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Modeling the Effects of Preview Scale and Timing on Performance of Movies: A Copula Approach

시사회 규모와 시점이 영화 흥행에 미치는 영향

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Abstract

Modeling the Effects of Preview Scale and Timing on Performance of Movies: A Copula Approach

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This study develops and tests a model of both the initial and final performance of a movie, with a specific focus on the decision related to the film preview that distributors need to consider to maximize box office revenue. The aim of this study is to show that the current decisions made by distributors are suboptimal in most cases, and as a result, the authors suggest a more systematic approach. In line with previous studies, this research indicates that inviting a large audience to the preview improves the final box office performance of the movie. In addition, the results suggest that there is a quadratic relationship between the time lag from the initial preview to the opening and the final audience numbers during high season. Specifically, the model reveals that the optimal average time lag in high season is 36.5 days, compared with the actual average of 15.4 days. This model can improve managerial decision making by providing the ability to estimate the optimal time lag for specific movies to maximize movie sales.

Keywords: Entertainment marketing, movie preview, copula modeling, timing optimization, marketing strategy
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1. Introduction

Marketing managers often have to make decisions about how to trigger word-of-mouth or when they should implement a particular promotional plan. Managers who want to generate word-of-mouth (WOM) before a new product release, for instance, must decide what marketing tactic to use and when to put it in play. Making optimal timing decisions can mean a considerable boost in the performance of a product or of the firm itself. For example, providing product samples too late could reduce consumer appeal, while, on the other hand, starting too early could generate buzz that disappears before the product launch. These decisions are crucial, especially when consumers are unable to evaluate the quality of a product before its use and depend on other consumers' WOM. In this study, we consider the decisions made around movie preview scale and preview timing as typical product samples in the movie industry.

We model and identify the impact of preview scale and optimal preview timing by separating a movie's success into its first weekend ticket reservation rate and its final audience numbers. Most research on the movie market pays attention to final box office sales due to the short lifecycle of a movie. However, tracking box office performance throughout its lifecycle is essential considering that "success breeds success" and that a dynamic marketing strategy is needed to cope with weekly updated competition. In fact, a huge proportion of a movie's ticket sales comes within the first week or two of its opening (Lehmann and Weinberg 2000).

In Korea, film previews are a common marketing approach used to generate awareness and positive WOM for the movies set to be released. Since a movie is an experiential good where the value cannot be judged prior to consumption, consumers rely extensively on information from other consumers (Hanson and Putler 1996). Previews are also considered a less costly approach compared, for example, to other alternatives such as TV commercials. For this reason, almost every commercial film released to the Korean movie market invites a large number of consumers to preview it, ranging from thousands to tens of thousands. In fact, the ratio of the preview audiences to the final audience exceeds 1.5%, on average.

In spite of its practical significance, previous research has not focused on preview screenings due to inaccessible data on this. Fortunately, the Korean Film Council has now made available its database tracking not only box office sales but also preview records of every film released in the Korean domestic market. Using their data, our aim is to identify the optimal time lag between a film's initial preview and its official release as well as verify the value of allocating marketing resources to invite audiences to previews. Our assumption is that both factors are key to a movie's success. As distributors need enough time to spread WOM, having a preview too early may not be effective because of the ephemeral nature of buzz. Therefore, there may be an optimal timing window for a preview to maximize the positive effect of WOM, and ultimately, the financial performance of the movie.

To identify this optimal timing, we present a new approach that jointly models the initial and final performances. Specifically, we use copula modeling to investigate the dependence between the outcomes in question (Frees and Valdez 1998; Genest and Favre 2007; Zhang, Zhang, and Kuwano 2012). Copula modeling, which is popular in finance and actuarial studies, has recently been introduced in the marketing field to model consumer response (Danaher and Smith 2011; George and Jensen 2011; Kobayashi et al. 2014). By allowing the simultaneous examination of the factors driving both the initial and the final performance, this method can offer us a better understanding of the impact of preview timing on the success of the movie. In fact, based on the non-normal distribution of movies caused by blockbusters and flops, copula is an ideal approach to capture the fat tails typical of this market.

The remainder of this article is organized as follows. First, we explore previous research that examined explanatory factors of box office performance as well as the impact of movie previews on performance. Second, we propose the conceptual framework and related hypotheses. Third, we present the data and the statistical model for testing the relationships outlined in the theoretical framework. Fourth, we explain the results, and finally, we end with managerial implications of the findings and opportunities for future research.

2. Relevant Literature

The majority of movie related research has focused on revealing the antecedents of box office performance. Various factors have been shown to affect film performance including the number of screens (Basuroy, Chatterjee, and Ravid 2003), star power (Elberse 2007), director power (Litman and Kohl 1989), critical reviews (Eliashberg and Shugan 1997), the volume and valence of WOM (Duan, Gu, and Whinston 2008), whether the distributor is a major player (Neelamegham and Chintagunta 1999), its motion picture association of America (MPAA) rating (Ravid and Basuroy 2004), the genre (Desai and Basuroy 2005), and seasonality (Einav 2007).

Among them, a few studies have tried to separate box office performance based on time in the market to more accurately reflect reality. Elberse and Eliashberg (2003) distinguished opening week performance from that of later weeks considering that moviegoers rely on external sources to assess a movie's quality in its opening week, whereas they rely on WOM later in a movie's run. Liu (2006) used weekly revenue for eight weeks after a movie's release to explain the dynamic relationship between box office sales and WOM. Chang and Ki (2005) differentiated the first week box office and total box office based on the assumption that some independent variables affect the dependent variables differently. However, although pre-release performance and post-release performance are considered highly correlated, little research has modeled the dependency between these performance indices. This disjointed view has identified a need for jointly modeling diversified performances.

Hennig-Thurau, Houston, and Sridhar (2006) model the impact of studio actions and movie quality on a movie's performance during different time spans, and incorporate a causal relational path from the opening-weekend sales to long-term sales in their modeling. In spite of embodying the causal relationship between the two outcomes, the approach does not capture a complex dependency structure that goes beyond a simple linear relation. In this vein, we aim to help managers maximize financial performance by establishing distinct marketing strategies throughout the movie’s life cycle.

As various consumer-generated data, such as user ratings and comments on social networking services, become accessible, many researchers have taken an interest in the relationship between WOM and the box office performance of movies. Duan, Gu, and Whinston (2008) modeled a positive feedback mechanism between WOM and retail sales through a dynamic simultaneous equation system, assuming online WOM for related movies was both a precursor and an outcome of box office sales. Karniouchina (2011) examined the impact of buzz on movie distribution and box office success by separating the buzz into two categories: the first, about the stars, and the second, about the movie itself. Gopinath, Chintagunta, and Venkataraman (2013) focused on the effects of pre- and post-release blog volume and valence on the box office gross while including the volume and valence of the user ratings in the model.

