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ARTICLE

Broadcaster Choice and Audience Demand for Live Sport Games: Panel Analyses of the Korea Baseball Organization

Kihan Kim,[1] Hojun Sung,[2] Yeayoung Noh,[3] and Kimoon Lee[4]

[1]Department of Physical Education/Institute of Sport Science, Seoul National University, Seoul, Korea; [2]Division of Health & Kinesiology, Incheon National University, Incheon, Korea; [3]National Assembly Okyeong Lim's Office, The National Assembly of the Republic of Korea, Seoul, Korea; [4]Public Media Institute, Korean Broadcasting System (KBS), Seoul, Korea

This study investigated the determinants of television viewership and its relation to broadcasters' choices of matches for live telecasts. Also, factors driving the broadcasters' choices were examined. A panel data set from the 2018 Korea Baseball Organization league pennant race was analyzed. Broadcasters' choice order of matches and the actual television ratings of each match were regressed on a series of antecedent factors related to the game characteristics and audience preferences. It was found that the broadcasters' choice order of matches positively affected the television ratings, suggesting that the broadcasters' decisions were well reflected in the actual viewership. It also appeared that broadcasters' choices were based on popularity and team performance/quality, whereas viewers showed preference for current games' on-field performance. There was no evidence of audience preference for games with higher outcome uncertainty, whereas the broadcasters tended to choose games with more certain, rather than uncertain, outcomes. Theoretical and practical implications of the findings were discussed.

Keywords: sport spectatorship, broadcasters' match selection, viewership

Broadcasts of sporting events account for a large proportion of the revenue source for both networks and successful professional sport leagues and teams (Fort, 2006). The role of media in delivering sport content seems to be gaining further importance as professional sport leagues seek to expand their influence domestically and internationally. This importance has been reaffirmed since the outbreak of the COVID-19 pandemic, as the absence of stadium ticket sales has forced networks and professional leagues to rely on revenue sources beyond the stadium. Accordingly, the revenues generated from the sales of media rights and from media content distribution of live sporting events have become more important than ever (World Economic Forum, 2020). Finding ways to satisfy fans' desires for media consumption of sport content will be pivotal to improve the future of the sport business.

Most sport demand studies are rooted in attendance research, which investigates the determinants of stadium attendance in various professional sports, including the European football leagues and North American college and professional sports (Borland & MacDonald, 2003; Szymanski, 2003; Villar & Guerrero, 2009). However, the attendance data present inherent problems with understanding the overall demand for professional sport, such as the possible bias season ticket holders cause, unobservable and excessive demands for sport that go beyond stadium capacity, and a generally high proportion of home supporters (Feehan et al., 2003; Forrest et al., 2005). Since previous works have found sport fans watching televised sporting events to have heterogenous preferences compared to those of fans attending games at a stadium, a separate investigation of viewership is needed to draw a more accurate implication (Mongeon & Winfree, 2012; Sung et al., 2019). Viewership studies have gained much attention in recent years to overcome such shortcomings, as well as to comprehend the ever-increasing size and significance of the sport media market (Ryu et al., 2019; Tainsky, 2010; Tainsky & Jasielec, 2014).

Most viewership studies use television ratings as a proxy for live sport demand (Alavy et al., 2010; Pérez et al., 2017; Tainsky & Jasielec, 2014; Wang et al., 2018). However, the immediate client for any professional sport is the broadcasting network, which acts as a patron, providing matches for its viewers (Evens et al., 2013). Only after the media company has purchased the media rights, and after the broadcaster has selected a match for televising, does a match become available to the audience for viewing. Therefore, it is of great importance to understand on what grounds broadcasters choose matches to televise, and whether broadcasters' choices of matches are associated with the actual audience demand as reflected in the television ratings.

Unfortunately, there are only a few studies (Forrest et al., 2005, 2006) that have focused on broadcasters' choices of sporting events. These studies, despite providing useful insights to researchers and practitioners, are rather outdated and are restricted to a single league in a specific period: the English Premier League (EPL) during its inception in the 1990s. Because the cultural background of professional sport fans and the socioeconomic environment surrounding each professional league vary from one country to another (Agah & Dixon, 2021; Jang, 2019; Ryu et al., 2019), the results of the aforementioned studies may limit the understanding of the latest trends in sport media consumption in other sport leagues. Specifically, each sport league within and across borders has different policies for broadcasting sporting events (Ma & Kurscheidt, 2020). European countries and the United States have varying policies regarding the accessibility of sporting events, degree of government intervention, and competition policies (Hoehn & Lancefield, 2003).

This study aims to fill the gap in the literature by investigating broadcasters' choices of matches for televising and their relation to actual television viewership. First, we examined the determinants of television viewership and its relation to broadcasters' choices of

Noh (gsmnoh@snu.ac.kr) is corresponding author.

matches for live telecasts in order to understand whether the games to which broadcasters give a higher priority are indeed associated with higher television ratings. Sport broadcasters are rational decision makers and artistic producers of sport programs. Therefore, whether their choices of matches lead to higher audience demand is an open empirical question. Second, we examine the factors driving broadcasters' choices of matches to be televised, in order to understand their general decision patterns. The former is investigated through the "viewership model" and the latter is investigated through the "broadcaster choice model."

This study is conducted in the context of the Korea Baseball Organization (KBO), the highest-level professional baseball league, serving in Korea since 1982. The KBO provides a unique research setting not available in other professional leagues in that, with only a few exceptions, all matches in a season are televised nationally, and broadcasters are faced with a decision about selecting which matches to televise the next week and throughout the season. This distinctive structure allows broadcasters to choose which games to televise on a regular basis, making the KBO best suited to studying their decisions without having to study those of other competitors in the broadcasting rights market. The accumulated data based on the broadcasters' weekly decisions during a KBO baseball season can provide practitioners and academicians with valuable insights to understand the general decision-making patterns. In addition, while the previous studies on networks' selection of games to broadcast focus on North American and European sports broadcasting (Forrest et al., 2005), the current study contributes to the literature by extending this stream of research to Asian markets.

Literature Review

Determinants of Viewership for Sport

Most of the determinants of demand used to explain gate attendance in previous works could also explain a major part of viewership, while the effect of these determinants may show dissimilar trends (Tainsky, 2010). As one of the many determinants of the demand for sport, the uncertainty of outcome hypothesis presented by Rottenberg (1956) has driven a body of literature on understanding sport fans' choices and preferences. Although Rottenberg's original work was based on gate attendance demand, much of the viewership literature has also incorporated the topic to understand fans' responses to outcome uncertainty. For instance, Buraimo and Simmons (2009) and Cox (2018) found that fans watching games on television preferred matches that were closely competitive or unpredictable, whereas this effect was unobservable in gate attendance.

