movie appears in the following sequel and 0 when he/she (they) does (do) not. Similarly, director continuity takes the value of 1 if the same director(s) appears in the sequel and 0 otherwise.
Each continuity dummy variable is coded by an expert judge and cross-checked by the other. To account for prior perception, the study uses the average ratings assigned by critics. Critics’ ratings can play an important role in consumer decision-making and are included in this study (Eliashberg and Shugan, 1997). The critics’ rating information was gathered from Rotten Tomatoes (missing values were added from IMDb), which provides critical review information as a percentage of favorable reviews prior to the release of the motion picture. Genre for each movie is obtained from The Numbers. For some rare cases where movies are not listed on The Numbers, genre is obtained from IMDb. Following previous research, movies are categorized into six genres as action, horror, comedy, drama, adventure, and animation. Additionally, MPAA-ratings were obtained for the motion picture sequels from The Numbers. It should also be noted here that the genre and MPAA-rating variables were used as control variables as they were found to be relevant in previous studies and no attention will be payed to their inference in this study.

In modeling the U.S. gross of a motion picture with sequels, the study considers a Bayesian hierarchical structure. Subsequently, let $Y_i$ represent the U.S. gross of the $i$th movie (adjusted accordingly as discussed in the previous section) and $s_i$ represent the sequel index within a franchise for the $i$th movie. Also it is assumed that $Y_i$s are realizations from a probability distribution. As shown in the histogram and the smoothed empirical density estimate in Figure 1, the sample values of $Y_i$s are defined in the positive real line (scaled by 1,000,000) and are realizations from a right skewed distribution.

The first candidate for the distribution of $Y_i$s is the exponential that can be considered due to its straightforward estimation and whose density can be written as follows

$$p(Y_i|\lambda_i) = \lambda_i e^{-\lambda_i Y_i}, \quad (1)$$

where $\lambda_i > 0$ and is the rate parameter with expected value (mean) $1/\lambda_i$, namely the average U.S. gross of the $i$th movie. In addition, it is assumed that the parameter $\lambda_i$ is a multiplicative function of deterministic predictor variables and random sequel effects and is given by

$$\lambda_i = \theta_s e^{\beta z_i}, \quad (2)$$

where $i = 1, \ldots, I$ and $s_i = 1, \ldots, S$, with $I$ and $S$ representing the maximum number of motion pictures and the maximum number of sequels, respectively. In Equation 2, the deterministic effect comes from $\beta$, which is the vector of coefficients, and $z_i$, which is the vector of predictor variables for the $i$th movie. The random effects of sequels can be captured via $\theta_s$s, representing the overall contribution of the $s_i$th sequel on $Y_i$. Being able to obtain the posterior joint distribution of $\theta_s$s can provide a myriad of managerial insights to motion picture practitioners. For instance, one can quantify the probability that the effect of the first sequel of a franchise will be higher (or lower) than that of the second sequel on the U.S. gross given the data. Furthermore, another attractive feature of such a structure is the availability of posterior correlations between $\theta_s$s which is investigated in our analysis section. Such an analysis would not have been possible using classical estimation methods.

The second candidate for the distribution of $Y_i$s is the Weibull density, which is more flexible in terms of the density shapes it can exhibit as opposed to the exponential model. The Weibull density function given its two parameters, $\lambda_i$ and $\nu$, can be written as

$$p(Y_i|\lambda_i, \nu) = \nu \lambda_i Y_i^{\nu - 1} e^{-\lambda_i Y_i^\nu}, \quad (3)$$

Figure 1. Histogram Plot (Left) and Smoothed Empirical Density Plot (Right) for the U.S. Gross
for $\lambda > 0$ and $\nu > 0$. It is noted here that when $\nu = 1$, Equation 3 reduces to the exponential model as in Equation 1. For the scale parameter, $\lambda$, a similar multiplicative structure as in Equation 2 with $\theta_s$ can be considered. In estimating the model parameters for both cases, the Bayesian inference point of view is adopted and its details/estimation using Markov chain Monte Carlo (MCMC) methods are discussed in the Appendix.

