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Do High Ratings Signal a Good Movie? An Empirical Investigation of Signaling Effectiveness*

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Abstract

The objective of this study is to examine the effectiveness of signals and advancing our understanding of the relationship between ratings and audience decisions based on the signaling theory. Though many studies argue that information asymmetry affects decision making, few studies have examined two key signaling factors: its potential to have multiple sources and the effect of time on its effectiveness. This study examined how experts' and the general audience's ratings affect decision making. We also considered change patterns in ratings to explore how time effect on ratings affect selection behavior. We tested our hypotheses using the latent growth model based on signaling theory and behavior approaches. The results show that a general audience's ratings is perceived as more credible than are those of experts and that audience members are significantly affected by upward patterns in ratings. The findings suggest that general audiences play a critical role as signal providers. Thus, market participants such as producers should pay more attention to the general audience's ratings in order to increase revenues. They should also consider the time effect of signaling, such as upward trends in ratings.

Key words: signaling theory, information asymmetry, signaling effectiveness, cultural industry

Ⅰ. INTRODUCTION

High Level of uncertainty and high risk are regarded as the fundamental concepts in new venture context(Lee, 2017). New ventures hard to predict the market opportunity and consumers' need exactly(Park & Byun, 2012). In a similar vein, markets for cultural products are typically characterized by a high degree of uncertainty. It is hard for audiences to evaluate cultural products before purchase and for producers to predict frequently changing audience preferences(Connelly et al., 2011; Kang, 2008; Kim & Jensen, 2014; Moon et al., 2010; Ozmel et al., 2013; Sambharya, 2011). For film audiences, a new film is risky because of the uncertainty concerning the benefits of its consumption. The rapidity of films' opening and closing confronts audiences with the challenge of having to select among products relatively quickly(Lampel & Shamsie, 2000). Market signals are thus critical mechanisms for reducing uncertainty about product quality by providing useful information(Connelly et al., 2011; Kim & Jensen, 2014; Spence, 2002). Producers signal their films' quality using tools such as high-profile casts and special effects. However, such signals are costly and do not always reduce uncertainty(Kim & Jensen, 2014; Lampel & Shamsie, 2000). Audiences know they are designed to persuade and are swamped with them(d'Astous & Touil, 1999; Eliashberg & Shugan, 1997; Li & Hitt, 2008; Moon et al., 2010; Sawhney & Eliashberg, 1996). Accordingly, it is worthwhile determining which signals of film quality impact an audience's selection through their signal effectiveness.

This paper explores the role of ratings as market signals in the film industry. As audiences face similar signals in producers' promotions and advertisements, ratings can be crucial if audiences can be aware of product quality through them. The literature indicates that market signals from ratings can influence audience choice by greatly reducing uncertainty about a movie's unobservable quality(Basuroy et al., 2006; Certo, 2003; Connelly et al., 2011; Kim & Jensen, 2014; Moon et al., 2010). Lampel & Shamsie(2000) suggest that the information provided by

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ratings (e.g., critic ratings) and independent sources can help resolve information asymmetry. Moreover, because film quality is determined by audience response rather than by the nature of the film itself(Eliashberg & Shugan, 1997; Holbrook & Hirschman, 1982), ratings' signaling effect on audiences may be particularly important.

Although much of the research demonstrates the strategic benefits of signaling, studies have largely ignored two key signaling factors: the potential for multiple signal sources, and the effect of time on its effectiveness. A few studies indicate that the information provided by multiple independent sources can help resolve information asymmetry(Lampel & Shamsie, 2000; Moon et al., 2010). However, the research has yet to explore the possibility that contradictions within the information provided by multiple sources can affect signaling effectiveness. The signaling theory research has yet to explore satisfactorily how signal changes over time affect signaling effectiveness. Since signal receivers organize a coordinated series of signals into meaningful, comprehensive wholes(Rindova et al., 2002, as cited by Connelly et al., 2011), the order in which signals are presented can affect their interpretation. Signaling effectiveness is linked to audience interpretations of signals. If a signal changes over time, audience interpretations may also change. Thus, changing signal patterns should be interpreted differentially. As audience interpretation is an inherently human factor, a behavioral perspective must be incorporated into the analyses.

The limitations of prior research on signaling provide the principal motivation for this study. Utilizing a theoretical framework combining signaling theory and behavior perspectives, this study investigates data on ratings in the film industry covering 2002 to 2013. The remainder of this paper is organized as follows. The next section reviews the relevant research to provide the theoretical basis for the study, which posits that, as per signaling theory, movie ratings effectively represent a movie's quality. Next, hypotheses are proposed based on the arguments presented in the previous sections. The next section describes the sample, measurement procedures, and dynamic model used to test the hypotheses. Finally, the results of the analysis and the study's implications are discussed.