More specific to the KBO viewership, Chung et al. (2016) examined the difference between pregame expectations and within-game expectations of outcome uncertainty. The authors found that fans were more responsive to predicted winning probability (i.e., the pregame expectation of outcome uncertainty) before a game started, whereas they were more responsive to real-time changes in winning probability (i.e., the within-game expectation of outcome uncertainty) after a game started. Similarly, Ryu et al. (2019) found that higher ratings of televised KBO matches were associated with greater outcome uncertainty. Additionally, Jung et al. (2020) found asymmetric responses from KBO attendance data: Home team fans showed less interest when the home team was more likely to win (i.e., less outcome uncertainty). However, there was no such effect when the visiting team was more likely to win. These findings align with those of Meehan et al. (2007) that fans tend to be attracted to a well-performing visiting team regardless of the outcome uncertainty. However, evidence of outcome uncertainty is still convoluted because many other studies have reported no evidence of uncertainty of outcome hypothesis (Buraimo & Simmons, 2015; Paul & Weinbach, 2015; Pérez et al., 2017; Sung et al., 2019). Overall, uncertainty of outcome hypothesis is a form of speculation of fan preferences, which are assumed to be inherently different from individual to individual. Thus, further investigation is needed to reveal fan preferences in various contexts, as Fort (2017) noted.

Common factors that could be considered with respect to the demand for sport include the effects of superstars (i.e., star athletes); proximity between competing teams (i.e., distance); rivalry; and duration of a sport team's presence (i.e., team age). First, the superstar effect is characterized by a few individuals providing a large return based on their highly valued talent (Rosen, 1981). That is, in the sport context, a handful of athletes who show on-field prowess will earn higher salaries compared to other less talented athletes, making them a valuable product. Further, superstars generate externalities not only for their home teams but also for the overall league. Hausman and Leonard (1997) estimated the value of Michael Jordan for the National Basketball Association and found it to be more than 50 million dollars—more than any other player in the National Basketball Association. This superstar effect was also found in European soccer leagues (Buraimo & Simmons, 2015; Czarnitzki & Stadtmann, 2002), Major League Soccer (DeSchriver et al., 2016; Lawson et al., 2008; Sung & Mills, 2018), and Major League Baseball (Lewis & Yoon, 2018; Mullin & Dunn, 2002; Ormiston, 2014).

Distance between competing teams also has an impact on demand. According to Hotelling's (1929) location model, demand for a certain firm is dependent on the distance between consumer and product. That is, all else being equal, products that are farther away from a consumer become less ideal as the associated costs may increase. Hence, a negative linear relationship between consumer demand and distance exists. Empirically, previous studies have shown that an increase in distance is negatively associated with attendance demand, and this effect becomes more pronounced as the season progresses (Forrest & Simmons, 2002; Lemke et al., 2010). This effect could also be related to substitution behavior, according to which sport fans switch their favorite teams based on the distance of their residence to the sport team. Winfree et al. (2004) found that introducing a new team in a region with an existing one can lead to a decrease in fans for the existing team because the new team may absorb this loss. In terms of viewership markets, Tainsky and McEvoy (2012) found that distance had a negative impact on demand; specifically, when no home team match was televised, out-of-market teams that were located closest to fans were preferred.

Relevant to distance, literature suggests that rivalry can boost fan interest in matches (Beckman et al., 2012; Buraimo & Simmons, 2008; Lemke et al., 2010; Paul, 2003). However, the definition of "rival" is different across leagues. There are various factors that influence the formation of rivalry, such as history, geographical proximity, frequency of meeting, and similarity (Kilduff et al., 2010; Tyler & Cobbs, 2015). Sung et al. (2017) urged that the investigation of sport rivalry in demand studies should take intensity, direction, and duration into account. In other words, how strongly a fan feels about the rivalry, whether both teams' fans feel the same way or not, and how long the rivalry has been in existence are important factors to be taken into consideration when examining the influences of rivalry.

Finally, sport teams with a longer history and existence influence fan loyalty and, thus, viewership (Coates & Humphreys, 2005). Over time, a team with a longer presence in a particular region is more likely to form a loyal fan base (Borland & MacDonald, 2003). Because higher fan loyalty implies a greater demand for the team, previous demand studies have widely used team age as a proxy to measure the effects of fan loyalty on demand (Coates & Humphreys, 2005; Sung & Mills, 2018; Tainsky & Jasielec, 2014; Wooten, 2018).

Determinants of Broadcasters' Demands and Choices

For the last several decades, the exposure of televised sport content has increased, and, as a result, so have the media rights fees because of the uptick in demand from more broadcasters (Noll, 2007). In particular, Noll speculated that the growth in commercial broadcasters has increased the demand for broadcasting rights. Hence, the fees for the right to air a program and airing hours have significantly increased. However, the objectives of public and commercial broadcasters differ from each other. Public service broadcasters, established to support the public welfare, are more concerned with program diversity and providing programs of merit goods characteristic than commercial broadcasters, which are primarily interested in profit maximization (Solberg, 2007). For this, many public service broadcasters receive license fees (e.g., BBC in the United Kingdom), whereas commercial broadcasters seek to maximize television ratings to pursue the highest possible revenues from advertisements and subscriptions (Gratton & Solberg, 2007).

Unfortunately, research on the determinants that influence broadcasters' choices of matches to televise is limited. Among the dearth of literature, Forrest et al. (2005) examined the choices of British broadcasters for EPL games. They found that broadcasters preferred matches involving contenders for the EPL championship or European Championship League qualification, matches between local rivals, and matches held on weekends. Also, matches with greater unpredictability, and a larger sum but a smaller gap between the competing teams' wages, were selected by broadcasters with higher priority. Forrest et al. (2006) examined broadcasters' choices for EPL matches based on a five-season data set and reported a similar pattern of results.

Broadcasting of the KBO League and Research Questions

Established in 1982, the professional KBO league has a long history in Korea, and it is the most popular professional sport league in Korea (KBO, 2020). The KBO league was founded with six teams and in 2015 it expanded to 10 teams. Unlike Major League Baseball in North America, comprised of three divisions (i.e., West, Central, and East Divisions), the KBO league comprises a single division of 10 teams. There is also a minor league called the KBO Futures League, which is similar to Minor League Baseball in the United States.

Until 1994, only national terrestrial broadcasting networks were able to televise KBO matches (Ha, 2014). Subscription-based cable and satellite channels started broadcasting KBO games in 1995 and 1997, respectively. In the early 2000s, sport channels were established in the pay TV market, expediting the expansion of the sport broadcasting market.