The final step is to assess the fit performance of the proposed models. In order to do so, three sets of measures are considered that are used with sampling-based methods. The first fit measure is the Bayes factor approximation of models with MCMC steps; this measure is referred to as the Bayes factor-harmonic mean estimator (BF-HME), which has been discussed by Gelfand, Dey, and Chang (1992) and Kass and Raftery (1995) and is computed in the log-scale as $\log(p(Y))$. An alternative method to compare models with sampling-based methods is the calculation of the pseudo Bayes factor using the conditional predictive ordinate in the log-scale, log(CPO). Following Gelfand (1996), the comparison criteria makes use of a cross-validation estimate of the marginal likelihood by leaving the observations one by one from the analysis. The main advantage of this approach is that it also assesses the predictive performance of proposed models by following a leave-one-out type of approach. The final measure considered in this study is due to Spiegelhalter, Best, Carlin, and Linde (2002) and is referred to as the deviance information criteria (DIC). The advantage of the DIC is that it consists of both a measure of fit and of complexity. Previously discussed measures do not penalize for complexity thus do not account for the possibility of over-fitting the data. A smaller DIC value indicates a more adequate model.

### Analysis of Motion Picture Data

In this section, the proposed models are estimated using the data and the inference methods are described in the Appendix. While doing so, the following abbreviations are used to preserve space in the narrative.

- **M1-Exp**: a model where the likelihood is exponential as in Equation 1 with random sequel effects and deterministic predictor variables (budget, genre, MPAA-rating, distributor intensity, and critics’ rating).
- **M1-Wei**: a model where the likelihood is Weibull as in Equation 3 with random sequel effects and deterministic predictor variables (same as above).
- **M1-Exp-NoSeq**: a model where the likelihood is exponential as in Equation 1 with NO random sequel effects and deterministic predictor variables (same as above).
- **M1-Wei-NoSeq**: a model where the likelihood is exponential as in Equation 1 with random sequel effects and deterministic predictor variables (same as above).
- **M2-Exp**: a model where the likelihood is exponential as in Equation 1 with random sequel effects and deterministic predictor variables (budget, genre, title continuity, director continuity, star continuity, time lag, distributor intensity, and critics’ rating).

### MCMC Implementation and Convergence

In order to obtain the posterior samples of model parameters, a combination of MCMC methods were used (see the Appendix). To generate the samples, the WinBUGS software was used, and the code is available via e-mail upon request from the authors. In addition, flat but proper priors were assumed for model parameters when required. Specifically for M1-Exp, M1-Exp-NoSeq and M2-Exp, $\theta_j \sim G(.001, .001)$ were used and $\beta_k \sim N(0, .001)$ for M1-Wei and M1-Wei-NoSeq, $\log(\nu) \sim N(0, .001)$ was used in addition. Note also that the inference of model parameters was not sensitive to the choices of priors as long as they were flat but proper. To assess the convergence of the algorithms, three parallel chains were run with different initial points. The chains were run for 50,000 iterations as the burn-in period and 15,000 samples were collected with a thinning interval of 3. For the sake of preserving space, a detailed summary of convergence for all model parameters will be omitted. Only results for some of the parameters for M1-Exp are presented and similar results were obtained for the rest.

In obtaining the posterior samples, convergence problems are not encountered. This can informally be observed from the trace plots in Figure 2.

A more formal way of assessing convergence is due to the Brooks and Gelman plots and the shrink factor; see Brooks and Gelman (1998). If the shrink factor is around 1, then convergence is said to have been attained. The Brooks and Gelman plots are shown in Figure 3 where the shrink factor approaches 1 as the number of iterations increases. The estimated shrink factors were between 1 and 1.01 for all parameters. Thus, there were no convergence issues.

### Model Fit and Comparison

In assessing and comparing the adequacy/fit of our proposed models, three sets of measures are considered:
BF-HME, PBF-CPO, and DIC. Table 1 shows the marginal likelihood contributions and cross validations in the log-scale and the DICs for our proposed models. M1-Exp, which is the exponential model with the sequel effects, has the highest log-likelihood value and log-cross validation (> 20 in the log-scale to its closest competitor) and the smallest DIC value (> 60 to its closest competitor), which shows evidence of adequacy/fit in its favor. Another interesting point is that the models which do not take into account the random sequel effects, M1-Exp-NoSeq and M1-Wei-NoSeq, are significantly worse than their counterparts with random sequel effects. When comparing the DICs which penalize for model complexity, the models without the random sequel effects have higher values, which is encouraging since it further justifies the use of the gamma structure on the $\theta_i$s; namely, the sequel effects. Such a result shows decisive support in favor of accounting for brand extension effects (sequels in our study) of an experience product’s performance in addition to core attributes when trying to assess market performance (measured by the box office performance in our study). Such a finding further justifies the claim that sequels influence the consumer perception of product quality and subsequently attitude towards the purchase.