Ⅱ. THEORETICAL BACKGROUND

2.1 Signaling in Film Markets

Signaling theory is relevant for decision making under information asymmetry(Connelly et al., 2011; Kim & Jensen, 2014; Kang, 2008). Following Spence(1974) who defined "market signal" as an "individual in a market which, by design or accident, alter the beliefs of, or conveys information to, other individuals in the market," scholars have explored how and when signals reduce uncertainty in markets(Kim & Jensen, 2014; Kim et al., 2008; Connelly et al., 2011). Spence(1974) showed that more productive employees cannot receive higher wages than less productive ones unless they engage in activities that signal that they are both observable and costly to imitate(Ozmel et al., 2013). Kim & Jensen(2014) suggested that commercial success and artistic acclaim are important market signals for film audiences by providing information about film quality. Early commercial performance and artistic acclaim help reduce information asymmetry and enhance later performance(Sawhney & Eliashberg, 1996). Basuroy et al.(2006) also suggested that sequels and advertising expenditures are important market signals for audiences.

Selecting a film is fraught with uncertainty because of the attributes of film as a product. Holbrook & Hirschman(1982) proposed an experiential perspective in which movie consumption is considered "a primarily subjective state of consciousness with a variety of symbolic meanings, hedonic responses, and aesthetic criteria"(Holbrook & Hirschman, 1982). This perspective explores the implications of consumption in terms of the enjoyment and pleasure derived from it. Hence, uncertainty is created by not only the objective information asymmetry but also the subjective information asymmetry in the film industry, such as that involving fun. As film quality is usually judged based on subjective factors (e.g., enjoyment), audiences' film selections depend on subjective rather than objective information. Hence, though film producers may offer objective information such as a star-studded cast or a famous director, this will not convince audiences of the film's quality because they judge it in terms of enjoyment value. Potential audiences seek credible and observable indicators that signal not only objective but also subjective worth(Basuroy et al., 2006; Kang, 2008; Ozmel et al., 2013).

Amid the many types of signals in the film industry(Basuroy et al., 2006; Lampel & Shamsie, 2000), the ratings of experts and general audiences can generate particularly important signals about films' unobservable quality because they provide audiences with accurate judgments, including hedonic and aesthetic information(Deephouse, 2000). Moreover, the higher the uncertainty about the quality of a product, the more likely audiences are to rely on independent information providers when making purchasing decisions(Deephouse, 2000; Huang et al., 2011; Lampel & Shamsie, 2000; Moon et al., 2010). Thus, the high uncertainty about films increases audiences' reliance on observable and credible signals from independent information providers(Basuroy et al., 2006). It is therefore not surprising that expert and general audience ratings are not only important indicators of film quality but also commonly used to reduce uncertainty(Moon et al., 2010). These ratings generally fall outside the control of film producers but are often used in promotions and are typically easily observed. The importance of expert and general audience ratings as market signals is particularly well-established in the film industry(Kim & Jensen, 2014; Basuroy et al., 2003; d'Astous & Touil, 1999; Eliashberg & Shugan, 1997; Li & Hitt, 2008; Moon et al., 2010; Sawhney & Eliashberg, 1996).

<TABLE 1> Review of Previous Studies

Author	Theory	Journal	Key Findings
Basuroy, et al.(2003)	Information-seeking behavior	Journal of Marketing	Positive and negative reviews are correlated with weekly box office revenue
Cattani, et al.(2008)	Ecological theory and network theory	Administrative Science Quarterly	How consensus is affected by the structure of interaction in the network connecting social audiences to candidate organizations.
d'Astous & Touil(1999)	Information-processing perspective	Market Research	The impact of film reviews on the way moviegoers interpret the critics' evaluations
Duan, Gu, & Whinston(2008)	Awareness perspective of human behavior	Journal of Retailing	No significant impact of online user reviews on movies' box office revenue
Gemser, et al.(2008)	Selection system theory and Signaling theory	Journal of Management	Awards granted by a jury composed primarily of consumers, peers, or experts each have a different effect on film success.
Durand & Jourdan(2012)	Resource dependence theory and neoinstitutionalism	Academy of Management Journal	The critical role of minority logic holders in filmmakers' release decisions in the French film industry
Ebbers & Wijnberg(2012)	Selection system theory	Journal of Business Venturing	The impact of different types of producer and director reputations on investment decisions
Eliashberg & Shugan(1997)	Information-seeking behavior	Journal of Marketing	The influence of critics' reviews on film success
Hsu(2006)	Organizational ecology	Administrative Science Quarterly	The key role audience perceptions play in the trade-off associated with different niche strategies
Lampel & Shamsie(2000)	Signaling theory	Journal of Management	Studios incorporate anticipated responses of critics into their strategy
Li & Hitt(2008)	Self-selection bias & information-seeking behavior	Information Systems Research	The influence of average ratings declines over time; early consumer reviews affect consumers' self-selection effect
Moon, et al.(2010)	Signaling theory	Journal of Marketing	How viewers' viewing and ratings influence box office revenue: 1) movie-level effect and 2) general viewer-level effect
Ravid(1999)	Signaling theory	Journal of Business	Two alternative explanations for the role of stars in motion pictures: (1) star-studded films bring in higher revenue; (2) big budget and sequels also contribute to revenue.
Sawhney & Eliashberg(1996)	Information-seeking behavior	Marketing Science	Modeling framework for forecasting a movie's box office gross revenue
Shamsie, Martin, & Miller(2009)	Dynamic capability	Strategic Management Journal	In project-based industries, firms must concentrate on the further development of capabilities in those project categories in which their rivals are not already successful.
Reinstein & Snyder (2005)	Information-seeking behavior	Journal of Industrial Economics	Importance of positive/negative reviews on movie demand
Zuckerman & Kim(2003)	Structural role theory	Industrial and Corporate Change	The impact of market identity on film success