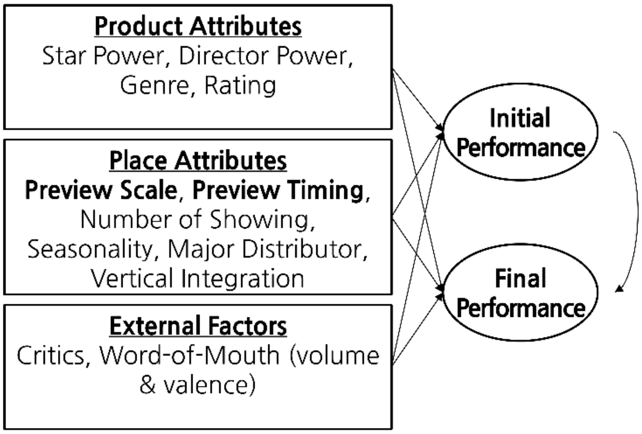
However, despite the repeated evidence about the positive relationship between WOM and box office success, it is hard to find research investigating how to generate and spread WOM related to movies. According to Dichter (1966), consumers recommend a product to others to reduce the tension induced by its consumption. Sundaram, Mitra, and Webster (1998) stated that consumers generated WOM due to their excitement from product use. The research on the motivation for creating WOM commonly assumes the necessity of product usage experience. Based on this assumption, some studies have investigated the effect of pre-performance from the initial market on the following success in the context of sequential introduction. Elberse and Eliashberg (2003) studied a setting where a movie was introduced first in its domestic market and at a later stage in foreign markets. They found evidence that the performance in the domestic (U.S.) market was positively related with the opening week performance in the four foreign markets. Chintagunta, Gopinath, and Venkataraman (2010) directly investigated the role of WOM in increasing the sales of movies on the basis of sequential release practice in the U.S. market. They conclude that the valence of online WOM from markets where the movie was already released affects the performance of succeeding markets positively. However, despite the fact that film preview is a common marketing practice to generate WOM before a movie's release, studies exploring movie previews are rare. McKenzie (2009) examined the influence of a preview on a movie's longevity at the box office by using a dummy variable. Lee, Cha, and Kim (2017) reveal the positive impact of preview scale, measured by audience numbers invited to previews, on the market potential coefficient using the Bass model. To extend this research stream, our study examines not only the effect of preview scale but also the influence of preview timing on the movie's financial performance.

This study is the first to jointly model the opening week performance and the long−term performance of movies by adopting the copula approach. As a result, we can capture the complex dependency that a simple correlation cannot illustrate. In contrast to prior research, our study focuses attention not on WOM itself but on the film previews, one of the major marketing tactics used to spread WOM.

3. Conceptual Framework and Hypotheses

This research emphasizes concurrently modeling the effects of preview scale and preview timing on the initial and final performance of movies. Figure 1 introduces the conceptual framework that illustrates the relationships between a movie's characteristics and the two dependent variables, initial and final performance.

FIGURE 1. CONCEPTUAL FRAMEWORK



3.1. Preview Scale and Box Office Performance

Product sampling is an effective tool for introducing and promoting a new product. Although there is a cost associated with offering samples, marketers agree it is a necessary expense to reach the consumers who can generate WOM recommendations that lead to product market success. In the movie market, preview screening is a particular form of product sampling to generate WOM. Preview screening can provide information on the quality of a movie, thereby attracting greater attendance (Elliott and Simmons 2008). Offering a preview also has a similar impact as an advertisement by increasing public awareness and attracting consumers to watch the movie (Zufryden 1996). When a product has a high coefficient of imitation in the Bass model, as a movie does, the sampling scale must be large enough to disseminate WOM (Jain, Mahajan, and Muller 1995). There is, of course, a down side, meaning that inviting too many audiences to the preview may decrease the audience numbers at the initial release phase (Lee, Cha, and Kim 2017). Nevertheless, having a preview can extend the longevity of the movie at the box office as well as change user ratings more favorably (McKenzie 2009). As a result, we expect a positive association between preview scale and performance of the movie as follows.

H_1: Preview scale will positively relate to a) initial and b) final performance of the movie.

3.2. Preview Timing and Box Office Performance

Generally, managers give preview screenings a couple of weeks before a movie's release to build excitement around the film. The earlier the film holds its preview, the more people have a chance to be exposed to WOM created by preview audiences. However, a film will not maintain excitement endlessly. Therefore, it is crucial for distributors to figure out the optimal timing for preview screenings. The WOM originated from early previews can increase awareness and lead subsequently to greater ticket sales (Liu 2006). The Bass model suggests that paid audiences (imitators) are influenced by preview audiences (innovators) (Mahajan, Muller, and Bass 1991). Although buzz may exist around a movie, this WOM is perishable (Luan and Sudhir 2006). Elberse and Eliashberg (2003) also argued that buzz or momentum generated among initial adopters could wear out quickly. On top of this, existing WOM triggered by a preview could be superseded by WOM of newer films when a film is introduced too long after its preview (Ahmed and Sinha 2016). This means that distributors need to try to balance the advantage of offering a preview early enough to attract a large audience and the disadvantage of it being so early the buzz dies out. As a result, we expect a non-monotonic effect in the relationship between preview timing and box office performance as follows.

H_2: There is an inverted U-shaped relationship between preview timing and the a) initial and b) final performance of movies.

Next, we investigate the possibility that the proposed curvilinear preview timing-performance relationship is moderated by seasonality. Seasonality is associated with the market environment that more sales are concentrated during high seasons and some buyers stop buying during off seasons. Based on this definition, Radas and Shugan (1998) showed how to apply known seasonal patterns to any dynamic model by transforming time to move faster during high seasons. Because of this sudden increase in demand, studios release most of their promising blockbusters in high seasons to boost their revenue streams. This then stimulates fierce competition among these movies (Krider and Weinberg 1998). Considering that consumers with low-involvement selectively watch movies that have already been qualified by other consumers, this sales augment is caused by the moviegoers who rarely visit theaters. Kim and Lee (2013) unveiled that increasing returns to information are stronger during high season due to the concentration of complaisant moviegoers. Due to the intense competition induced by multiple releases and the introduction of low-involved consumers during high seasons, consumers react to other consumers' words more sensitively. In other words, generating and disseminating WOM is more critical for a movie's success. This implies that if there is an optimal preview timing to maximize financial performance of the movie, this decision would provide a greater outcome during a high season than a low one as follows.

H_3: Seasonality will moderate the inverted U-shaped relationship between preview timing and the a) initial and b) final performance such that movies released in a high season will achieve greater levels of a) initial and b) final performance in response to intermediate preview timing than those released in a low season.

3.3. Dependence between Initial and Final Performance

Optimizing both the initial performance and final performance individually is not sufficient when there is interdependence. Various drivers of this dependence may exist. First, there is empirical evidence that a strong initial performance of a movie, measured by the reservation rate for its first weekend, increases its return on investment (ROI) (Lee and Kim 2013). Hennig-Thurau, Houston, and Sridhar (2006) also found that the box office receipts from the opening weekend had a positive impact on the remainder of a movie's theatrical run excluding the opening weekend amount. Second, the product lifecycle of a movie shows an exponential decaying pattern, generating most of the revenues in the first week (Jedidi, Krider, and Weinberg 1998; Sawhney and Elaishberg 1996). Third, the initial success of a movie could signal its quality, namely, the success-breeds-success trend (Elberse and Eliashberg 2003; Elliott and Simmons 2008; Kirmani and Rao 2000). Last, there is a commonality in what drives a moviegoer to the theatre in both time spans, resulting in unobserved dependencies between the performances. As a result, we expect a positive dependence between the initial and the final performance as follows.

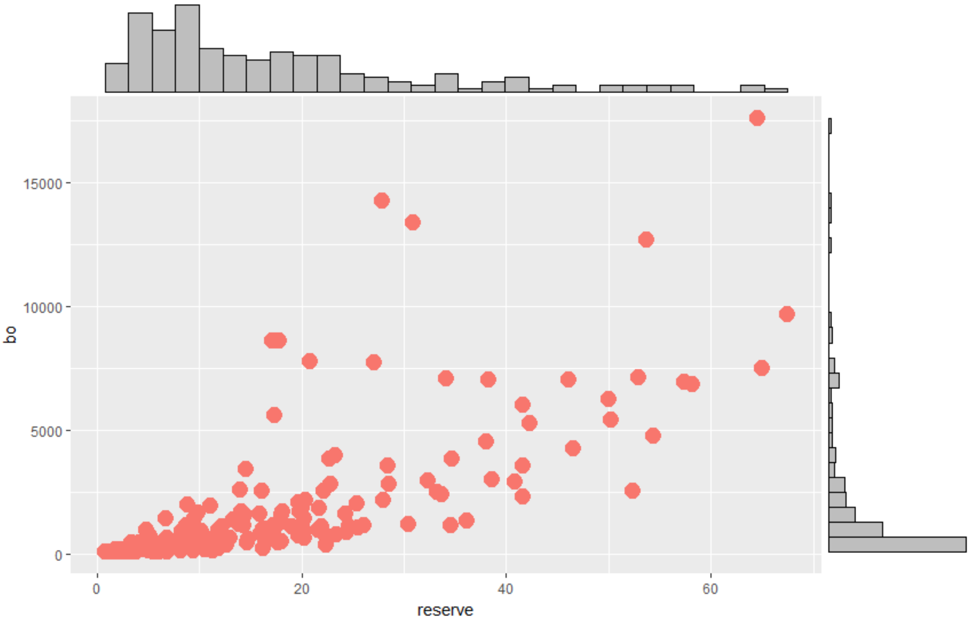
H_4: There is positive dependence between the initial performance and the final performance of a movie.