**Posterior Inference and Analysis**

Since M1-Exp was determined to be the best fit model, the posterior analysis is conducted based on its output. Figure 4 shows the boxplot of the random sequel effects posterior distributions given the predictor variables, where a higher value implies lower box office performance. In other words, given the same level of core attributes or signals (e.g., same level of prior perception,
budget, etc.), several conclusions can be drawn regarding the relationship between the parent product (first movie) and its extensions (sequels). The findings can conclude that the first sequels generally do worse than the parents; however, the second sequels (i.e., the third movie in a series) do better than the first sequels given similar core attributes. After the second sequel, the overall effect of the parent product diminishes until the sixth sequel. One of the advantages of the Bayesian paradigm is that it allows us to quantify uncertainty via probability distributions, making it easier for practitioners and managers to interpret and to make use of the results. For instance, based on the posterior results of Figure 4, the probability of the effect of the parent being higher on the performance as opposed to that of the first sequel can be calculated via $P(\theta_1 < \theta_2|D)$ (which in our case was calculated approximately to be equal to one). In addition, as the number of sequels increase, the uncertainty about their effect on the performance increases as can be observed from the size of the boxplots. This is quite intuitive since there are not that many franchises with more than five-six movies, that is, when the uncertainty significantly starts increasing and is one of the main advantages of using Bayesian analysis, which does not require large samples for each unit to carry out statistical inference unlike classical methods (Rossi and Allenby, 2003).

Another interesting finding about the random sequel effects is their posterior correlation structure as shown in Table 2, which shows that the parents are highly correlated with the firsts, seconds, and thirds after which its effect significantly diminishes. It can fairly be argued that

### Table 2. Posterior Correlations for $\theta$s

<table>
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<tr>
<th>$\theta_i$</th>
<th>$\theta_1$</th>
<th>$\theta_2$</th>
<th>$\theta_3$</th>
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<th>$\theta_5$</th>
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<td>.152</td>
<td>.108</td>
<td>.129</td>
<td>.094</td>
<td>1.0</td>
<td>.080</td>
<td>.090</td>
</tr>
<tr>
<td>$\theta_{11}$</td>
<td>.291</td>
<td>.292</td>
<td>.278</td>
<td>.253</td>
<td>.208</td>
<td>.187</td>
<td>.156</td>
<td>.144</td>
<td>.126</td>
<td>.080</td>
<td>1.0</td>
<td>.087</td>
</tr>
<tr>
<td>$\theta_{12}$</td>
<td>.262</td>
<td>.267</td>
<td>.252</td>
<td>.229</td>
<td>.204</td>
<td>.175</td>
<td>.146</td>
<td>.131</td>
<td>.120</td>
<td>.090</td>
<td>.087</td>
<td>1.0</td>
</tr>
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</table>
for franchises running longer than three sequels, the parent product’s success starts losing its importance, which could indicate that the established “brand name” of a franchise is what keeps the franchise moving forward. On the other hand, however, the parent product’s success can be argued to be more relevant at the infancy of the franchise for the sake of the “brand name” to continue growing given similar signals. Even if franchises that are running longer than six movies are ignored due to their small sample sizes, the correlation structure for the first six still indicates that the relationship between the parent and its extensions exhibits a decay as the number of extensions increase (with respective estimates of .94, .89, .80, .65, .58 that are consistently decreasing).