The research has suggested that expert and general audience evaluations assist individuals in selecting a movie, but little empirical effort has been made to distinguish between these influences. Generally, experts provide ratings that signal unobservable product quality, offering a professional perspective from which individuals can make informed decisions(Kirmani & Rao, 2000; Moon et al., 2010).

Although it is useful for audiences to obtain information from critics, audiences may be confused by expert ratings due to the fundamental differences in knowledge and preferences between experts and audiences (Holbrook, 1999; Moon et al, 2010; Sawhney & Eliashberg, 1996). This might be why studies have failed to produce consistent results (see Table 1).

Building on previous research, we argue that expert and general audience ratings are critical signals in the film industry. We focus on the fact that different information providers (e.g., expert vs. general audience) may hold (and express) divergent opinions about the same movie and that signals transmitted from different audiences may differentially affect signal receivers' interpretations.

2.2 Signaling Effectiveness of Expert Ratings in a Market of Experience Goods

Research has shown that individuals' purchasing decisions are often influenced by the opinions of others(Bearden & Etzel, 1982). A direct, positive relationship has been found between difficulty in assessing product quality and reliance on purchasing decisions made by others as a reference for making purchasing decisions(Moon et al., 2010). A movie is an "experience good" judged in terms of the enjoyment it provides audiences(Holbrook & Hirschman, 1982; Sawhney & Eliashberg, 1996).

The pre-consumption quality of an experience good is difficult to assess without having an experience associated with the good. Accordingly, moviegoers are likely to seek credible signals with which to predict how they will enjoy the movie. The quality of the input to which they refer (e.g., the movie's budget) is generally related to the quality of the movie(Lampel & Shamsie, 2000; Zuckerman & Kim, 2003). However, movies are special experiential goods with unique properties, and their quality cannot be communicated through signals that are considered critical in other industries. Film experts' opinions about a movie can serve as a credible signal of its quality. Unlike major studios' signals (e.g., advertising, marketing), expert ratings provide metrics related to the perceived value of a film rather than the components of its production. Moreover, expert opinions provide subjective information (e.g., emotions, perceptions).

Thus, rating scores can serve as effective indicators of a film's quality. Movies that receive high ratings are therefore more likely to attract audiences and succeed in the long run.

Stated simply, the perceived quality of a film can be classified in terms of its rating. For example, the ratings of the Motion Pictures Audience Association (MPAA) comprise a vertical classification evaluation system based on the degree to which the films possess a particular attribute(Fleischer, 2009). The MPAA ratings affect audience viewing decisions most strongly soon after a movie is released, when audience members lack sufficient information about the movie to make informed judgments. In an environment characterized by uncertainty, audience members must gather and process a greater number of outside perspectives to construct a satisfactory reference group. Because there are very few referents to which audience members can turn prior to a movie's release (as very few people will have seen the film), moviegoers are more likely to rely on experts' ratings. In this scenario, signal receivers are likely to pay greater attention to movie ratings prior to the movie's release.

Based on these ratings, they will form expectations about the movie's quality and, by extension, the enjoyment they would derive from it. Based on these expectations, they will decide whether to see the movie. Accordingly, the following is proposed:

Hypothesis 1: Pre-release expert ratings are positively associated with a film's success.

2.3 Tensions from Multiple Sources' Signaling in the Film Industry

Markets feature various signals(Kang, 2008; Kim & Jensen, 2014; Ozmel et al., 2013; Pollock & Gulati, 2007). For example, Pollock & Gulati(2007) noted that different markets influence the visibility of signals differently.