4. Data and Measurements

We collect data from various archival sources, in particular, the Korean Film Council (www.kobis.com) and the Naver Movie (movie.naver.com) websites. The data consist of 174 movies released from January 2014 to June 2017 in Korea. Due to different marketing approaches and moviegoer attitudes, imported movies and animated movies were not considered here. Movies that scored less than .1 million in audiences were regarded as noncommercial and excluded from the data. We classify the performance of movies into two categories: initial performance and final performance. The initial performance is measured by the averaged ticket reservation rate during the first weekend (Friday, Saturday, and Sunday). This reservation rate indicates market share of the focal movie among the number of movies playing. We measure the final performance by the total audience number after release. The independent variables related to pre-release marketing decisions are preview scale and preview timing. The former is assessed as the total number of preview audiences before release and the latter is assessed as the length of time from the first preview to the movie's release.

Across all of the movies reviewed, the average reservation rate (RR) was 17.82% and the average box office (BO) performance was 1.98 million moviegoers. The average preview scale (PREVIEW) was 11,695 moviegoers and the average time lag (TIMELAG) was 19.8 days. To figure out the shape of the distributions of the two dependent variables, we plot the joint and marginal distributions in Figure 2. The marginal distributions demonstrate that they are asymmetric with long and heavy right-hand tails, which originate from the release of major blockbusters. Additionally, as assumed, there are strong dependencies between the two marginal distributions because a movie that attracts moviegoers well at the early phase is also likely to score high box office performance in the end. The movies in our data show great heterogeneity in various movie characteristics. The descriptive statistics for the data are in Table 1.

FIGURE 2. JOINT DISTRIBUTION OF RESERVATION RATE AND BOX OFFICE PERFORMANCE



Notes: Reservation rate is in percentage (%) and box office performance in thousands of audiences.

TABLE 1. DESCRIPTIVE STATISTICS AND CORRELTAION MATRIX

Variable	Mean (S.D.)	1	2	3	4	5	6	7	8	9
1. RR	17.817 (14.674)	1								
2. BO	1978.954 (2840.916)	.725 (.000)	1							
3. PREVIEW	11.695 (7.935)	.330 (.000)	.473 (.000)	1						
4. TIMELAG	1.980 (1.899)	−.162 (.033)	−.117 (.124)	.013 (.862)	1					
5. SHOWING	3.140 (1.631)	.924 (.000)	.742 (.000)	.438 (.000)	−.242 (.001)	1				
6. STAR	7.716 (7.608)	.437 (.000)	.468 (.000)	.154 (.043)	−.235 (.002)	.498 (.000)	1			
7. DIRECTOR	1.903 (3.051)	.391 (.000)	.580 (.000)	.310 (.000)	−.144 (.058)	.439 (.000)	.259 (.001)	1		
8. CRITIC	5.777 (1.020)	.248 (.001)	.214 (.005)	.258 (.001)	.203 (.007)	.211 (.005)	.173 (.022)	.165 (.030)	1	
9. WOMVAL	8.537 (0.972)	.098 (.198)	.025 (.745)	.098 (.200)	.120 (.113)	.036 (.633)	.055 (.469)	−.096 (.205)	.187 (.014)	1
10. WOMVOL	.834 (1.110)	.129 (.090)	.174 (.022)	.274 (.000)	.044 (.561)	.149 (.050)	−.035 (.644)	.090 (.238)	.029 (.704)	−.335 (.000)
MAJOR	Major distributor: 90 (51.7%)									
VERTICAL	Vertically integrated distributor: 90 (51.7%)									
RATING	G: 3 (1.7%) / PG12: 43 (24.7%) / PG15: 86 (49.4%) / R: 42 (24.1%)									
GENRE	Thriller: 18 (10.3%) / Romance: 20 (11.5%) / Action: 38 (21.8%) / Drama: 49 (28.2%) / Comedy: 22 (12.6%) / Horror: 11 (6.3%) / Other: 16 (9.2%)									
SEASON	High season: 71 (40.8%)									

We control for a number of movie attributes relevant to box office performance. Table 2 summarizes the definition and source of the variables. The number of screens the movie appears on determines the maximum audience size affecting box office performance (Jedidi, Krider, and Weinberg 1998; Sawhney and Eliashberg 1996). Considering the fact that some theaters allocate a screen to more than two movies in a day, we use the number of showings per day instead of the number of screens per day. Star power, director power, and critical reviews are crucial indicators of appeal (Basuroy, Chatterjee, and Ravid 2003; Elberse 2007; Eliashberg and Shugan 1997; Sochay 1994). Elliott and Simmons (2008) argued that the factors signaling product appeal help consumers determine their willingness to view a movie. We also control for WOM, which may influence consumers' movie choices (Neelamegham and Chintagunta 1999). We separate WOM into WOM valence (the average of the ratings) and WOM volume (the total number of the ratings). Duan, Gu, and Whinston (2008) revealed that both factors impact movie revenues. In addition, movies distributed by major firms attract more audiences than those distributed by independent or minor distributors (Litman and Kohl 1989). Similarly, we control for the vertical integration of a distributor and a theater franchise because more than 95% of the Korean movie market is held by three major theater franchises (CGV, Lotte Cinema, and Megabox). Vertically integrated theaters may allocate more favorable screens to a movie distributed by their affiliate. The rating and genre of a film are also important determinants of box office performance (Desai and

Basuroy 2005; Ravid and Basuroy 2004). Finally, we control for seasonality. We capture this phenomenon by having a dummy variable indicating four monthly peaks and two major holidays (Einav 2007).

TABLE 2. DEFINITION OF THE VARIABLES

Variable	Measurement	Source
RR	averaged ticket reservation rate during the first weekend (Friday, Saturday, and Sunday)	naver.com
BO	total number of audiences after release (in thousand)	kobis.or.kr
PREVIEW	total number of preview audiences before release (in thousand)	
TIMELAG	time lag from the first preview to the premiere (in ten days)	
SHOWING	maximum number of showing per day within a week after release (in thousand)	
STAR	total number of audiences of the last two films in which the two main actor or actress involved as main actor or actress (in million)	naver.com
DIRECTOR	total number of audiences of the last two films in which the director involved as director (in million)	
CRITIC	arithmetic mean of professional critic review registered on NAVER	
WOMVAL	arithmetic mean of user ratings registered on NAVER before release	
WOMVOL	count of user ratings registered on NAVER before release (in thousand)	
MAJOR	dummy variable indicating whether the distributor belongs to the market share top five of the year or not	

VERTICAL	dummy variable indicating whether the distributor belongs to the vertically integrated media group operating multiplex theaters (CJ, Lotte, and JoongAng) or not	
RATING	dummy variables for four ratings (G, PG12, PG15, and R, with G as the base variable)	
GENRE	dummy variables for seven genres (thriller, romance, action, drama, comedy, horror, and other, with other as the base variable)	
SEASON	dummy variable indicating whether the first two weeks after release incorporate high season (December, January, July, August, Lunar New Year's Day, and Korean Thanksgiving Day) or not	

5. Model

Our model simultaneously investigates the determinants of the reservation rate and box office performance. Examining these two separately without accounting for the dependence between the outcomes may lead to suboptimal consequences. In addition, since reservation rate and box office performance are highly correlated (α = .725), incorporating dependence is a reasonable approach. We also believe that the reality of the major blockbusters in the motion picture industry and, as a consequence, the non-normal with fat tail distribution of the financial performance of movies justifies inviting an alternative method to capture these phenomena. Our approach is to apply copula modeling to reflect this dependence between the two outcome variables.