The uniqueness of the KBO television market is that, unlike other professional sport leagues in the United States and Europe, all games, with only a few exceptions, have been televised nationally via pay TV sport channels since 2008. This is because the KBO requires sport channels to air at least 95% of total matches. The three terrestrial channels in Korea have to air a minimum of 10 matches. Both sport channels and the three terrestrial channels provide national coverage, so all KBO matches are televised nationally. Because of pay TV's reasonable subscription prices, the penetration rate of pay TV services in the Korean broadcast market has reached almost 100%; the basic program package includes all five sport channels responsible for KBO broadcasts at a cost of approximately $20 USD per month (KISDI Report, 2019).

KBO games are scheduled from Tuesday through Sunday. Five games are played each day, and five sport channels are available to televise the matches. To distribute the games without dispute, a system was implemented to determine the order of pick for match selection. At the beginning of each season, the order of pick (e.g., 1–5) is decided randomly through a number draw and assigned to the five channels. The channel with the first pick receives priority in selection, and according to the established order, each channel chooses which game to televise the following week from the available matchups. The order of selection rotates sequentially every week. Thus, if one channel chooses first in one round, it chooses second in the next round and so on. Under these circumstances, a unique situation is created where broadcasters face decisions every week about the most preferred games to televise. The selection process results in a lineup of matches each week that are ranked according to the broadcaster's choice order, thus providing a unique opportunity to examine the determinants that influence broadcasters' choices.

On the one hand, sport broadcasters of the KBO league can be viewed as skilled professionals, making logical and rational decisions to maximize the viewership of the televised matches. On the other hand, the broadcasters can be seen as artistic producers of sport programs who base their decisions more on intuition and feelings than evidence and hard data. Thus, whether the games broadcasters give a higher priority to actually lead to greater audience demand is an open empirical question. This study also examines what other factors affect television ratings. Based on the above discussion, the following research questions (RQ) are proposed:

RQ1: Does the broadcasters' choice order for the televised games affect the television ratings of the game?

RQ2: Which factors, besides the broadcasters' choice order, affect the television ratings of the game?

RQ3: What are the determinants of the broadcasters' choice order for the games to be televised?

Methods

Data Structure

A panel data set, that is, a data set containing cross-sectional time-series data, was collected from the game record data of the 2018 KBO league pennant races held from March to October 2018. There are 10 teams in the league, and each team plays every other team 16 times, resulting in 144 games for each team. This results in 720 games total. A total of 718 games were televised; the two games not televised by any channel were excluded from the analysis. Further, three terrestrial TV channels in Korea chose 10 games to televise, and the sport channels televised the remaining games. These 10 games were excluded from the analysis because the sport channels' choices of games to be televised was the key variable of interest. As a result, a total of 708 games were analyzed in the panel data set. The panel variable was the matchup ($i = 1, \ldots 45$), and the time variable was the round of the game ($t = 1, \ldots 16$).

Model and Analyses

Two regression models were examined. The first, the viewership model, examined which factors, including the broadcasters' choice order, affected a game's television ratings (i.e., DV = log-transformed TV ratings). The second model, the broadcaster choice model, examined the factors affecting the broadcasters' choice order for the games to be televised (i.e., DV = broadcasters' choice order). Broadcasters' choices for games were decided a week in advance; thus, game choice decisions were made on a weekly basis for the following week's games. Each of the five available sport channels took turns choosing first out of the five available games each week. In practice, broadcasters may have their own agendas within the market, so the demand for a certain type of content, such as baseball games, may vary from one broadcaster to another. Therefore, an analysis of the data set based on the game choices of all available sports channels and the respective television ratings of the televised games can reveal valuable insights to understand the broadcasters' decision-making patterns and their relation to the actual audience demand for the live sport broadcast.

Seminal works in sport demand studies, such as Rottenberg (1956), Borland and MacDonald (2003), and Fort (2006), identified factors determining stadium attendance, such as price, income, population, stadium capacity, viewing quality at stadium, game characteristics, substitutes, and consumer preferences. Some of these factors, such as price, stadium capacity, and viewing quality, are only relevant to stadium spectatorship and are not applicable to this study focusing on TV viewership. Additionally, income and population do not apply to the TV audience market of the KBO league because there are no local broadcasts like in the United States (i.e., all games are televised nationally), leaving the income and population factors constant in the TV audience market. Considering the nature of the KBO broadcasting environment, we focused on game characteristics and audience preferences. An overview of the dependent and independent variables is presented in Table 1.

For the viewership model, the dependent variable was log-transformed TV ratings (*LnRatings*), and the primary independent variable was the broadcasters' choice order (*ChoiceOrder*). Other predictors of *LnRatings* included the following five categories of factors: (a) past records of the same matchup (i.e., past game

Table 1 Descriptions of Variables

Categories	Variables	Descriptions	Type
TV ratings	*Ratings*[a]	Mean TV ratings per minute of the live game	Continuous
	LnRatings	Log-transformed *Ratings*	Continuous
Choice order	*ChoiceOrder*	Broadcasters' choice order (First choice through fifth choice)	Ordinal
Past game attributes	*LnLagRatings*	Log-transformed mean ratings of the same matchup's most recent game series	Continuous
	LagScoreDiff	Mean score difference of the same matchup's most recent game series	Continuous
	HomeRank	Current standing of home team up to most recent game	Continuous
	AwayRank	Current standing of away team up to most recent game	Continuous
Current game attributes	*SumScore*	Sum of both team's score	Continuous
	ExtraInnings	Whether the game went into overtime (extra innings = 1 and no extra innings = 0)	Dummy
	ScoreDiff	Final score difference	Continuous
Predicted game attributes	*Theil*	Measure of uncertainty of outcome by Theil (1967) times 100 for interpretation	Continuous
	BetReverse	Reverse bet outcome defined as any outcome that has turned out to be opposite of a priori information	Dummy
Team attributes	*SumTeamAge*	Sum of competing teams' age	Continuous
	Rival	Whether the matchup is between two rival teams or not (rival = 1 and nonrival = 0)	Dummy
	LagPostSeason	Whether the matchup involves a team which appeared in at least one game from the previous season's postseason games (yes = 1 and no = 0)	Dummy
	LnTotalSalary	Log-transformed sum of total salary of both home and away team	Continuous
	Allstar	Number of players designated for Allstar game in 2018	Continuous
External factors	*Dist*[a]	Distance between the two teams' home stadiums in kilometers	Continuous
	LnDist	Log-transformed *Dist*	Continuous
	Weekend	Whether the game is part of the weekday series (weekend series = 1 and weekday series = 0)	Dummy
	NightTime	Whether the game was held during the night time (night game = 1 and daytime game = 0)	Dummy
	Temp	The highest temperature of the game day in Celsius	Continuous
	Weather	Whether the day was sunny (sunny = 1 and cloudy/rainy = 0)	Dummy
	Month	Month (March/April, May, June, July, August, September, and October)	Categorical
	Network	Network channels (KBS N Sports, MBC Sports+, SBS Sports, SPOTV, SPOTV2, and Multi)	Categorical

[a]Raw data before log transformation.

attributes); (b) the attributes of the game being watched (i.e., current game attributes); (c) predicted on-field performances of each team and the associated match outcomes (i.e., predicted game attributes); (d) attractiveness of the matchup (i.e., team attributes); and (e) other external factors.