As different information is provided by multiple sources, an important question is whether audiences pay attention to the specific signals. The relevant research has suggested that critics' and general audience members' evaluations assist individuals in selecting movies, little empirical effort has been made to distinguish between the influences of these evaluations or offer rigorous theoretical explanations. Thus, it is worthwhile investigating whether and how the tensions between multiple signals determine signaling effectiveness.

After a movie is released, both professional critics and general audiences provide ratings. Both sources communicate signals related to unobservable product quality and assist audiences in making purchasing decisions(Basuroy et al., 2006; Deephouse, 2000; Moon et al., 2010; Podolny, 1993). Given that they both offer movie ratings, we conceptualize both (a) experts and (b) audiences as providers of signals related to movie quality.

Following this conceptualization, a movie's quality can be evaluated from two viewpoints: critics are more likely to focus on a movie's technical features (e.g., story structure, special effects), while audience members are more likely to assess a film's quality as a function of their overall sense of enjoyment. Therefore, movie ratings differ as a function of whether they are offered by experts or general audience members. This is consistent with Moon et al.(2010), who claimed that experts and ordinary audience members differ fundamentally in terms of knowledge and preferences.

Differences in the signals communicated by different raters may affect audience members differentially. A general audience may be more responsive to audience ratings than expert ratings. When this occurs, signal recipients' similarities to the raters (i.e., common interests and viewpoints) become salient(Fleischer, 2009; Ibarra, 1992; McPherson et al., 2001), and potential audiences are more likely to be influenced by other "ordinary" viewers.

Although film experts tend to be considered more reliable sources of film-related information, the perceived knowledge gap between experts and ordinary viewers diminishes when those ordinary viewers are perceived as being similar to the signal recipients(Moon et al., 2010). Moreover, the evaluations of experts may be perceived as too technical and therefore difficult to interpret.

Given how similarity affects perceptions of movie evaluations, moviegoers may be more attentive to ordinary viewers' opinions than to experts'. Thus, if discordant signals about movie quality are offered by critics and ordinary viewers, audience members are more likely to be persuaded by the opinions of the latter. Therefore, the following is proposed:

Hypothesis 2: Having lower expert ratings than audience ratings is positively associated with a film's success.

2.4 Upward Pattern in Ratings

The effectiveness of a source's signals can weaken or strengthen as a function of their pattern(Connelly et al., 2011). Studies have suggested that signals represent single evaluations of an unobservable quality at a particular point in time(Moon et al., 2010). Although the signaling theory research has generally focused on specific signals, scholars have begun to evaluate more complex signal formulations(Connelly et al., 2011).

For example, because information that is useful for signal recipients is dynamicand constantly changing, audiences learn more about the quality of a film after it is released, which is where a signaling interpretation may be relevant.

Kim & Jensen(2014) argued that market signals' effectiveness is related to how audiences interpret them. Most studies assume static signals and audience interpretations. This study challenges this assumption and focuses on receivers' interpretation of changing signal patterns over time because audiences may perceive the changing patterns of a film's ratings as accurate reflections of its quality. This study focuses on positive growth patterns, as an upward pattern not only indicates the film's success but also affects growth momentum. An upward pattern occurs when early positive ratings incite potential audience members to see the film. We expect that audiences use these ratings as a decision-making guide, as doing so reduces the costs associated with searching and other associated risks. These behaviors are indicative of what are known as "herding behaviors."

Herding has been defined as common behavior among a group of individuals over a period of time(Sias, 2004), as well as a correlation among behavior patterns among individuals(Devenow & Welch, 1996). In stock trading, for example, herding occurs when a correlation forms among institutional investors' information. This can happen when investors attend to and follow the same signals(Sias, 2004).

Shiller & Pound(1989) focused on the behavioral model of herding and found that investors did not seem to be systematic in their purchasing decisions. Instead, among both institutional and individual investors, initial interest in a stock was stimulated by demonstrations of interest by other investors. The behavioral approach to herding considers issues related to individual psychology, interpersonal interaction, and interest contagion. Upward patterns in movie ratings can be interpreted as a form of contagion based on positive initial ratings.

In addition to the value judgments of movie reviewers, the intrinsic characteristics of the film industry may also facilitate herding behavior. For example, Pingle(1995) performed an experiment on imitation to determine when individuals are most likely to follow others. The results showed that imitation was more likely to occur when information asymmetry was high.

A unique facet of the film industry that selecting a movie always involves a high level of information asymmetry may thus facilitate herding behavior. Topol(1991) introduced the concept of "mimetic contagion" with reference to institutional herding, arguing that, due to information asymmetry, traders will herd and adjust their prices relative to other traders' prices. Movieaudiences face a similar information asymmetry and engage in herding behavior; they tend to simply follow other moviegoers who evaluate the film positively. This perspective also transforms general audiences from being mere signal providers to being participants in the social construction process(Deephouse, 2000).