5.1. Modeling Dependence through Copulas

This section summarizes the key concept of copulas, the copulas investigated in the research, and the details of the model.

Modeling the joint distribution of two or more random variables demands understanding not only the marginal distributions but also the dependency between them. Customarily, prior research has assumed simple joint distributions, such as multivariate normal or independence between the variables in question. These approaches force the researcher to employ marginal distributions that insufficiently mirror reality or to admit incorrect assumptions. Copulas, however, allow the researcher to model multivariate relationships with the marginal distributions and dependency structure separated. There are, indeed, two alternative techniques for creating multivariate distributions. A researcher can employ a common variable to induce dependencies among multiple random variables (i.e., structural equations modeling). Alternatively, a researcher can treat the parameters of a distribution as random and common among several conditional distributions, thereby inducing dependencies (i.e., longitudinal data modeling and hierarchical linear modeling). Both techniques use latent variables to explain the dependencies. However, copulas link observations directly to a multivariate distribution without constructing artificial latent variables.

The word *copula* originates from the Latin noun for a link or tie that connects two different things. In a statistical sense, a copula is a multivariate distribution whose marginal distributions are all uniform over [0, 1] (Yan 2007). Copulas have been implemented in various fields: economics (Zimmer and Trivedi 2006), finance (Rodriguez 2007), actuarial studies (Frees and Valdez 1998; Spreeuw 2006), hydrology (Genest and Favre 2007), and tourism (Zhang, Zhang, and Kuwano 2012). Recently, marketing literature has begun to introduce this idea to explain consumer response or product performance (Ahmed and Sinha 2016; Danaher and Smith 2011; George and Jensen 2011; Kobayashi et al., 2014; Park and Gupta 2012). Sklar's theorem (1959) states that there is a p-dimensional copula C for all x in the domain of F, and simply, any given two univariate marginal distributions $F_1(x_1)$ and $F_2(x_2)$ can form a multivariate joint distribution, such that:

$$F(x_1, \ldots, x_p) = C\{F_1(x_1), \ldots, F_p(x_p)\}$$

$$F(x_1, x_2) = C\{F_1(x_1), F_2(x_2)\}. \qquad (1)$$

The copula function C ties two or more marginal distributions and describes the dependence structure between the variables. The researcher is not restricted to assume a specific marginal distribution because the copula allows for arbitrary combinations of marginal distributions with complex dependency structures (Trivedi and Zimmer 2007). The copula density and the joint density can be obtained by differentiating equation (1):

$$f(x_1, x_2) = c\{F_1(x_1), F_2(x_2)\} \times f_1(x_1) \times f_2(x_2) \qquad (2)$$

Equation (2) shows that the copula allows the modeling and estimation of the distribution of random vectors by separating the marginal and dependency structures.

Most parametric copula families have the parameter α that controls the strength of dependence. These copulas belong to one of two families of copulas: elliptical copulas and Archimedean copulas. Elliptical copulas, represented by the Gaussian (normal) copula, are radially symmetric, capturing commensurate upper and lower tail dependence. Archimedean copulas, such as Clayton (1978), Frank (1979), and Gumbel (1960), are popular due to easy derivation and their capability to capture a wide range of dependence. Similar to the Gaussian copula, the Frank copula also depicts symmetric dependence; however, it is weaker in capturing tail dependence. The Clayton copular and the Gumbel copular are appropriate for positive dependence; however, the former exhibits greater dependence in the left tail, while the latter does so in the right tail.

5.2. Modeling the Performance of Movies

As the first step, we define the marginal distributions of the two performance indices in question to apply copula modeling. The data consist of the first weekend reservation rate and the final audience numbers for the Korean movie market for three and a half years. We model the marginal distribution for the reservation rate (RR) to follow a gamma distribution with the mean as a function of the preview scale and the time lag between the initial preview to the opening as well as the other covariates and a common scale parameter υ_{RR},

$$\mathrm{RR_i} \sim \mathrm{G}(\mu_i^{RR}/\upsilon_{RR}, \upsilon_{RR}), \text{ and}$$

$$\begin{aligned}\mu_i^{RR} = \exp(&\beta_0 + \beta_1\mathrm{PREVIEW} + \beta_2\mathrm{TIMELAG} + \beta_3\mathrm{TIMELAG}^2 \\ &+ \beta_4\mathrm{SEASON} + \beta_5\mathrm{SEASON} \times \mathrm{TIMELAG} \\ &+ \beta_6\mathrm{SEASON} \times \mathrm{TIMELAG}^2 + \beta_7\mathrm{SHOWING} \\ &+ \beta_8\mathrm{STAR} + \beta_9\mathrm{DIRECTOR} + \beta_{10}\mathrm{CRITIC} \\ &+ \beta_{11}\mathrm{WOMVAL} + \beta_{12}\mathrm{WOMVOL} + \beta_{13}\mathrm{MAJOR} \qquad (3) \\ &+ \beta_{14}\mathrm{VERTICAL} + \beta_{15}\mathrm{PG12} + \beta_{16}\mathrm{PG15} \\ &+ \beta_{17}\mathrm{R} + \beta_{18}\mathrm{THRILLER} + \beta_{19}\mathrm{ROMANCE} \\ &+ \beta_{20}\mathrm{ACTION} + \beta_{21}\mathrm{DRAMA} + \beta_{22}\mathrm{COMEDY} \\ &+ \beta_{23}\mathrm{HORROR})\end{aligned}$$

where each term is defined in Table 2. In the identical manner, we model the final box office performance (BO) with a gamma distribution where the expected audience number of the ith movie is a function of the preview scale and the time lag, controls, and a scale parameter, υ_{BO}. Namely,

$$\mathrm{BO_i} \sim \mathrm{G}(\mu_i^{BO}/\upsilon_{BO}, \upsilon_{BO}), \text{ and}$$

$$\begin{aligned}\mu_i^{BO} = \exp(\beta_0 &+ \beta_1 \mathrm{PREVIEW} + \beta_2 \mathrm{TIMELAG} + \beta_3 \mathrm{TIMELAG}^2 \\ &+ \beta_4 \mathrm{SEASON} + \beta_5 \mathrm{SEASON} \times \mathrm{TIMELAG} \\ &+ \beta_6 \mathrm{SEASON} \times \mathrm{TIMELAG}^2 + \beta_7 \mathrm{SHOWING} \\ &+ \beta_8 \mathrm{STAR} + \beta_9 \mathrm{DIRECTOR} + \beta_{10} \mathrm{CRITIC} \\ &+ \beta_{11} \mathrm{WOMVAL} + \beta_{12} \mathrm{WOMVOL} + \beta_{13} \mathrm{MAJOR} \\ &+ \beta_{14} \mathrm{VERTICAL} + \beta_{15} \mathrm{PG12} + \beta_{16} \mathrm{PG15} \\ &+ \beta_{17} \mathrm{R} + \beta_{18} \mathrm{THRILLER} + \beta_{19} \mathrm{ROMANCE} \\ &+ \beta_{20} \mathrm{ACTION} + \beta_{21} \mathrm{DRAMA} + \beta_{22} \mathrm{COMEDY} \\ &+ \beta_{23} \mathrm{HORROR})\end{aligned} \tag{4}$$

where all terms are as characterized in Table 2. In both equations, the variable PREVIEW represents the total number of preview audiences, allowing us to test if inviting as many moviegoers as possible is a valid strategy. The variable TIMELAG captures the effect of having advanced previews on the initial and final performance, whereas $\mathrm{TIMELAG}^2$ supports nonlinear effects. A negative quadratic term (inverted U-shape) with a positive linear term would suggest an optimal timing for the first preview. The interactions between SEASON and $TIMELAG^2$ enable us to examine how the nonlinear effect of a timing decision varies depending on seasonality. By modeling the marginal distributions of the reservation rate and the box office audience with gamma distributions, we estimate the joint distribution through the dependence using the copula as follows:

$$F(RR_i, BO_i) = C(G(\mu_i^{RR}/\upsilon_{RR}, \upsilon_{RR}), G(\mu_i^{BO}/\upsilon_{BO}, \upsilon_{BO}); \alpha). \tag{5}$$