The explanatory variables related to past game attributes included *LnLagRatings*, *LagScoreDiff*, *HomeRank,* and *AwayRank*, and *LnLagRatings* was the log-transformed mean rating of the same matchup's most recent game series. The most recent game series referred to the two or three consecutive games between the same matchup teams. KBO usually schedules three games between the same matchup teams in a row, but occasionally organizes only two consecutive games. *LagScoreDiff* was the mean score difference of the same matchup's most recent game series. *HomeRank* and *AwayRank* were the home and away teams' standings within the league up to the most recent game.

The explanatory variables related to current game attributes included *SumScore*, *ScoreDiff*, and *ExtraInnings*. *SumScore* represented the sum of both teams' scores, and *ScoreDiff* was the final score difference. *ExtraInnings* was a dummy variable indicating whether the game went into overtime (extra innings = 1 and no extra innings = 0).

The explanatory variables related to predicted game attributes included *Theil* and *BetReverse*. *Theil* is the measure of uncertainty of outcome (Theil, 1967), which has been used in previous attendance and viewership studies (Buraimo & Simmons, 2008; Cox, 2018; Pawlowski & Anders, 2012; Schreyer et al., 2018; Sung et al., 2019). *Theil* is then calculated as follows:

$$Theil = \sum_{i=1}^{2} \frac{p_i}{\sum_{i=1}^{2} p_i} \log \frac{\sum_{i=1}^{2} p_i}{p_i}.$$

Each p_i is the probable outcome of any game (i.e., win or loss) based on betting odds. $\sum_{i=1}^{2} p_i$ is then equal to one because it is the sum of all possible outcomes. The *Theil* value increases as uncertainty increases. We multiplied the *Theil* index by 100 for better interpretation. *BetReverse* was the reverse bet outcome defined as any outcome that turned out to be opposite to a priori information. That is, it was a dummy variable that indicated matches where a team that had a lower probability of winning based on betting odds eventually won the game.

The explanatory variables related to the team attributes included *SumTeamAge*, *Rival*, *LagPostSeason*, *LnTotalSalary*, and *Allstar*. *SumTeamAge* was the sum of competing teams' ages. *Rival* was a dummy variable indicating whether the matchup was between two rival teams or not. There were four historical rival matchups in KBO, which were coded as *Rival* (rival = 1 and nonrival = 0). The rivalry in the KBO did not convert mechanically to the matches between the two geographically adjacent teams; instead, the historical rivalry naturally originated from teams sharing the same hometown or region. *LagPostSeason* was a dummy variable indicating whether the matchup involved a team that appeared in at least one game from the previous post season (yes = 1 and no = 0). *LnTotalSalary* measured the log-transformed sum of the home and away teams' wages of players as a proxy of team quality. *Allstar* was used as an indicator of the total number of players in a match who were designated as All-Star players in the 2018 season, to account for the superstar effect of high-profile players in the current year.

The variables related to the external influencers included *LnDist*, *Weekend*, *NightTime*, *Temp*, *Weather*, *Month*, and *Network*. *LnDist* was the log-transformed distance between the two teams' home stadiums in kilometers. *Weekend* was a dummy variable indicating whether the game was a part of the weekday series (weekend series = 1 and weekday series = 0). Weekday series included games held on Tuesday through Thursday, and the weekend series included games held on Friday through Sunday. *NightTime* was a dummy variable indicating whether the game was held at night (night game = 1 and daytime game = 0). Day games were those that started at 2:00 p.m. and night games started at 6:30 p.m. *Temp* was the highest temperature of the game day in Celsius. *Weather* was a dummy variable indicating whether the day was sunny (sunny = 1 and cloudy/rainy = 0). *Month* represented a categorical variable indicating the month when the game was held (March/April through September). Because there were only a few games held in March, March and April were combined into one category, March/April. Finally, *Network* was a categorical variable indicating the broadcast channel. The games were televised via one of the five channels or sometimes by multiple channels simultaneously; thus, the total number of categories of the *Network* was six (five channels plus simultaneous broadcasts by multiple channels). Quite reasonably, broadcasters avoided choosing the game already selected by another broadcaster, so that each channel could televise different games. But there were some exceptional cases when a broadcaster selected a game that was already selected by another broadcaster in an earlier order, resulting in the same game being televised by multiple channels simultaneously; these cases occurred when part of the daily game lineup was canceled due to bad weather conditions. Although only 24 games (3.3% of the 708 games) were televised by multiple channels, it was necessary to control for the effects of simultaneous broadcasting in the regression model by having the variable *Network* include a category representing the case when multiple channels broadcast the same game.

The viewership model was specified as follows:

$$LnRatings_{\mathrm{it}} = \beta_0 + \beta_1 ChoiceOrder_{\mathrm{it}} + \sum_{j=2}^{5} \beta_j PGA_{jit} + \sum_{k=6}^{8} \beta_k CGA_{kit} + \sum_{l=9}^{10} \beta_l PreGA_{lit} + \sum_{v=11}^{15} \beta_v TA_{vit} + \tau_{it} + \varepsilon_{it},$$

where $LnRatings_{it}$ is the log-transformed mean of the television ratings per minute of the live game for the ith matchup ($i = 1 \ \ldots\ 45$) of the tth round of game ($t = 1 \ \ldots\ 16$). For independent variables, $ChoiceOrder_{it}$ is the ordinal value of broadcasters' choice order, PGA_{jit} is the jth past game attribute, CGA_{kit} is the kth current game attribute, $PreGA_{lit}$ is the lth predicted game attribute, TA_{vit} is the vth team attribute, τ_{it} is external factors, and ε_{it} is the error term. Using Stata (version 16; StataCorp LLC, College Station, TX), the dependent variable was regressed on the set of independent variables with the random-effects model and the feasible generalized least squares (FGLS) model.