Thus, potential audiences tend to be more attentive to practices that form upward patterns via the positive evaluations of previous adopters, as they reduce ambiguity and uncertainty. The following is therefore proposed:

Hypothesis 3: A film's upward ratings trend positively influences its success.

Ⅲ. METHOD

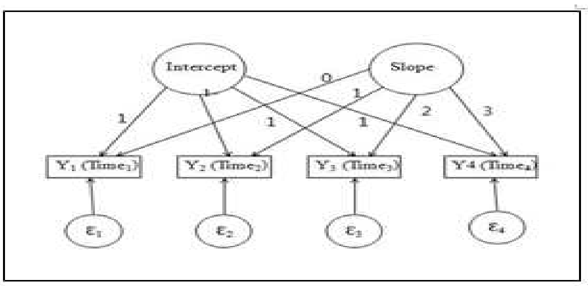
3.1 Sample and Analytical Strategy

This study tests its hypotheses using data on 1,141 movies released between 2003 and 2012 taken from the Korean Film Council (http://www.kobis.or.kr). Films seen by fewer than 1,000 people were excluded, as their ratings and success are largely uncorrelated. The study used NAVER (http://movie.naver.com) to identify the sample films' ratings. Films with fewer than five ratings were excluded. Using NAVER, each movie's evaluation was divided into five periods (i.e., pre-release, first week, second week, third week, fourth week). Experts' pre-release ratings of the sample films were taken from Cine21 (www.cine21.com). The sample consisted of over 5,000 observations.

The study tested the time effect hypotheses using a latent growth curve model. The most prominent feature of this longitudinal model is the inclusion of a latent (i.e., unobserved) common factor, estimated from the repeated observations of a single variable. This factor was used to determine longitudinal correlations, variances, and means(McArdle & Epstein, 1987).

For studying dynamic relationships over time, latent growth modeling (LGM) offers methodological advantages over other, more traditional techniques. Most notably, it facilitates the modeling of change within and between variables. For each variable, data were modeled over consecutive quarters by specifying latent slope factors. The hypothesis tests were based on these latent slope factors. The slopes indicated whether the trends for each variable were increasing or decreasing, as well as the strength of this change(Ployhart et al., 2011).

Using LGM made it possible to examine how changes in one construct affected changes in other constructs(Chan, 1998). The key aspects of the LGM developed for this study are illustrated in <Figure 1>.



<FIGURE 1> A Latent Growth Model[1]

3.2 Variable Specifications

3.2.1 Dependent Variable

The outcome measure was film success, operationalized in terms of the number of people who viewed the film.

3.2.2 independent Variables

Movie rating scores were evaluated using NAVER, which classifies ratings according to four organizational categories: overall ratings for the pre-release week and the four weeks following release; age; gender; and expertise (expert vs. general audience).

All scores in each category were rated on a scale from 1 to 10. Rating scores from Cine21 were also used to complement the pre-release ratings of film experts. Following Mishina et al.(2010), an independent variable was created to measure experts' lower rating scores relative to audiences' rating scores; greater positive values represented greater disagreement between the experts' and ordinary audience members' ratings. This variable was calculated as follows:

Experts' lower rating score relative to audiences' rating score
= Audiences' rating score - experts' rating score
if audiences' rating score < experts' rating score = 0,
if audiences' rating score experts' rating score = the positive values

A time variable was created to indicate the rating time period. T0 represented the period prior to the film's release; T1signified the first week after release; T2 indicated the second week; T3 indicated the third; and 5) T4 indicated the fourth.

3.2.3 Control Variables

Variables were added to the model to control for unwanted influences on the outcome measure. First, Eliashberg et al.(2006) found that the number of screens on which a film is presented is a significant predictor of box office revenue. The number of screens also acts as a proxy for the power of distributors. Therefore, the number of screens on which the movie appeared was used to control for these effects.

Second, Simonton(2009) found that a film's success was somewhat contingent on its genre. Therefore, a variable was added to control for genre. Third, Dodds & Holbrook(1988) found that the receipt of Academy Awards for Best Picture, Best Actor, and Best Actress had significant effects on post-award revenues. Therefore, control variables controlling for film director, actors/actresses, and distributors were included. Fourth, studies have shown that the planning of a sequel can signal a film's quality(Lampel & Shamsie, 2000).

Thus, a variable was added to control for this sequel effect. Finally, Ravid(1999) revealed a relationship between the season of a film's release and its success. Therefore, a variable was added to control for the film's release date.