The parameter α describes the dependence between the two performances. The vector of the parameters for the full model can be written as follows:

$$\theta = (\beta^{RR}, \upsilon_{RR}, \beta^{BO}, \upsilon_{BO}, \alpha)'. \tag{6}$$

The data log−likelihood is

$$\begin{aligned} l(\theta) = {} & \textstyle\sum_{i=1}^{N} \log(g(RR_i; \beta^{RR}, \upsilon_{RR})) + \\ & \textstyle\sum_{i=1}^{N} \log(g(BO_i; \beta^{BO}, \upsilon_{BO})) + \\ & \textstyle\sum_{i=1}^{N} \log(c(G(RR_i; \beta^{RR}, \upsilon_{RR}), G(BO_i; \beta^{BO}, \upsilon_{BO}); \alpha)). \end{aligned} \tag{7}$$

Last, the maximum likelihood estimator of θ is

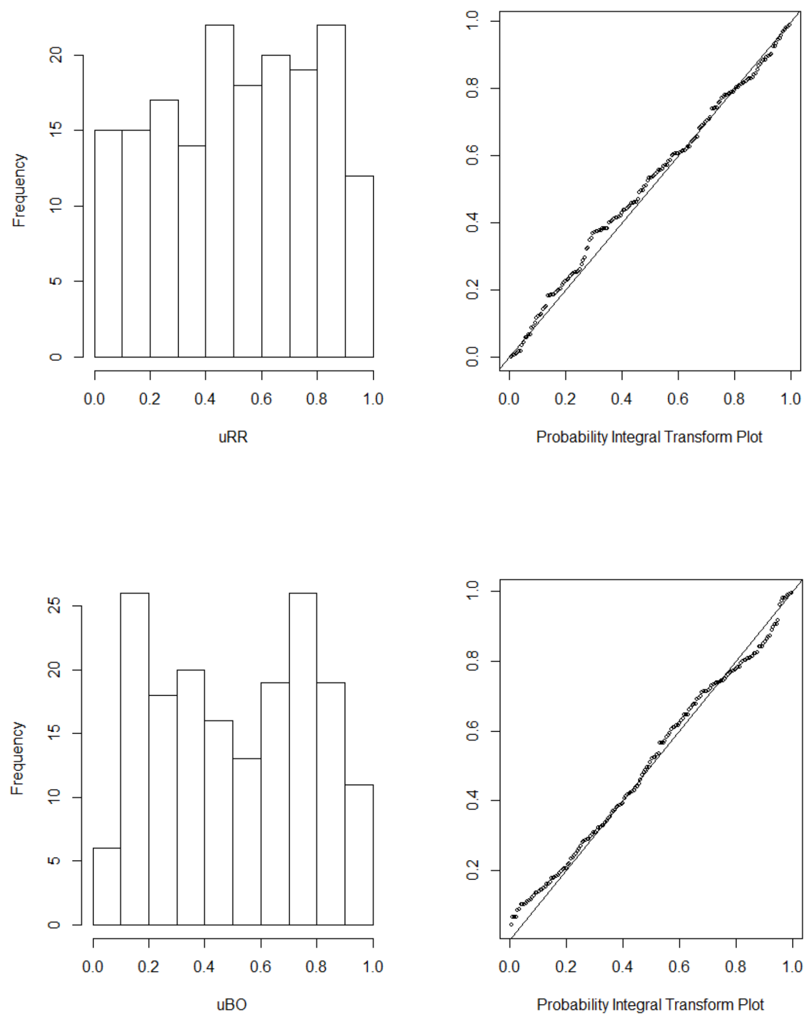
$$\hat{\theta}_{ML} = \underset{\theta \in \Theta}{\operatorname{argmax}}\, l(\theta). \tag{8}$$

6. Results

6.1. Copula Selection and Hypotheses Testing

Prior to estimating the multivariate regression, we assess the four types of cupulas to select a proper one based on likelihood. To calculate the likelihood of each copula, we apply probability integral transformation to the dependent variables to convert them to random variables having a standard uniform distribution. From the independent gamma regression fit, the mean and dispersion can be estimated for each movie. By using these, we calculate a distribution function F_i that depends on movie-specific parameters. Last, we apply the probability integral transformation to get $uRR_i = F_i(RR_i)$ and $uBO_i = F_i(BO_i)$. As a result, uRR_i and uBO_i are approximately i.i.d. U[0,1]. Figure 3 illustrates the results of probability integral transformation for the gamma regression fit.

FIGURE 3. PROBABILITY INTEGRAL TRANSFORM FOR THE GAMMA REGRESSION FIT



Next, we fit the transformed scores to the four classes of copulas. Based on the maximum likelihood parameter estimates, the Gaussian copula was chosen [$\theta_{\text{Gaussian}} = 0.414$ ($I(\theta) = 12.8$) / $\theta_{\text{Frank}} = 2.63$ ($I(\theta) = 12.6$) / $\theta_{\text{Clayton}} = 0.473$ ($I(\theta) = 9.33$) / $\theta_{\text{Gumbel}} = 1.34$ ($I(\theta)$

= 11.4)]. The small difference in likelihood between the Gaussian copula and the Frank copula implies that the reservation rate and the box office performance show symmetric dependence. The Gaussian copula is a special type of elliptical distribution so that if two random variables have a joint elliptical distribution, then the conditional distribution of one variable given the other also has an elliptical distribution. The Gaussian copula can be written as follows:

$$C(u_1, u_2) = \Phi_2(\Phi^{-1}(u_1), \Phi^{-1}(u_2)) \tag{9}$$

where Φ_2 is a standard bivariate normal distribution function with correlation parameter θ and Φ is a standard normal distribution function.

Given its greater likelihood value, the rest of the analysis uses the Gaussian copula. The parameter estimates for the Gaussian copula are reported in Table 3. According to the results, preview scale (H_1) has a significant positive effect on box office performance (β_{BO} = .02, $p < .001$) but not on reservation rate (β_{RR} = −.003, p = .28). This means that inviting more audiences to previews has no impact on the initial performance but ultimately generates greater box office sales. This is consistent with the prior findings that preview scale can reduce the number of innovative audiences in the early phase but can boost potential demand for the movie (Lee, Cha, and Kim 2017). Without considering the interaction between seasonality and time lag, the lag between the preview and release (H_2) has no significant main effect and a negative quadratic effect both on reservation rate and box office sales. However, when the interactions are included in the model, the time lag (H_3) has a significant positive main effect ($\beta_{BO} = .503$, $p = .001$) and a significant negative quadratic effect ($\beta_{BO} = -.069$, $p < .001$) on final performance only in high season. This indicates a significant inverted U−shaped relationship between preview timing and box office sales in peak season. Finally, the results suggest significant dependence between the two marginal distributions ($\alpha = .253$, $p < .000$), supporting H_4 and highlighting the necessity to model both distributions simultaneously rather than individually. The results of the hypotheses developed in “Conceptual Framework and Hypotheses” are summarized in Table 4.