Unlike classical methods, there are two ways of representing inference results in Bayesian analysis: as a summary of statistics in the form of tables or graphically in the form of posterior density plots. Table 3 shows the posterior summary statistics for the coefficients of the respective predictor variables. In assessing the effects of the predictor variables on performance, keep in mind that a negative (positive) coefficient estimate implies a positive (negative) effect due to the mean parametrization of the exponential distribution. Since all inference is probabilistic in Bayesian inference, the 95% credibility intervals can be interpreted as probabilities using the same logic used for the posterior summary of statistics. For instance, the whole support for the coefficient of the critics’ rating variable used to account for prior perception is in the negative real line, implying a positive effect on performance given all the other predictors with probability one. In other words, it can be concluded that there is a 100% chance that a higher prior perception will lead to a higher box office performance given the same level of all other predictor variables (given the same level of budget, distribution intensity, genre, and MPAA-rating). The same arguments can be made regarding the effects of the budget and the distribution intensity variables based on their posterior density plots.

In order to investigate the effects of brand-extension–specific attributes such as product continuity and extension timing in addition to predictor variables of budget, critics’ rating, and distributor intensity, a model referred to as M2-Exp is estimated. Consequently, the parent movies were excluded so that brand-extension–specific effects of title, director, star continuity, and extension timing can be captured since they can only be defined relative to a previous observation. A parent product will not have such attributes since all four are defined with respect to a previous reference which the parent does not have. However, for subsequent extensions (i.e., first, second, third sequels, etc.), they can be defined with respect to the previous installment. In M2-Exp, the likelihood is exponential with random sequel effects (same as M1-Exp in terms of the model structure). Table 4 shows posterior summary statistics for coefficient parameters and Figure 6 their posterior density plots. Based on the 95% credibility intervals, all three product continuity attributes show strong positive effects on the domestic performance given the other predictor variables. The findings imply that when extending experience product brands, a key signal is product continuity measured by title, director, and actor continuity variables in our study. The results about director and actor continuity are not

---

Table 3. Posterior Statistics Summary for Coefficients, βs, in M1-Exp

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>St. Dev</th>
<th>2.5Q</th>
<th>Median</th>
<th>97.5Q</th>
</tr>
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<tbody>
<tr>
<td>Budget</td>
<td>-.010</td>
<td>.002</td>
<td>-.015</td>
<td>-.009</td>
<td>-.005</td>
</tr>
<tr>
<td>Genre: Action</td>
<td>-.245</td>
<td>.242</td>
<td>-.715</td>
<td>-.240</td>
<td>.213</td>
</tr>
<tr>
<td>Genre: Horror</td>
<td>-.068</td>
<td>.256</td>
<td>-.560</td>
<td>-.064</td>
<td>.422</td>
</tr>
<tr>
<td>Genre: Comedy</td>
<td>-.401</td>
<td>.243</td>
<td>-.874</td>
<td>-.395</td>
<td>.072</td>
</tr>
<tr>
<td>Genre: Drama</td>
<td>.019</td>
<td>.277</td>
<td>-.514</td>
<td>.020</td>
<td>.561</td>
</tr>
<tr>
<td>Genre: Adventure</td>
<td>-.557</td>
<td>.249</td>
<td>-.104</td>
<td>-.554</td>
<td>-.073</td>
</tr>
<tr>
<td>Genre: Animation</td>
<td>.053</td>
<td>.281</td>
<td>-.496</td>
<td>.056</td>
<td>.5832</td>
</tr>
<tr>
<td>MRating: R</td>
<td>.126</td>
<td>.163</td>
<td>-.203</td>
<td>.131</td>
<td>.441</td>
</tr>
<tr>
<td>MRating: PG</td>
<td>-.126</td>
<td>.229</td>
<td>-.593</td>
<td>-.120</td>
<td>.310</td>
</tr>
<tr>
<td>MRating: UR</td>
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<td>.040</td>
<td>-.199</td>
<td>.007</td>
<td>19.57</td>
</tr>
<tr>
<td>MRating: G</td>
<td>.207</td>
<td>.373</td>
<td>-.584</td>
<td>.229</td>
<td>.881</td>
</tr>
<tr>
<td>Dist. intensity</td>
<td>-.325</td>
<td>.489</td>
<td>-.420</td>
<td>-.328</td>
<td>-.289</td>
</tr>
<tr>
<td>Critic rating</td>
<td>-.176</td>
<td>.165</td>
<td>-.209</td>
<td>-.176</td>
<td>-.445</td>
</tr>
</tbody>
</table>
surprising; however, title continuity implies that franchises with the same title (defined as a numbered title as in Highlander, Highlander 2, and Highlander 3) perform better contrary to what has been said in the literature (Sood and Drèze, 2006). It is possible that when the title of a franchise changes, the perception of the customer towards the brand name shifts since it suggests a different story line that could be perceived not to be a continuation of what the original fan base expects. Another brand extension attribute whose effect was found to be strong but negative given the other predictor variables is the extension timing measured by the time lag (in months) between two installments. The results suggest that there is approximately a 98% chance (can be roughly seen based on the posterior density plot in Figure 6 of the time lag variable) that launching the next extension sooner than later will contribute positively to the performance of the installment. On the other hand, the findings indicate that given the same core attributes and signals, there is still a 2% chance that a late launch will improve the box office performance. This is probably due to the existence of special well-known franchises that launched late sequels, such as Indiana Jones and Star Wars, for which even after decades there were vast fan bases.