Ⅳ. RESULTS

Correlation coefficients for all variables are presented in Table 2, and Table 3 summarizes the results of the OLS regression. In Table 3, Model 1 presents the regression results for a model that includes all control variables. Model 2 shows the effects of experts' pre-release ratings on a film's success. Model 3 shows how differences between experts' and audiences' ratings affect film success.

Correlation coefficients for the variables are presented in Table 2. The number of screen (r=0.45, $p<0.01$), the power of distributor (r=27, $p<0.01$), the director (r=0.07, $p<0.05$), the power of actor (r=0.41, $p<0.01$), and the sequel (r=0.08, $p<0.05$) are positively correlated with the film success. These findings are consistent with the past empirical research(Basuroy et al.,

1) First-order LGCM for viewers' rating of Yk(k=timepoint)measurd for weeks after the movie launched(k=1,2,3,4; Ek=error variables). The model assumes latent growth and equals pacing between time points.

2003; Lampel & Shamsie, 2000; Moon et al., 2010).

As Model 2 shows, experts' pre-release ratings do not significantly influence film success, which fails to support Hypothesis 1. While we hypothesized a positive relationship between experts' pre-release ratings and film success, the result was contrary to our expectation. We think that this is an interesting finding because this result contradicts the traditional perspective regarding experts' ratings. Our result may indicate that audiences like movies that are fun to watch but experts do not. This may because expert's evaluations are too technical and then general audiences reluctant to choose expert's preferred movies.

As Model 3 shows, differences between experts' and audiences' ratings significantly and positively influence a film's success (β=0.25, p<0.01), providing strong support for Hypothesis 3.

These results indicate that movies rated more positively by audiences are more likely to be box office hits. Concerning ratings growth trajectories as time-variant predictors of film success, all models were estimated using Mplus 7.11 (Muthen & Muthen, 2013), and model fit was evaluated using several standard fit indices, including chi-square, comparative fit index (CFI), root-mean-square error of approximation (RMSEA), and standardized root-mean-square residual (SRMR). The linear model specification fits the data well according to traditional standards of model fit (χ2=9606.475, df=45; RMSEA=.057; CFI=0.995; SRMR=0.024; Hu & Bentler, 1999; Jokisaari & Nurmi, 2009).

The results of LGM are as follows. First, a large negative score on the slope factor indicates a pattern of decreasing movie ratings.

<Figure 2> shows the observed individual growth curves for all ratings in the sample for the first four weeks. On average, the initial rating was 5.92. Second, after covariates were controlled for (see the variables in Table 2), the latent variable of the slope shows a positive coefficient when box office success is predicted. This indicates a positive association between upward-trending movie ratings and box office success (β=0.08, p<0.01). Taken together, these findings empirically support Hypothesis 3.

Additional analysis was conducted to ensure the robustness of the results. Despite every attempt to collect data appropriate for an analysis on the relationship between ratings and film success, the evaluators used might distort the ratings(Moon et al., 2010).

Data validity was thus checked through correlation analysis with two other data sources: (1) Rotten Tomatoes (http://www.rottentomatoes.com) and (2) IMDb Internet Movie Database (http://www.imdb.com). Both have millions of users and have been employed as data sources in many studies(Dodds, 2006; Neville et al., 2003; Moon et al., 2010). Both sites have improved accessibility by providing not only website services but also application services for mobile phones.

They provide general audience ratings as well as critic ratings. Using random selection in SPSS, ratings from 2003 to 2012 for 100 movies were randomly collected from the three data sources (NAVER, Rotten Tomatoes, IMDb). Table 4 shows the result of the correlation coefficient analysis, presenting the relationship between NAVER and Rotten Tomatoes (r=.61, p<.01) and between NAVER and IMDb (r=.70, p<.01).

<TABLE 2> Descriptive Statistics and Correlations for Variables[a]

Variables	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13
Peakb	0.30	0.46	1												
Screenc	130.01	196.73	.06	1											
Director	0.05	0.22	-.01	.03	1										
Distributor	0.51	0.90	.02	.11	.13	1									
Actor	0.29	0.46	.01	.24	.09	.18	1								
Sequel	0.02	0.13	.04	.02	.04	.09	-.02	1							
Omnibusd	0.98	0.15	.033	.07	-.14	.07	.09	-.02	1						
Docue	0.94	0.24	.04	.14	.06	.14	.15	.01	-.04	1					
female	7.62	1.45	-.04	.11	.05	.02	.00	-.05	.04	-.19	1				
male	6.85	1.49	-.09	.05	.05	.03	.03	-.06	.05	-.16	.65	1			
Expert's rating	5.51	1.35	-.06	.00	.17	-.00	.03	-.08	-.06	-.11	.36	.41	1		
Differencef	2.89	2.60	-.02	-.25	-.02	.03	.01	.01	.05	-.09	.20	.26	-.18	1	
Success	12.04	2.52	.18	.45	.07	.27	.41	.080	.21	.32	-.02	-.00	-.07	.05	1