Regarding the broadcasters' choice model, it was reasoned that broadcasters would likely select the game matchup which is expected to produce the highest ratings when making a choice about the coming week's games for telecast, based on either experience or hard data from a similar set of variables as those of the viewership model. Current game attributes are not available to broadcasters who need to make decisions at least a week ahead of the actual games. Also, while a 10-day forecast was available in Korea, the forecast data of the past dates were not available for data collection. Therefore, the three current game attributes (*SumScore*, *ExtraInnings*, and *ScoreDiff*) and the two game-day factors (i.e., *Temp*, *Weather*) were excluded from the broadcaster choice model. All other explanatory variables were identical to those in the viewership model.

The broadcaster choice model was specified as follows:

$$ChoiceOrder_{it} = \alpha_0 + \sum_{j=1}^{4} \alpha_j PGA_{jit} + \sum_{k=5}^{6} \alpha_k PreGA_{kit} + \sum_{l=7}^{11} \alpha_l TA_{lit} + \tau_{it} + \varepsilon_{it},$$

where $ChoiceOrder_{it}$ was the broadcasters' choice order (ordinal variable, the first choice through the fifth choice) for the ith matchup ($i = 1 \ldots 45$) of the tth round of game ($t = 1 \ldots 16$). For independent variables, PGA_{jit} is the jth past game attribute, $PreGA_{lit}$ is the lth predicted game attribute, TA_{vit} is the vth team attribute, τ_{it} is external factors, and ε_{it} was the error term. Because of the ordinal nature of the dependent variable, *ChoiceOrder* was regressed on the independent variables using both the ordered logistic model and ordered probit model. Both the ordered logit and ordered probit models were fit via the maximum likelihood random-effects estimators.

Findings and Discussion

Descriptive Statistics

Table 2 shows the descriptive statistics of the key variables. The highest television rating for the KBO games was 4.13%, whereas the mean rating was 1%. That is, approximately half a million fans watched KBO games on average. The highest viewership level was recorded at approximately 2.15 million.[1] Regarding the game attribute dummy variables, a total of 7% of the games went into extra innings, whereas 9% of games were between rivals. Additionally, about 43% of the total games resulted in reverse outcomes, based on betting predictions. For other external factors, 48% of the total games were played on the weekend, and as many as 86% of the games were played after 6:30 p.m. Games played in sunny weather accounted for almost half the games, whereas the rest were played under cloudy or rainy weather conditions.

Factors Affecting Television Viewership (RQ1–2)

To examine RQ1 and RQ2, the viewership model was analyzed. The log-transformed TV ratings (*LnRatings*) were regressed on the broadcasters' choice order (*ChoiceOrder*), and a predetermined set of independent variables, including five time-invariant variables (*SumTeamAge*, *Rival*, *LagPostSeason*, *LnTotalSalary,* and *Allstar*). The number of cases used in the analyses was 592. A total of 116 cases were dropped from the analyses because two variables related to the past game attributes—*LnLagRatings* and *LnScoreDiff*—were not available for the season's opening game series.

The random-effects and FGLS models were used to analyze the viewership model. Because the effect of the time-invariant variable was unidentifiable in the fixed-effects model, the random-effects model was first employed to analyze the data. The results of Breusch–Pagan's Lagrangian Multiplier test for the random-effects model were statistically significant, $\chi^2(1) = 64.39$ ($p < .01$). Rejection of the null hypothesis of the Breusch–Pagan's Lagrangian Multiplier test (i.e., the variance of the unique errors [u_i] of the panels does not differ from zero) indicated the existence of random effects; therefore, the unique panel characteristics needed to be accounted for in the regression model, which the pooled Ordinary Least Squares was unable to do. In addition, the result of the likelihood ratio test for the heteroscedasticity of error terms was statistically significant, indicating the presence of heteroscedasticity, $\chi^2(44) = 114.77$ ($p < .01$); thus, clustered robust *SE*s were used for the random-effects regression. Meanwhile, there was no evidence of significant multicollinearity issues, as indicated by the fact that all variance inflation factor values were below four. The random-effects model was significant, $\chi^2(31) = 2516.01$ ($p < .01$); the overall R^2 was 84.13%, and the ρ, or the fraction of variance due to the panel variable, was 17.22%.

The random-effects model, however, imposed a strong assumption that the unique errors (u_i) of each panel were uncorrelated with the predictors [i.e., $\mathrm{cov}(X_{it}, u_i) = 0$]. The Hausman test is typically used to examine this assumption; the test compares the differences in the coefficients estimated from the random-effects model to those of the fixed-effects model, which does not require the assumption of independent covariance. However, the viewership model in the current study includes several time-invariant variables. The specifications of the random- and fixed-effects models cannot be the same, because the former includes time-invariant variables, whereas the latter does not; for this reason, the Hausman test was not performed.

Instead, we used the FGLS model, which does not require the assumption that the random-effects model imposes, that is, that the unobserved heterogeneity is uncorrelated with the predictors. Further, the FGLS generates more efficient estimators than the Ordinary Least Squares in the presence of heteroscedasticity and autocorrelation in the panel data set (Bai et al., 2021). The Woodridge test for autocorrelation was also performed, and the result was significant, $F(1, 44) = 32.89$ ($p < .01$), indicating the existence of a first-order correlation within panels. Therefore, the FGLS model was used while correcting for heteroscedasticity and autocorrelation. The FGLS model was significant, $\chi^2(31) = 2{,}246.38$ ($p < .01$); heteroscedasticity was allowed, and a common first-order autocorrelation of .359 was used in the FGLS model.

Because both heteroscedasticity and autocorrelations were corrected for in the FGLS model, and the random-effects model requires a strong assumption that the unobserved heterogeneity is uncorrelated with the independent variables, the FGLS model was deemed more appropriate for the given data—even though the analyses of the two models resulted in a similar pattern of results. Table 3 shows the results of both the random-effects and FGLS models, but the following interpretations focus on the results of FGLS model.

With respect to RQ1, *ChoiceOrder* had a significant and positive impact on *LnRatings* ($\beta_{FGLS} = -0.155$, $p < .01$). The significant coefficient for broadcasters' choices of matches (*ChoiceOrder*) indicates that the broadcasters' selection priorities were well aligned with the actual television ratings. This result, however, should be interpreted with caution because it does not indicate that the rank of the games decided by the broadcasters, which is not revealed to consumers, changes consumer preference for the games. Rather, the result indicates that broadcasters' choices of games were well reflected in the future audience demand for the sport telecasts.

Regarding RQ2, it appears that all of the current game attributes were significant in predicting television ratings. However, not all variables related to the past game attributes, the team attributes, and the external influencers had significant impacts on the audience viewership, while none of the predicted game attributes were statistically significant.