TABLE 3. PARAMETER ESTIMATES FOR THE GAUSSIAN COPULA MODEL

	Reservation Rate				Box Office Performance			
	β	t	Pr(>|t|)		β	t	Pr(>|t|)	
(Intercept)	−.649	−1.552	.061		3.287	7.926	.000	***
PREVIEW	−.003	−.583	.280		.020	4.374	.000	***
TIMELAG	.015	.281	.390		−.025	−.499	.309	
TIMELAG^2	−.001	−.310	.378		.000	.028	.489	
SEASON	−.265	−1.465	.073		−.318	−1.733	.043	*
SEASON× TIMELAG	.190	1.263	.104		.503	3.310	.001	**
SEASON× TIMELAG^2	−.030	−1.556	.061		−.069	−3.452	.000	***
SHOWING	.459	17.574	.000	***	.512	19.336	.000	***
STAR	−.004	−.968	.167		−.006	−1.282	.101	
DIRECTOR	.005	.457	.324		.053	4.735	.000	***
CRITIC	.028	.847	.199		.072	2.213	.014	*
WOMVAL	.104	3.102	.001	**	.089	2.659	.004	**
WOMVOL	.051	1.573	.059		.107	3.119	.001	**
MAJOR	−.034	−.452	.326		−.015	−.192	.424	
VERTICAL	.217	3.024	.001	**	.142	2.018	.023	*
PG12	.672	2.931	.002	**	.470	1.998	.024	*
PG15	.616	2.700	.004	**	.448	1.941	.027	*
R	.725	3.102	.001	**	.313	1.316	.095	
α	.253	5.268	.000	***				

Notes: Dummy variables for movie genres were included in the model, but not reported in here due to insignificance.

*: $p < .05$, **: $p < .01$, ***: $p < .001$

TABLE 4. SUMMARY OF THE HYPOTHESES TESTING

	Hypothesis	Result
H_1	Preview scale will positively relate to a) initial and b) final performance of movies.	a) Not supported b) Supported
H_2	There exists an inverted U-shaped relationship between preview timing and a) initial and b) final performance of movies.	a) Not supported b) Not supported
H_3	Seasonality will moderate the inverted U-shaped relationship between preview timing and a) initial and b) final performance such that movies released in high season will exhibit greater levels of a) initial and b) final performance in response to intermediate preview timing than those released in low season.	a) Not supported b) Supported
H_4	There is positive dependence between initial performance and final performance of movies.	Supported

Multiple parameters for the control variables are consistent with prior research and intuition. As expected, the number of showings has a significant positive relationship with the reservation rate and box office sales. In contrast to the findings of prior research, star power does not have a significant effect on either performance. At the same time, director power shows a significant positive impact only on the final audience numbers. Similar to director power, the averaged value of professional critics only produces a significant positive influence on the final performance. Even though the volume of WOM shows a slightly marginal p-value on the reservation rate, both variables related to consumer WOM have positive impacts on the dependent variables as predicted. Notably, the vertical integration of a distributor and a theater franchise has a significant positive relationship with both indices, while the variable indicating whether or not the distributor is a major firm does not have any significance with the outcome variables. This means that in a country having no restrictions on the vertical integration of theater operators, distributors having multiplex theaters as affiliates could enjoy a higher success by dominating the movie distribution channels. In terms of ratings, PG-12, PG-15, and R rated movies have an advantage in attracting audiences not only in their first weekends but also across their lifecycles compared to G rated ones. The reason for this is that most G rated films are adolescent targeted, narrowing their market, and then neglected by adult moviegoers.

6.2. Determining Optimal Preview Timing Policies

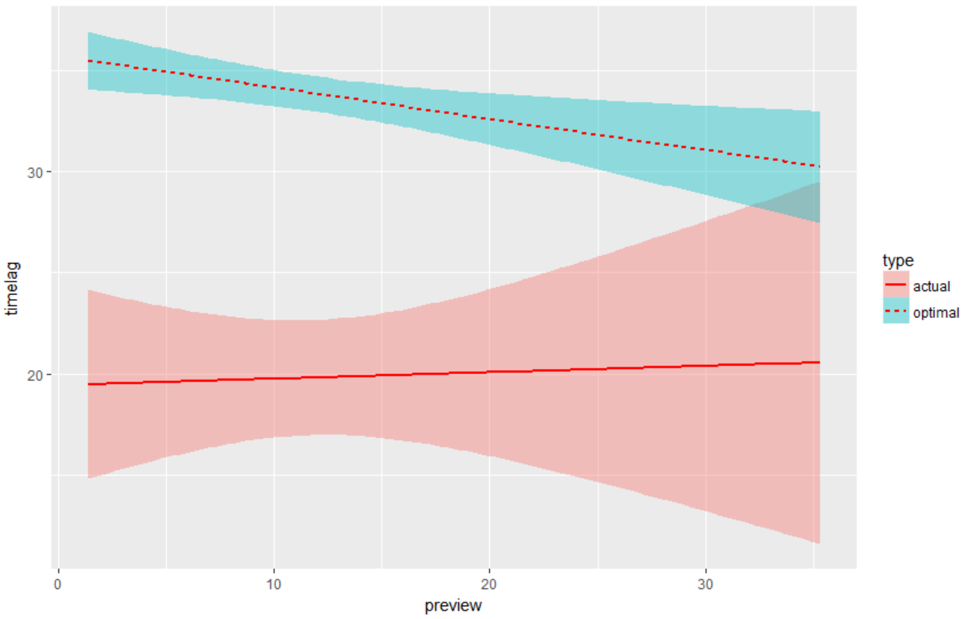
Our model presents a non-monotonic relationship between time lag and the final performance of a movie. The differentiation result of the estimated quadratic function indicates that the optimal time lag from the initial preview to the release date in high season is, on average, 36.5 days. This means, on average, there should be 21 more days from the first preview to the opening to maximize the total audience numbers compared with the current market average of 15.4 days in high season. Table 5 selectively summarizes the list of movies released in high season, their actual and optimal time lags, and the impact of the difference between actual and optimal time lag on the final audience numbers for each movie. For example, *In-cheon Sang-ryuk Jak-jeon (Operation Chromite)*, a blockbuster movie, launched the initial preview seven days before its theater release and scored 7.9 million moviegoers at the box office. However, our model suggests that the optimal preview timing to maximize the box office performance would have been 36.5 days, which would have resulted in increase of 12% in the total number of moviegoers. In contrast, a movie scoring a low level of box office receipts, *Yeo-gyo-sa (Misbehavior)*, launched its first preview 49 days prior to its opening and sold approximately .4 million tickets. The optimal time lag of 36.5 days would have resulted in an increase in box office performance of 266%.

TABLE 5. RESULTS OF THE POLICY ANALYSIS

Movie	Release Date	Actual BO	Actual Lag (days)	Expected BO	Potential Improvement (%)
Yeo-gyo-sa (Misbehavior)	17.01.04	115,183	49	421,537	266
Pandora	16.12.07	4,565,451	22	8,107,085	78
Guk-ga Dae-pyo 2 (Run Off)	16.08.10	681,269	15	2,445,954	259
In-cheon Sang-ryuk Jak-jeon (Operation Chromite)	16.07.27	7,037,764	7	7,895,613	12
All (71 movies)		3,121,397	15.37	6,368,706	129