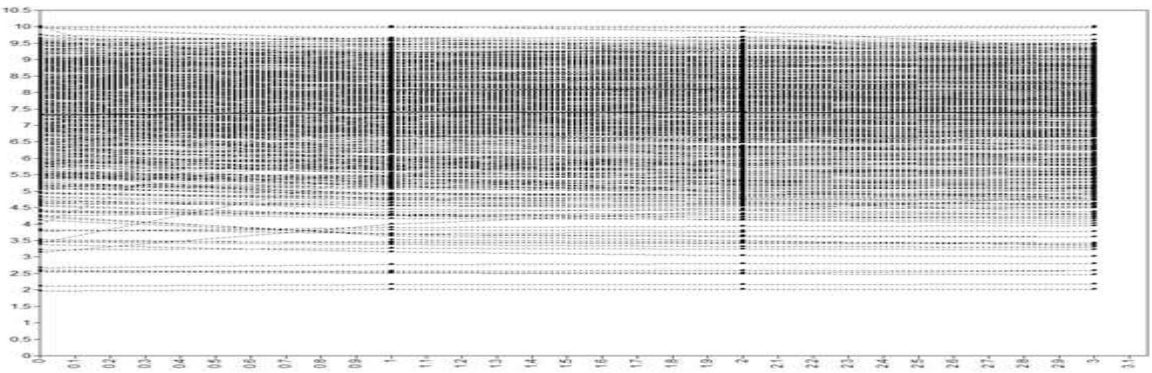
a Values greater than 0 .08 are significant (p < 0 .05); values greater than 0.06 are significant (p <0 .01).
b Peak season = 1, off season = 0.
c Number of screens.
d General film = 1, omnibus = 0.
e General film = 1, documentary = 0.
f Difference between expert rating and general audience rating

<TABLE 3> Regression Analysis of the Model for Film Success[a]

Independent variable	Model 1		Model 2		Model 3	
	Beta	s.e.	Beta	s.e.	Beta	s.e.
Peak	0.12***	0.14	0.11***	0.14	0.11***	0.14
Screen	0.32***	0.00	0.32***	0.00	0.40***	0.00
Director	0.04	0.31	0.04	0.31	0.03	0.30
Distributor	0.16***	0.07	0.16***	0.07	0.14***	0.07
Actor	0.25***	0.15	0.25***	0.15	0.22***	0.14
Sequel	0.05*	0.54	0.05*	0.54	0.06*	0.51
Omnibus	0.15***	0.45	0.15***	0.45	0.14***	0.43
Docu	0.22***	0.28	0.22***	0.29	0.22***	0.27
Expert's Rating			-0.01	0.05	0.02	0.05
Difference					0.25***	0.02
R2	0.42		0.42		0.48	
Adjusted R2	0.42		0.42		0.47	
F	73.43***		65.23***		73.01***	
F Change	73.43		0.25		81.98	
*+ p<0.1, * p<0.05, ** p<0.01, *** p<0.001*						

<TABLE 4> Pearson's Correlations

Variable	Mean	S.D.	1	2	3
NAVER	7.63	1.23	1		
Rotten Tomatoes	6.87	0.85	0.61**	1	
IMDb	6.76	1.01	0.70**	0.87**	1
*p<0.1, * p<0.05, ** p<0.01, *** p<0.001+*					



<FIGURE 2> The Observed Individual Growth Curves for All Individual Ratings

Ⅴ. DISCUSSION

This study explores the theoretical possibility that combining signaling theory and a behavioral perspective on audience interpretation signals may enhance our understanding of viewing decisions. Recognizing the importance of information asymmetry in the film industry, this study seeks to demonstrate that audience decisions are influenced by the interpretations of various signals. This study contributes to signaling theory by examining a case in which multiple signalers are sending conflicting messages and by exploring the possibility that the signals change over time. Based on the notion of herding behavior, the study has demonstrated that considering signal changes is a useful framework in which to explain signaling theory's basic tenet of receiver interpretation.

The study's empirical analyses have generated several important findings. First, though a positive relationship between expert ratings and film success was predicted, the data indicated the opposite: experts' pre-release evaluations were inversely related to a film's success. This result suggests that expert ratings may not be the best indicator of film success. One possible explanation for this outcome is that audiences like movies that are fun to watch but experts do not; this would be consistent with the finding in Moon et al.(2010) that expert evaluations are too technical.