Table 2 Descriptive Statistics of the Key Variables

Categories	Variables	Mean (frequency)[a]	*SD* (%)[a]	Minimum	Maximum	*N*	Type
TV ratings	*Ratings*[b]	1.00	0.56	0.10	4.13	708	Continuous
	LnRatings	–0.17	0.61	–2.26	1.42	708	Continuous
Choice order	*ChoiceOrder*	2.95	1.41	1.00	5.00	708	Ordinal
Past game attributes	*LnLagRatings*	–0.17	0.58	–1.88	1.01	592	Continuous
	HomeRank	5.40	2.93	1.00	10.00	708	Continuous
	AwayRank	5.38	2.84	1.00	10.00	708	Continuous
	LagScoreDiff	4.04	1.97	0.50	13.50	592	Continuous
Current game attributes	*SumScore*	11.14	5.17	1.00	30.00	708	Continuous
	ExtraInnings	0.07	—	0.00	1.00	708	Dummy
	ScoreDiff	4.11	3.11	0.00	18.00	708	Continuous
Predicted game attributes[c]	*Theil*	29.39	0.92	15.67	30.10	708	Continuous
	BetReverse	0.43	—	0.00	1.00	708	Dummy
Team attributes	*SumTeamAge*	45.06	15.81	12.00	72.00	708	Continuous
	Rival	0.09	—	0.00	1.00	708	Dummy
	LagPostSeason	0.22	—	0.00	1.00	708	Dummy
	LnTotalSalary	23.45	0.16	23.10	23.76	708	Continuous
	Allstar	4.78	3.80	0	15	708	Continuous
External factors	*Dist*[b]	210.22	126.79	<0.01[d]	405.35	708	Continuous
	LnDist	4.82	1.94	–6.91	6.00	708	Continuous
	Weekend	0.48	—	0.00	1.00	708	Dummy
	NightTime	0.86	—	0.00	1.00	708	Dummy
	Temp	20.95	5.89	3.90	33.40	708	Continuous
	Weather	0.50	—	0.00	1.00	708	Dummy
	Month	—	—	—	—	708	Categorical
	March/April	146	20.62	—	—		
	May	119	16.81	—	—		
	June	120	16.95	—	—		
	July	109	15.40	—	—		
	August	63	8.90	—	—		
	September	117	16.53	—	—		
	October	34	4.80	—	—		
	Network	—	—	—	—	708	Categorical
	KBS N Sports	138	19.49	—	—		
	MBC Sports+	134	18.93	—	—		
	SBS Sports	140	19.77	—	—		
	SPOTV	135	19.07	—	—		
	SPOTV 2	137	19.35	—	—		
	Multi[e]	24	3.39	—	—		

[a]Frequency and percentage for dummy and categorical variables. [b]Raw data before log transformation. [c]Predicted game attributes. [d]Two teams share the same stadium, and the distance between these two teams was coded as 0.001 km. [e]Multi indicates the games were televised simultaneously by more than two channels.

Specifically, three of the four past game attributes were statistically significant. *LnLagRatings* had a positive influence on TV ratings ($\beta_{FGLS} = 0.171$, $p < .01$), indicating the existence of an inertia of interest from the previous matchups. *LagScoreDiff* ($\beta_{FGLS} = -0.011$, $p < .01$) was also statistically significant. The results indicated that a one-point increase in the mean score difference of the same matchup's most recent game decreased ratings by 1.1%. That is, KBO fans preferred games where the previous result of the same matchup had a smaller final score difference. Finally, between the home and away teams' standings in the league, only *HomeRank* was found to negatively influence ratings ($\beta_{FGLS} = 0.009$, $p < .01$); this result indicates that the matchups involving a home team with higher league standing are associated with greater television viewership.

The three current game attributes, *SumScore* ($\beta_{FGLS} = 0.005$, $p < .01$; $\beta_{\mathfrak{R}} = .006$, $p < .01$), *ExtraInnings* ($\beta_{FGLS} = 0.135$, $p < .01$; $\beta_{\mathfrak{R}} = .149$, $p < .01$), and *ScoreDiff* ($\beta_{FGLS} = -0.032$, $p < .01$; $\beta_{\mathfrak{R}} = -.031$, $p < .01$) significantly affected TV ratings. The games with higher scores that went into extra innings and with smaller final score differences were associated with higher TV ratings. That

Table 3 Regression Results of Viewership Model

	Variables	Random effects	Robust *SE*	FGLS	*SE*
Choice order	*ChoiceOrder*	–0.131***	0.016	–0.155***	0.014
Past game attribute	*LnLagRatings*	0.131***	0.040	0.171***	0.033
	LagScoreDiff	–0.008	0.005	–0.011**	0.005
	HomeRank	–0.005	0.004	–0.009***	0.003
	AwayRank	0.001	0.004	0.002	0.003
Current game attribute	*SumScore*	0.006***	0.002	0.005***	0.002
	ExtraInnings	0.149***	0.036	0.135***	0.032
	ScoreDiff	–0.031***	0.004	–0.032***	0.003
Predicted game attribute	*Theil*	–0.001	0.006	0.009	0.009
	BetReverse	0.034*	0.019	0.020	0.015
Team attribute	*SumTeamAge*	0.004*	0.002	0.002*	0.001
	Rival	0.002	0.053	–0.009	0.046
	LagPostSeason	-0.064	0.053	–0.068**	0.031
	LnTotalSalary	1.580***	0.260	1.322***	0.152
	Allstar	–0.004	0.007	0.002	0.004
External factors	*LnDist*	0.011	0.011	0.014	0.010
	Weekend	–0.044*	0.023	–0.046**	0.018
	NightTime	0.096***	0.031	0.095***	0.024
	Temp	–0.004	0.006	–0.005	0.004
	Weather	–0.012	0.022	–0.029*	0.016
	Month[a]	—	—	—	—
	May	0.204***	0.056	0.175***	0.046
	June	0.156**	0.064	0.154***	0.051
	July	0.094	0.073	0.073	0.063
	August	0.150*	0.088	0.199***	0.065
	September	0.017	0.059	–0.002	0.050
	October	0.018	0.082	–0.004	0.064
	Network[b]	—	—	—	—
	MBC Sports+	0.116***	0.038	0.129***	0.030
	SBS Sports	0.135***	0.033	0.137***	0.031
	SPOTV	-0.002	0.033	0.001	0.031
	SPOTV 2	–0.276***	0.043	–0.278***	0.030
	Multi	0.204**	0.085	0.107*	0.060

Note. FGLS = feasible generalized least squares.
[a]Reference month: March/April. [b]Reference channel: KBS N Sports; DV = *LnRatings*; $N = 592$.
*$p < .10$. **$p < .05$. ***$p < .01$.

is, similar to Alavy et al. (2010), viewers of KBO games showed interest in games with higher scores, while preferring a smaller gap in the score difference between the two teams rather than a blowout game. Additionally, higher ratings for games with extra innings implied viewer preference for games that were closely matched until the end of the game. Alternatively, games that went into extra innings might have drawn viewers from other games that ended earlier.