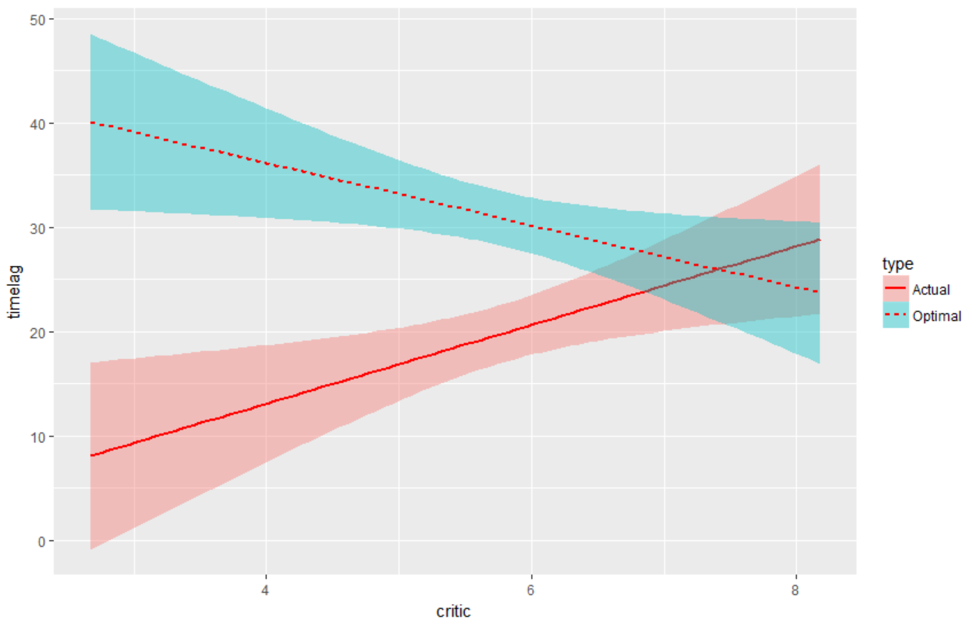
As managers are interested in optimizing the timing decision of a particular movie, we also assess the optimal preview timing dependent on other movie characteristics by using the copula model. Including interaction terms between the quadratic and linear terms of time lag and various movie attributes, we recalculate how the optimal preview timing varies based on other aspects of the movies. As an illustration, we select four characteristics that affect preview timing, namely, preview scale, professional critics, ratings, and genre. First, we examine the relationship between preview scale and optimal preview timing. Figure 4 exhibits how the actual and optimal preview timing vary by preview scale. According to current practice, distributors do not discriminate movies across preview scale, even though there are greater variations as preview scale increases. However, our model suggests that the optimal time lag decreases significantly as preview scale grows. Notably, the minimum value of the optimal time lag is still much greater than the maximum value of the actual time lag. This result is in accordance with common sense that having more previewers reduces the time requirement for disseminating WOM.

FIGURE 4. OPTIMAL PREVIEW TIMING BY PREVIEW SCALE



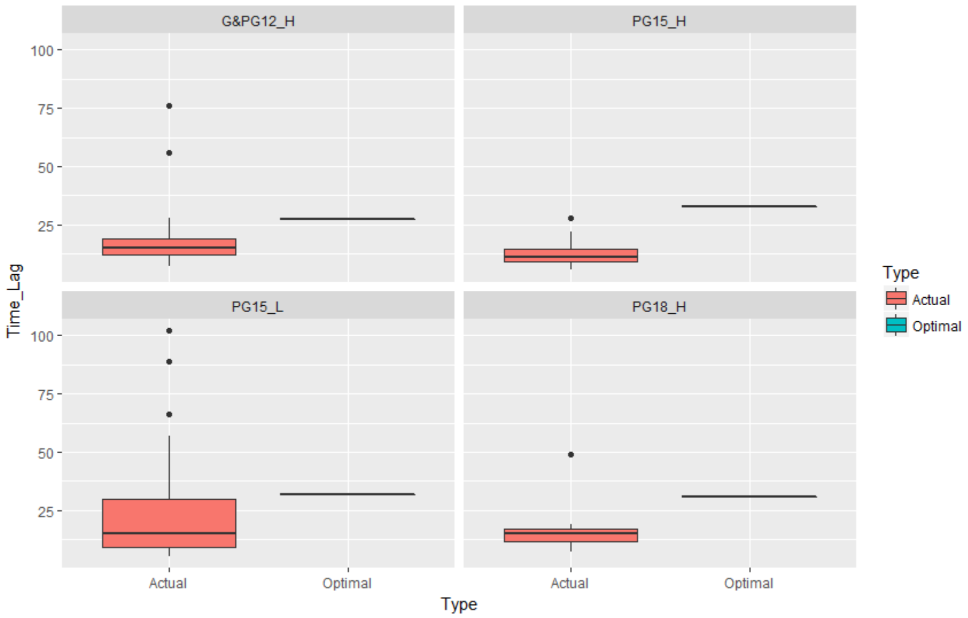
Next, we assess the relationship between professional critics and the optimal preview timing. Figure 5 shows that in current practice, distributors offer an earlier preview for movies with higher critical ratings. However, our modeling indicates an almost reversed linear relationship between professional critics and optimal time lag. In other words, the lower a movie's critical rating, the earlier managers should give the initial preview. In practice, distributors are afraid of proliferation of negative WOM for movies with lower critical ratings. This means they bypass a preview or release the movie right after the preview. However, the results indicate that a preview should be offered much earlier for low-rated movies and that the time lag should shorten for higher rated movies. In contrast to common practice, movies with low quality ratings could gain positive WOM if there was more time, thereby achieving better performance.

FIGURE 5. OPTIMAL PREVIEW TIMING BY PROFESSIONAL CRITIC



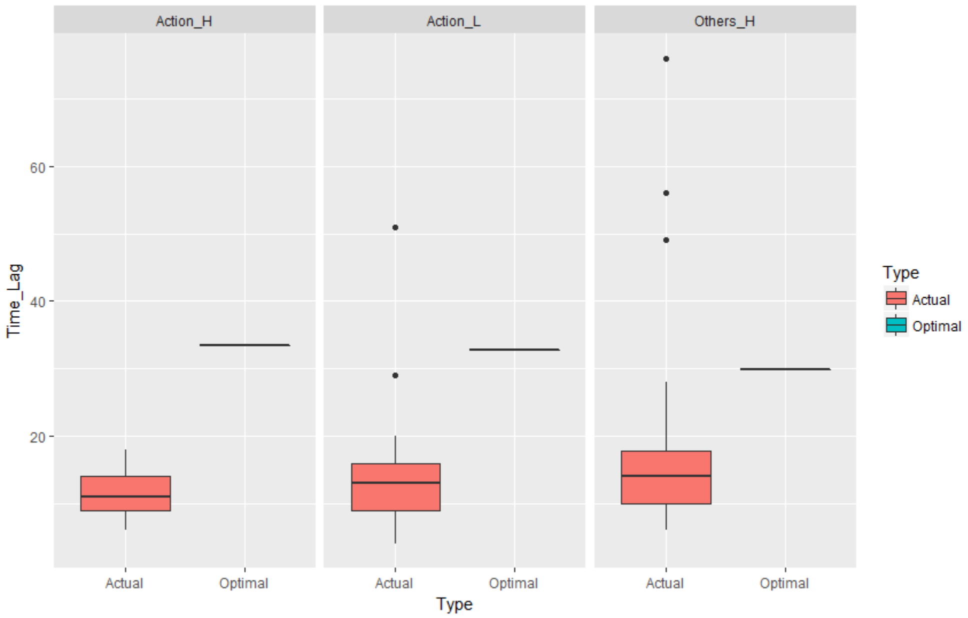
Furthermore, we also analyze the impact of ratings on optimal preview timing. For example, distributors may want to understand whether R-rated movies should offer a preview sooner than G or PG-12 rated ones. Due to the limited data points for G-rated movies, G and PG-12 were combined and treated as the base variable. The results are presented in Figure 6. We find that actual preview timing does vary by rating, suggesting that distributors should consider ratings in their timing decisions, although the results indicate that optimal timing does not vary significantly across ratings. Specifically, the optimal time lag for PG-15 movies to maximize the film's performance in high season is about 32.7 days and 31.6 days in low season, while the actual time lag is about 12.2 days in high season and 23.7 days in low season. For R−rated movies, in high season, the optimal time lag is 30.6 days, while the actual time lag is 17 days. The optimal time lag of G and PG−12 movies in high season shows the shortest time value of 27.3 days, while the actual is 18.4 days. In low season, the interaction terms for G and PG−12 and R are not significant. Although all optimal time lags are much longer than the actual time lags, the durations are quite different. In contrast to current practice, movies rated G and PG−12 demand the shortest time lags between initial preview and release, whereas PG−15 rated movies require the longest time for WOM diffusion.