**Discussion and Managerial Implications**

There is a growing trend for firms to take advantage of brand name recognition. This trend is particularly notice-
able when firms face an experience product that generally possesses a high degree of pre-purchase information shortage for consumers to judge its quality (Erdem and Keane, 1996). To cope with information scarcity, consumers are increasingly relying on brand names as quality signals. Consequently, many firms tend to pursue a strategy of generating revenue through proven brand names. The recent emergence of brand extensions best characterizes this trend. From the perspective of consumers, the high quality of a parent product signals the potential quality of a newly extended product due to the association between similar attributes (Aaker and Keller, 1990). Although the quality signals firms use to convey unobservable product information before consumption are an essential part of a product’s survival in the new product literature, little is known about the core product attributes that provide the finest quality signals for the consumers. The goal of this paper is therefore to contribute to the new product literature by identifying brand extension signals that impact an experience product’s

Figure 6. Posterior Density Plots for Most Significant Coefficients in M2-Exp
performance as well as exploring the performance relationship between the parent product and its subsequent extensions.

First, the study offers a collection of core attributes theorized as signals that can lead to successful experience product franchises. A key signal is identified as the product continuity, measured by the collection of title, director, and actor continuity variables in the case of motion picture sequels, all of which are determined to have positive effects on performance with probability 1 given the effects of all other predictor variables. As signaling theory argues, such a strong continuity signal increases the perception of a product’s credibility and consistency and, in turn, decreases perception of risk inherently attached to the new product. The model indicates that the newly introduced product should demonstrate strong continuity of key attributes from the parent to be accepted by the consumer. This is an important insight for experience product managers of franchises that are in the process of extending their parent product, as the continuity of core product attributes is essential. One of the most influential continuity attributes is the title continuity. Contrary to recent suggestions in the consumer marketing literature that dissimilar brand extensions are rated higher than similar ones, more specifically, sequels with descriptive titles are rated higher than those with numbered titles (Sood and Drèze, 2006), our findings suggest that franchises that use a numbering title strategy perform better than those of using a naming title strategy. Given all other predictor variables, the model implies that, keeping the same title of an extension by simply numbering it has a very strong positive effect on the extension launch performance. This result has provided some of the strongest evidence to date linking a naming title strategy to signal the continuity of core product attributes. Consequently, it can be inferred that when the title of a franchise moves from numbering to descriptive naming, a different story line is implied and is therefore not perceived by customers as a continuation of the parent product.

Other core attributes in the form of signals that are determined to strongly influence the performance of an extension are the prior perception measured by the critics’ rating and distribution intensity. Critics’ ratings prior to the release signal customers about which movies will be worth their investment, whereas the distribution intensity acts in the form of a word of mouth type effect. Because studios usually screen motion pictures in advance for the critics to assess their initial reactions, critics’ rating as a signal is available to customers a priori. The favorable enhanced buzz from ratings contributes to enhanced talks among consumers and reinforces their positive view about the product. Given that the diminishing fan base for subsequent sequels is indicated by the prior literature (Basuroy and Chatterjee, 2008), complementing the favorable critics’ rating with strong marketing efforts provides much-needed support for the new product’s success and, more importantly, a long series. Similarly, the effect of distribution intensity will be available to customers as a key signal because greater distribution intensity expands awareness of the brand in the market and may signal strength and quality of the product. As such, managers should target higher initial distribution intensity, particularly when working with the short life cycle of experiential products due to the limited availability of a short window of opportunity.