None of the two predicted game attributes, *Theil* (the outcome uncertainty) and *BetReverse,* significantly influenced TV ratings. This contradicts the previous literature, which found fans' preference for outcome uncertainty in the KBO context (Chung et al., 2016; Ryu et al., 2019).

For the five team attribute variables, it was most apparent that *LnTotalSalary* ($\beta_{FGLS} = 1.322$, $p < .01$; $\beta_{\mathfrak{R}} = 1.580$, $p < .01$) had significant and positive impacts on ratings, reflecting the preference of KBO fans for matchups between teams with higher-wage players. In other words, assuming total wages as a proxy of team quality, games between higher-quality teams attracted more viewers. For *LagPostSeason* ($\beta_{FGLS} = -0.068$, $p < .05$), fewer fans watched KBO games on TV when the matchup involved a team appearing in at least one game from the previous year's postseason. One possible reason for this relationship is that there is much fluctuation in each team's league standing from one season to another, so playing in the previous seasons' postseason may be associated with lower league standings in the following season; indeed, the Spearman's rank-order correlation between the league standings in 2017 and 2018 was only .20 and was not statistically significant. *SumTeamAge* ($\beta_{FGLS} = .002$, $p < .10$) had a positive and significant impact on ratings at the 90% significance level. The result indicates that an additional year of presence within the league increased ratings by 0.2%; this pattern is consistent with previous research suggesting that teams with a longer league history possess a greater fan base (Borland & MacDonald, 2003; Coates & Humphreys, 2005). However, rival matchups (*Rival*) did not have a significant effect on viewership. Finally, we were unable to detect any evidence of the superstar effect because the total number of 2018 All-Star players (*Allstar*) had no significant effect.

With respect to the external influencers, *Weekend*, *NightTime*, and *Weather* appeared to be significant predictors of television ratings. Nighttime games (*NightTime*, $\beta_{FGLS} = 0.095$, $p < .01$) were associated with higher television ratings. The television ratings for weekend series games were lower than those for weekday series games (*Weekend*, $\beta_{FGLS} = -.046$, $p < .05$). Further, sunny days were associated with lower television ratings when compared to cloudy or rainy days ($\beta_{FGLS} = -0.029$, $p < .10$), but only at the 90% level. These results suggested the possible substitute behavior of KBO fans; that is, during the daytime, on weekends, and on sunny days, other available substitutes to watching televised baseball games may exist, including physically attending the game or engaging in other non-baseball-related activities.

Factors Affecting Broadcasters' Choices of Games (RQ3)

To examine RQ3, broadcasters' choice order (*ChoiceOrder*) was regressed on the predetermined set of independent variables using ordered logit and ordered probit models. The number of cases for both models was 592. To test for the heteroscedasticity of error terms, the likelihood ratio test was employed to compare the log likelihood between the restricted model assuming homoscedastic error structure and the unrestricted model lifting the homoscedasticity assumption, thus allowing heteroscedasticity with no cross-sectional correlation. The result was statistically significant, indicating the presence of heteroscedasticity in the error structure, $\chi^2(44) = 151.01$ ($p < .01$). With the presence of heteroscedasticity, clustered robust SEs were used for the ordered logit and ordered probit analyses, which allowed for the intrapanel correlation of the observations. Both the ordered logit model, $\chi^2(25) = 135.44$ ($p < .01$), and the ordered probit model were significant, $\chi^2(25) = 151.56$ ($p < .01$).

The results presented in Table 4 show that both the ordered logit and the ordered probit models produced a similar pattern of results.

It appears that three of the four past game attributes played significant roles when broadcasters made decisions about which games to televise in the coming week. *LnLagRatings* ($\beta_{ologit} = -1.323$, $p < .10$; $\beta_{oprobit} = -0.822$, $p < .05$) was a significant and negative predictor of *ChoiceOrder*. This indicates that the higher the TV ratings of the most recent game series between the same matchup teams, the more the broadcasters prioritized the game. *AwayRank* ($\beta_{ologit} = 0.102$, $p < .05$; $\beta_{oprobit} = 0.056$, $p < .05$) was a significant and positive predictor of choice order; likewise, *HomeRank* ($\beta_{oprobit} = 0.044$, $p < .10$) was a significant and positive predictor of the broadcasters' choice order, but only for the ordered probit model at the 90% significance level. These results indicate that broadcasters preferred games between teams at higher league standings up to the most recent game, and that away teams' league standings (vs. home teams') were a more stable influencer of broadcasters' game choices. However, *LagScoreDiff* did not influence the broadcasters' choice order.

Of the two predicted game attribute factors, *Theil* ($\beta_{ologit} = 0.338$, $p < .05$; $\beta_{oprobit} = 0.182$, $p < .05$) had a positive and significant impact on *ChoiceOrder*; the positive relationship indicated that when a higher uncertainty of the outcome of a game is anticipated, broadcasters are less likely to choose the game for the next week's telecast. This indicates broadcasters' tendency to select games with more certain than uncertain outcomes. *BetReverse* did not influence the broadcasters' choice order.

Of the five team attribute factors, the sum of both teams' total salaries, *LnTotalSalary* ($\beta_{ologit} = -27.849$, $p < .01$; $\beta_{oprobit} = -15.474$, $p < .01$), was a significant and negative predictor of broadcasters' choice order, suggesting that broadcasters preferred to select games between teams with a higher total sum of wages. *LagPostSeason* ($\beta_{ologit} = 1.940$, $p < .10$; $\beta_{oprobit} = 1.138$, $p < .10$) had a significant and positive impact on *ChoiceOrder*, albeit at a weak level of significance. This implies that broadcasters did not prioritize teams that advanced into the prior postseason. One possible interpretation is that broadcasters took into account the inverse relationship between playing in the postseason in the previous season and TV ratings, as evidenced in our viewership model. The remaining three team attribute factors—*Allstar*, *Rival*, and *SumTeamAge*—did not show any statistical significance.

Finally, none of the external influencers, including the physical distance between teams (i.e., *LnDist*) and the day and time of the games (i.e., *Weekend* and *NightTime*), had a significant impact on broadcasters' choice order.