FIGURE 6. OPTIMAL PREVIEW TIMING BY RATING



Finally, we evaluate the effect of genre on the optimal preview timing. Figure 7 portrays how the actual and optimal preview timing differs by genre. The results reveal that only the interaction effect between the action genre and time lag is statistically significant. Particularly, the optimal time lag for action movies to maximize audience numbers in high season is 33.5 days and in low season 32.7 days, while the actual time lag is 11.5 and 17.2 days, respectively. The optimal time lag for all other genres is 29.8 days, while the actual is 17 days in high season. No significant interaction effect is found in low season. In current practice, action movies generally offer the first preview later than other genres. However, our model proposes that action movies should follow a longer time lag than that of other genres'. Overall, our policy analysis indicates that distributors in the Korean movie market have an unsystematic approach to preview timing decisions.

FIGURE 7. OPTIMAL PREVIEW TIMING BY GENRE



7. Discussion

Despite its important role in triggering and spreading WOM, movie previews have received little attention in the marketing literature. Our study develops and tests a model that includes both the initial and final performance of the movie, with a specific focus on the decision related to the film preview that distributors must consider to maximize box office revenue. The aim of this study is to show that the current decisions made by distributors are suboptimal in most cases and, as a result, to suggest a more systematic approach. Our model provides not only a tool to help managers make decisions but also the ability to forecast box office performance. In line with previous studies (e.g., Lee, Cha, and Kim 2017; McKenzie 2009), we find that inviting large audiences to previews improves box office performance. In addition, our results suggest that there is a quadratic relationship between the time lag from the initial preview to the opening and the final audience numbers in high season. Specifically, our model indicates that the optimal average time lag for high season is 36.5 days, compared with the actual average of 15.4 days.

The policy analysis for individual movies reveals that distributors are currently making suboptimal timing decisions. The net effect of optimizing preview timing would provide a 129% improvement in the final audience numbers for movies released in high season. We also illustrate how the optimal preview timing varies by specific movie characteristic such as preview scale, professional critics, ratings, and genre. Particularly, in current practice, distributors do not discriminate movies based on their preview scale. However, the model suggests that the optimal time lag should be shortened as preview scale grows. In contrast to common practice that the time lag increases as critical ratings go up, the results indicate that managers should offer previews sooner for low rated movies by critics. In addition, we found that movies rated PG−15 would benefit from the longest optimal time lag in high season, whereas the actual time lag for them is the shortest. Finally, our model also indicates that action films should offer their initial previews earlier than other genres.

This study is one of the first to utilize copula modeling to address the decision problem related to preview scale and preview timing. The main advantage of copula modeling is that researchers can link observations directly to a multivariate distribution without creating artificial latent variables or assuming a particular form of multivariate distribution. This allows us to jointly model the processes that lead to initial and final box office sales by capturing the fat tails of non−normal marginal distributions, ideal for the common occurrence of blockbusters and flops in the movie market.

Furthermore, the copula approach has another advantage of not making any assumptions about the dependence between the first week reservation rate and the final box office sales. While other structural models address individual effects between dependent variables in question, an aggregate perspective may provide a more useful solution for managers. Our model tries to capture the net effect of such underlying behavior as well as to reduce the burden to make assumptions. The parameter α used to model the dependence between the initial and final performances captures this net effect. For example, the cascade effect from the first week performance may increase the dependence and the decaying effect of negative WOM may decrease the dependence. Despite not explicitly capturing those specific effects, our model does capture the net effect.

The present model can be extended to examining any marketing related decisions for more than two performance indices throughout the product lifecycle of a movie. In particular, considering that a number of brand-new movies are introduced to the market every week, weekly updating of the marketing strategy is crucial for movie success. The model can be improved to capture the interdependencies between weekly box office performances across the movie lifecycle by using multivariate copulas (Aas et al. 2009). Copula can be utilized for an arbitrary number of marginal distributions by applying the generalized Archimedean or pair copula approach, where different copulas can be employed for different pairs. This means that a more generalized approach could enable distributors to make proper decisions throughout the lifespan of movies.

Moreover, our model can be extended to test the effect of the distributor's decision making in multiple channels such as DVDs, online streaming, and cable TV. Since distributors can replenish disappointing revenue stream from the box office by exploiting secondary channels, marketing strategies for follow-up mediums are important such as opt-in and opt-out or release timing decisions. While the present research deals only with the Korean local market, future research could explore dependencies across markets or different optimal timing in different countries caused by cultural gaps. Finally, another extension could bring dynamics into the model to reflect changes in market environment or moviegoer preferences.

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국문초록

본 연구는 영화의 흥행을 극대화하기 위해 배급사가 시사회라는 마케팅 수단을 어떻게 효과적으로 활용해야 하는지를 논하고 있다. 구체적으로는 시사회 규모와 시사회 시점이 영화 시장의 가장 주요한 흥행 지표인 개봉 첫 주말 예매율과 최종 관객수에 미치는 영향을 밝히고 있다. 시사회는 영화의 개봉 이전에 인지도를 높이고 구전을 확산시키기 위해 활용되고 있는 대표적인 프로모션 활동이지만, 지금까지 자료에 대한 접근이 제한되어 있다는 이유로 마케팅 분야는 물론이고 영화 시장을 다루고 있는 연구들에서 큰 주목을 받지 못하였다. 본 연구에서는 영화진흥위원회에서 제공하는 데이터를 바탕으로 영화 시사회의 효과에 대해 구체적인 실증을 시도하고 있다.

본 연구는 시사회의 규모가 영화 흥행에 미치는 영향력을 확인하는 것과 더불어, 영화 흥행을 극대화할 수 있는 최적의 시사회 시점을 찾고자 한다. 시사회 시작 시점과 영화의 개봉 시점 사이의 간극이 지나치게 클수록 시사회로 인한 구전 확산 효과가 사라질 수 있고, 그 간극이 지나치게 작을수록 구전 확산에 필요한 충분한 시간을 확보하기 어렵다. 분석 결과, 성수기의 실제 시차는 평균 15.4일 이었지만, 최적 시차는 약 36.5일인 것으로 나타났다. 최적 시차는 영화의 특성에 따라 달라질 수 있는데, 실제로는 시사회 규모에 따라 시사회 시점에 차이가 없었지만 분석 결과에 따르면 시사회 규모가 확대될수록 최적 시차가 감소하는 경향성이 확인되었다. 또한, 실제 업계의 행태와는 반대로 전문가 평점이 호의적일수록 최적 시차가 감소한다는 결과도 얻을 수 있었다. 이 외에도 영화의 등급과 장르에 따라서도 시사회의 최적 시점이 상이하다는 결과가 도출되었다.

본 연구는 영화 시장에서 주목하는 두 가지 성과 지표를 동시에 모형화하기 위해 코풀라를 활용한 연립방정식 모형을 제안하고 있다. 코풀라는 두 확률변수의 결합분포를 모형화하는 방법으로 지금까지 마케팅 문

헌에서 널리 다루어지지 않았다. 코풀라를 적용할 경우 두 종속변수간의 독립이나 단순한 결합분포를 가정할 필요가 없으며, 복잡한 상호의존성도 반영할 수 있다. 특히, 소수의 블록버스터 영화들이 시장 전체에 막대한 영향력을 미치고 있는 현실을 고려할 때, 분포의 극단에 위치하는 자료들의 상관성을 포착할 수 있는 코풀라 접근법이 이상적인 대안이 될 수 있다.

본 연구의 결과는 현재 영화 시장에서 이루어지고 있는 시사회와 관련한 의사결정에 상당한 개선이 요구됨을 시사하고 있다. 나아가, 본 연구에서 제시하고 있는 모형은 영화의 흥행을 예측하는 도구로도 활용될 수 있다.

주요어: 엔터테인먼트 마케팅, 시사회, 코풀라 모형, 시점 최적화, 마케팅 전략
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