Our findings also offer important new insights regarding the extension timing between two subsequent products being a strong signal. An interesting question in the analysis of successive product releases is whether there is an optimal amount of time that should elapse between product launches to maximize performance. The findings of our study, to a certain degree, are consistent with those of Basuroy and Chatterjee (2008), who found that a longer time lag between the parent and the sequel negatively influences the box office performance. This finding suggests that if the consumer favors a product, its effect is fresher when the consumer experiences an extension sooner. Firms seeking to enhance their new product performance should give considerable attention to the time lag between subsequent product releases in addition to the previously discussed signals of continuity.

After controlling for the effects of the core product attributes (or signals), there is still unexplained uncertainty left in what makes an extension a success. Our proposed model can also provide insights for experience product brand extension managers by capturing the random effects of the relationships between the parent and its several extensions. Given all the other predictor variables, our model confirms previous findings that the first sequels generally do worse in the box office than their parents (Basuroy and Chatterjee, 2008; Moon et al., 2010). However, our results also point out that the second sequels do better than the first sequels given all other predictor variables. A possible explanation for this might be that the success of the parent movie sets a very high expectation for the sequel, often leading to dissatisfaction (Moon et al., 2010; Oliver, 2010). As pointed out by Budra and Schellenberg (1998), even for cases when the sequel is as good as the parent, it may still be perceived as a disappointment for viewers whose first experience of the franchise was unmatched. Thus, for the next time
around, viewers do not generally have high expectations, mainly because the franchise name as a quality signal might have lost its appeal. Another possible explanation is that the studios make necessary adjustments for the third installment after the sequel receives less favorable views. For example, Men in Black III was released in May 2012 with the promise to be fresh and novel while keeping the core values of its parent (Fritz and Zeitchik, 2012). The movie has received generally positive reviews from critics and moviegoers. The consensus states that Men in Black III is better than its predecessor and manages to exceed expectations, largely due to its ability to recapture the spirit of the parent without sacrificing novelty. Therefore, the findings suggest that the key to franchise continuation is to ensure the success of a third movie in the series. Another interesting finding from our study is related to the length of a given franchise (i.e., number of movies in the series). Our findings indicate that the importance of support needed from a parent product diminishes after three or more sequels. Specifically, our model suggests that parent products’ performance is highly correlated with the first, second, and third sequels after which its effect significantly diminishes. It is apparent from the results that for franchises running longer than three sequels, the established “brand name” of a franchise is one of the determining factors for performance in addition to the signals previously discussed (or core attributes). On the other hand, the findings indicated that at the infancy of the franchise (the first two extensions), the success of the parent plays an important role in the performance of the next extensions. From a marketing communication perspective, our results indicate that managers should give greater emphasis for forming their communication effort around the parent product’s brand awareness, image, and core attributes for the first three extensions. The emphasis should gradually shift to a novel story line with a recollection to core attributes in the following extensions. Similar arguments can be made for other experience products such as video games and books.

Concluding Remarks

This study investigated the effects of multiple brand extensions and core attributes via signals on an experience product’s market performance and discussed general managerial insights. In doing so, Bayesian models were introduced with both deterministic (via predictor variables) and random components (via successive product extensions). The study considered exponential and Weibull candidates that are capable of capturing the right-skewed behavior exhibited by our data. MCMC methods to estimate the model parameters were used. The proposed models are able to capture the behavior of successive experience product releases unlike most of the literature, by taking into account the random effects of several successive product extensions that were found to be correlated a posteriori in our data. The random effects structure considered in the study allows for unobservable heterogeneity to be accounted for, and its inclusion in explaining product performance in brand extensions of experience products has been supported decisively by commonly used fit/predictive performance measures. To the best of our knowledge, such a structure and its managerial implications were not previously considered in the context of experience products within the brand extension literature and are major novelties of our study. In addition to the brand extension effects, our findings indicated the combined importance of signals such as product continuity, short timing between extensions, and positive prior perception for successful launches of extensions of a parent experience product. Even though some of these attributes were considered individually in the context of motion pictures, their combined effects on multiple sequels had not been considered previously in the literature.