Second, the limitations of expert ratings are more salient in the test of hypothesis 2, which proposes that the ratings of experts and ordinary audience members are interpreted differentially. While expert's evaluations commonly provide more reliable information about the quality of experience goods than the general's evaluations, the result shows moviegoers rely on the general audience's evaluation in the film market(Moon et al., 2010). We think that this can result from the characteristics of the film industry. As we mentioned above, films are experience goods for pleasure rather than an economic benefit(Eliashberg & Shugan, 1997). The moviegoers seek the fun and enjoyment from the movie consumption. Although audiences develop high expectations of movies that critics rate positively, the fundamental differences of the evaluation criteria between critics and general audiences may cause the latter's expectations of film quality to be disconfirmed. Accordingly, movies that receive high ratings may incite expectation disconfirmation when audience expectations and critic signals are inconsistent. The Guardian Datablog[2] provides interesting examples of movies loved by audiences and hated by critics. For example, "Rad" received a score of 89 from audiences and did well at the box office, but it received the lowest score (0) from critics. This shows the difference between the views of audiences and critics.

Third, this study's results show that movies with audience ratings that trend upward are likely to be a box office success. This may be attributable to herding behavior among moviegoers, whereby they are likely to follow others when they lack experienced referents. Because movies are experiential goods for which time constraints dictate when they can be experienced, consumers are likely to look to others to help determine their choice. This suggests that audience members place substantial value on the upward pattern of movie ratings as a signal of quality. This finding might be a valuable insight, as prior studies have typically focused on a given signal (e.g., Ravid, 1999) and ignored changes in signals over time. Growing positive rating patterns signal not only that the movie may be worth watching but also that the general audience agrees about its quality.

Finally, though the study did not hypothesize on relationships, the control variables demonstrate that a film's genre, star power, and distributor positively affect box office revenues. Similarly, the release time, planning of a sequel, and number of screens also positively influence a film's success (see Table 3), consistent with past research(Eliashberg et al., 2006; Eliashberg & Shugan, 1997; Li & Hitt, 2008; Litman, 1983).

Despite this study's contributions, it has several limitations that provide opportunities for future research. First, while the study controlled for two film genres (e.g., documentary and omnibus), future research would benefit from controlling for more specific genres. Current films often mix genres to appeal to diverse audiences, such as indie films with small number of audiences. Future research should try to determine genre through credible criteria. Second, this study showed convergent validity of several results from various sources (e.g., Rotten Tomatoes and IMDb), but future studies should use multiple data sources that reflect reviews from a broader population. Third, though the power of distributors was controlled for, the study did not analyze distributors' network relationships. As distributor networks influence audiences' choices, future research could take a more integrated approach by analyzing them.

Finally, future studies could examine ratings' signaling effectiveness in other performance settings. For example, the findings of this study could be expanded to areas that share the film industry's severe uncertainty and information asymmetry. Stock markets, which also feature information asymmetry(Cohen & Dean, 2005; Ozmel et al., 2013), might be a fruitful research area.

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좋은 평점이 항상 영화의 성공을 가져오는 것일까? 잠재 성장 모형을 응용한 Signaling 효과성에 관한 연구*

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국문요약

본 연구는 전문가와 일반인 관객의 평가가 영화 흥행성과에 미치는 영향을 신호 이론(Signaling Theory)과 정보 비대칭(Information Asymmetry) 논의를 기반으로 실증 분석하였다. 영화에 대한 평가가 영화 흥행 성과에 대한 기존 연구는 주로 전문가나 일반인 관객 중 한 주체의 평가에만 중점을 두어 이들의 효과에 대해 설명함으로써 신호의 효과성(Signaling effectiveness)를 검증하는 데에는 다소 미흡한 점이 있었다. 또한 시간이 지남에 따라 변화하는 영화 평가의 추이에 대해서는 분석이 제대로 이루어지고 있지 않아, 영화 평점의 신호 효과성을 깊이 있게 밝히는 데에는 제한적이었다. 따라서 본 연구는 1) 전문가 평가와 일반인 평가의 차이점과 2) 시간의 흐름에 따른 평가의 변화의 추이가 영화 성과에 영향을 미칠 것으로 보고 이들 간의 관계를 밝히고자 하였다. 이를 위하여, 영화진흥위원회와 네이버를 토대로 2003년부터 2012년까지 개봉했던 1,141개 한국 영화 데이터와 이들에 대한 평점을 수집하여 분석을 실시하였다. 실증 분석 결과, 영화 개봉 전 전문가의 평가는 영화 흥행 성적에 영향을 미치지 않으며, 개봉 후에는 일반인의 평가가 전문가의 평가보다 영화 성과에 긍정적인 영향을 미치는 것으로 나타났다. 또한 시간이 지남에 따라 영화에 대한 긍정적인 평가가 증가할수록 영화 흥행 성적은 향상되는 것을 보여주었다.

핵심주제어: 신호이론, 정보비대칭, 신호효과, 문화 산업

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