A number of limitations need to be noted regarding the present study. Previous research in the motion picture literature has argued that advertising expenditures increase consumer attention (Basuroy, Desai, and Talukdar, 2006; Joshi and Hanssens, 2009). Advertising expenditure as a quality signal in addition to the budget might be a factor to consider if the data were available. Although advertising expenditures in the motion picture industry are generally available, our sequel data dates back to 1976, which makes it very hard to incorporate in our current work. However, our study includes the total budget of a given motion picture that already contains the advertising expenditures. In fact, considering both the total budget and the advertising expenditures, which are on average a fixed percentage of the total budget, could have created multicollinearity problems. Thus, it is possible that the budget figures could at least be used as proxies in lieu of the advertising expenditures. Furthermore, to investigate if similar conclusions can be drawn regarding the core products’ attributes and brand extension effects for other experience products, the proposed model can be applied to video game and book franchise data. Such studies can further justify the robustness of the current findings and open up potential directions of research for experience product researchers. Another area that is missing from our study is the effect of sequels as quality signals for the international launch of sequels. It would be

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interesting to assess the value of sequels as quality signals in markets other than the United States. This would be a potential area of research that can be addressed in a future study. In addition, if sequel effects are believed to be dependent (correlated) a priori, another potential extension of our model is to introduce a dependent prior process such as the equivalence of an autoregressive process on the gamma structure of the $\theta$s. By doing so, one can take into account the effects of previous movies in the franchise when investigating the effects of the quality signals. Considering such a structure will complicate the estimation procedure of the current model and its usefulness may be investigated in a future study. Another extension possibility is to consider the optimal scheduling of movies in a theater complex by taking into account the sequel effects and the respective signals. Finally, while the current study focused on core product attributes in the form of signals and brand extensions, future research could extend the study by framing it around incremental (sequels as brand extensions) and radical (nonsequel new movies) innovations.

References


Appendix. Bayesian Inference

Bayesian analysis of any kind follows the likelihood principle, which implies that the likelihood function has all the information one needs to carry out inference. Assume that the domestic gross, $Y_i$ are either exponential or Weibull distributed. One of the major differences between classical and Bayesian estimation methods is the specification of the prior distributions for all model parameters. All Bayesian inference is conditional on the prior distributions and the likelihood function. For the exponential model, assume that the sequel effects are independent gamma distributed as $\theta_s \sim \text{Gamma}(a_s, b_s)$ for $s = 1, \ldots, S$ with $a$ and $b$ being the shape and rate parameters. In addition, the coefficients are assumed to be independent and normally distributed as $\beta_k \sim N(\mu_k, \tau_k)$, for $k = 1, \ldots, K$, where $\mu$ and $\tau$ are mean and precision (1/variance) parameters. $K$ represents the total number of predictor variables. For the Weibull model, assume that $\nu$ is lognormal as $\nu \sim \text{LN}(\mu_\nu, \tau_\nu)$. In general, the values of $a$, $b$, $\mu$, $\tau$, $\mu_\nu$, and $\tau_\nu$ are either elicited from expert knowledge (see Sándor and Wedel, 2011, for a marketing application) or are chosen such that our uncertainty about the model parameters is vague. In our analysis, the latter case is adopted.

The final step is to obtain/estimate the posterior distributions of all model parameters. Closed form posterior results can rarely be found in modern applications. Thus, the use of Markov chain Monte Carlo (MCMC) methods are key in Bayesian inference. To estimate the model parameters, the Metropolis–Hastings (MH) algorithm within the Gibbs sampler is employed (Chib and Greenberg, 1995; Smith and Gelman, 1992). One of the key requirements of the Gibbs sampler is to obtain the full conditional distributions of all model parameters (either in closed form or as a function up to a certain proportionality). For convenience, the notation $p(\ldots, D)$ is used to represent the full conditional distribution for a given parameter given all others. For the Weibull model, they can be summarized as

$$p(\theta_s \mid \ldots, D) \sim \text{Gamma} \left( \sum_{i=1}^r I(s_i = x) + a_s, \sum_{i=1}^r I(s_i = x)e^{\beta_s Y_i^*} + b_s \right), \text{for } s = 1, \ldots, S. \quad (4)$$

where $I(.)$ represents the indicator function. It is noted here that the full conditional (Equation 4) for the exponential model can be obtained by replacing $Y_i^*$ with $Y_i$. In addition,

$$p(\beta_k \mid \ldots, D) \propto \exp \left( \sum_{i=1}^r \beta_k z_k^i - \theta_s e^{\beta_s Y_i^*} Y_i^* \right) \times p(\beta_k | \mu_\nu, \tau_\nu), \text{ for } k = 1, \ldots, K. \quad (5)$$

where $p(\beta_k | \mu_\nu, \tau_\nu)$ denotes the normal prior density function for $\beta_k$. It is noted here that the full conditional (Equation 5) for the exponential model can be obtained by replacing $Y_i^*$ with $Y_i$. The full conditional distribution for $\nu$ would be as follows:

$$p(\nu \mid \ldots, D) \propto \nu \prod_{i=1}^r Y_i^{r-1} \exp \left\{ -\theta_s e^{\beta_s Y_i^*} Y_i^* \right\} \times p(\nu | \mu_\nu, \tau_\nu). \quad (6)$$

where $p(\nu | \mu_\nu, \tau_\nu)$ denotes the lognormal prior density function for $\nu$. Since most of the above full conditional...
distributions, with the exception of \( \theta_s \), are not well-known probability distributions, the MH algorithm is used to generate the necessary samples.

A Gibbs sampler coupled with the MH sampling algorithm is developed to generate samples from the joint posterior distribution of model parameters, \( p(\theta_1, \ldots, \theta_J, \beta, \nu | D) \) for the Weibull model with random sequel effects. Denoting \( l \) as the sample counter, the steps can be summarized as follows.

1. Initialize \( \nu^{(0)} \) and \( \beta^{(0)} \).
2. Generate samples of \( \theta_s^{(l)} \) for \( s_i = 1, \ldots, S \) from
   \[
   p (\theta_s | D) \sim \text{Gamma} \left( \sum_{i=1}^{l} I(s_i = x) + a_\nu, \sum_{i=1}^{l} I(s_i = x) e^{\beta^{(l-1)} \beta_i + b_\nu} \right)
   \]
   by Equation 4.
3. Generate samples of \( \beta^{(l)} \) for \( k = 1, \ldots, K \) from
   \[
   \exp \left\{ \sum_{i=1}^{l} \beta^{(l)} Y_{i}^{(l)} - \theta^{(l)} \theta_i Y_{i}^{(l-1)} \right\} \times p(\beta^{(l)} | \mu) 
   \]
   as given by Equation 5.
4. Generate samples of \( \nu^{(l)} \) from
   \[
   \prod_{i=1}^{l} \nu_i \exp \left\{ -\theta_i^{(l)} \theta_i Y_{i}^{(l)} \right\} \times p(\nu | \mu, \tau) 
   \]
   as given by Equation 6.

If the above is repeated for \( l = 1, \ldots, L \) where \( L \) is large, then samples from \( p(\theta_1, \ldots, \theta_J, \beta, \nu | D) \) are obtained. In addition, to generate samples from steps 3 and 4, a random walk MH algorithm is used whose proposal density is multivariate normal. Following Chib and Greenberg (1995), the steps in the MH algorithm for any parameter \( \psi \) (for step 3, \( \psi = \beta \) and for step 4, \( \psi = \nu \)) can be summarized as follows:

1. Generate \( \psi^* \) from \( q(\psi^* | \psi^{(l-1)}) \) and \( u \) from \( U(0, 1) \).
2. If \( u \leq \alpha(\psi^{(l-1)}, \psi^*) \) then accept \( \psi^{(l)} = \psi^* \); else repeat the previous step,

where

\[
\alpha(\psi^{(l-1)}, \psi^*) = \min \left\{ 1, \frac{\pi(\psi^*) q(\psi^{(l-1)} | \psi^*)}{\pi(\psi^{(l-1)}) q(\psi^* | \psi^{(l-1)})} \right\},
\]

where \( \pi(.) \) is the density that samples are generated from and \( q(.) \) is the multivariate normal proposal density whose variance-covariance matrix is determined via \((-H)^{-1}\) with \( H \) representing the approximate Hessian of \( \pi(.) \) evaluated at its mode (Gelman, Carlin, Stern, and Rubin, 2003). The algorithm for the exponential with random sequel effects will be similar to the above with the exclusion of the full conditional of \( \nu \) in step 4.