General Discussion

There is a dearth of literature on the topic of understanding the choices of broadcasters in the context of live sport programs and TV audiences' demands. The empirical results of the current study provide both broadcasters and academia with valuable insights to understand the sport broadcast market dynamics. The key findings of the current study were twofold. First, our analyses revealed that the broadcasters' choices of matches for live telecasts well reflected the actual TV audience demand. Second, different patterns of demand were observed for the broadcaster choice and the viewership models. Most notably, the predicted game attributes, such as outcome uncertainty, appeared to be significant predictors of the broadcasters' choice of games for live telecasts but not for the viewership; rather, viewership was determined by the past and current game attributes as well as the team attributes.

These findings serve as a useful avenue for discussion. The fact that the games selected with higher priority were indeed associated with greater audience viewership indicates that the KBO broadcasters, although they do not go through systematic analyses before selecting games for live telecasts, have a reasonably good sense of which games will result in high TV ratings. Thus, it is reasonable to assume that broadcasters are rational decision makers whose objective is to maximize ratings (Noll, 2007).

Nonetheless, there are some notable discrepancies in the results from the viewership model and the broadcaster choice model, indicating that broadcasters have less than perfect understanding of the factors driving TV audience demand, or there are some factors broadcasters are unable to consider at the time of game selection. First, smaller score difference in the same matchup in the most recent game series led to higher viewership, but broadcasters did not take into consideration the past games' score differences, despite the fact that such information is readily available to broadcasters when they select games. Second, broadcasters

Table 4 Regression Results of Broadcaster Choice Model

	Variables	Ordered logit	Robust *SE*	Ordered probit	Robust *SE*
Past game attributes	*LnLagRatings*	−1.323*	0.740	−0.822**	0.396
	LagScoreDiff	−0.181	0.121	−0.087	0.058
	HomeRank	0.068	0.048	0.044*	0.025
	AwayRank	0.102**	0.051	0.056**	0.025
Predicted game attributes	*Theil*	0.338**	0.165	0.182**	0.091
	BetReverse	0.141	0.206	0.081	0.109
Team attributes	*SumTeamAge*	0.012	0.042	0.008	0.023
	Rival	−1.326	1.742	−0.754	0.987
	LagPostSeason	1.940*	1.134	1.138*	0.638
	LnTotalSalary	−27.849***	4.607	−15.474***	2.456
	Allstar	0.044	0.161	0.016	0.090
External factors	*LnDist*	−0.334	0.232	−0.197	0.130
	Weekend	0.115	0.287	0.025	0.144
	NightTime	0.164	0.410	0.066	0.220
	Month[a]	—	—	—	—
	May	1.227	0.892	0.654	0.499
	June	1.013	0.760	0.520	0.428
	July	0.696	0.964	0.366	0.532
	August	1.338	0.976	0.725	0.536
	September	0.571	0.935	0.312	0.515
	October	−0.536	1.170	−0.319	0.644
	Network[b]	—	—	—	—
	MBC Sports+	−0.357	0.587	−0.282	0.319
	SBS Sports	0.152	0.750	0.022	0.384
	SPOTV	0.625	0.525	0.299	0.293
	SPOTV 2	−0.483	0.599	−0.326	0.324
	Multi	−1.982**	0.982	−1.388**	0.550

[a]Reference month: March/April. [b]Reference channel: KBS N Sports; DV = *ChoiceOrder*; $N = 592$.
$*p < .10$. $**p < .05$. $***p < .01$.

used prediction of possible outcome while viewers used real-time game information to make decisions. Specifically, unlike Forrest et al. (2005), broadcasters tended to choose games with lower outcome uncertainty while viewers showed little interest in the unpredictability of games. This might be due to the fact that the current ongoing game attributes are unavailable to broadcasters at the time of game selection but can be useful information for TV viewers as viewers can switch channels at any time. Third, broadcasters preferred games involving teams close to the top of the league standings, whereas viewership decreased for home team matches with higher league standings. A possible reason for these results might be that while broadcasters believed high-ranking teams or contenders for playoff spots could lure bigger TV audiences (Forrest et al., 2005), home fans might have chosen to physically attend at stadiums rather than watching the televised matches when their teams performed well. It should be noted, however, that such substitution effects were not directly examined in the current study. Future research should examine the possibility that home fans prefer to attend stadiums than watch games on TV when their teams are ranked high in the league standings.

There were also some similar patterns from the viewership and broadcaster choice models. Both TV viewers and broadcasters preferred games with higher TV ratings in the previous game series, showing evidence of the habitual nature of viewership demand for sport (Tainsky & Jasielec, 2014). This indicates that both viewers and broadcasters tend to maintain their interest levels in the same matchups. Alternatively, knowing that audience interest in each matchup has inertia to some degree, broadcasters could make risk-averse decisions by prioritizing matchups that previously generated high TV ratings. As Noll (2007) speculated, commercial broadcasters of the KBO ought to focus on the popularity of the game because of its potential for revenue from additional subscriptions and advertisement fees. Also, both TV viewers and broadcasters preferred games with greater sums of total salary. This result is consistent with prior research demonstrating a positive relationship between total salary and audience demand (Forrest et al., 2005). Interestingly, both TV viewers and broadcasters were less likely to prefer games that had appeared in the previous season's postseason. This result might be a reflection of the fluctuating pattern of the league standings of the KBO teams from 1 year to another; that is, one team may participate in a postseason series 1 year but not in the following year. However, there is no empirical data to support this argument except for the low rank–order correlation ($\rho = .20$, ns) between the 2017 and 2018 league standings of the 10 KBO teams.

This study has managerial and theoretical implications. First, managerially, the findings of this study can serve as guidelines for broadcasters when selecting games most likely to maximize viewership. Second, although the current research context is unique in that five rights-holding channels make weekly decisions to choose which games to televise throughout a season, the findings can be applied to other professional leagues and sports. This is because in most cases rights-holding broadcasters do not televise all available matches included in the media rights package, but select a subset of matches for live telecasts. Therefore, broadcasters are faced with decision tasks to select games for live telecasts, although the number of game selections may vary from one league to another. For example, Olympic rights-holding broadcasters do not televise all matches staged at the Olympic Games, just the ones they select. Theoretically, this study replicates the stream of research that investigates audience demand for media sport (Buraimo & Simmons, 2015; Chung et al., 2016; Jung et al., 2020; Paul & Weinbach, 2013; Sung et al., 2019; Tainsky, 2010) and extends it by incorporating broadcasters' demand for sport games, similar to Forrest et al. (2005).

Despite the contributions that our work makes to the current stream of literature, there are a few limitations that future research could address. First, our data cover a single year of observation, which can lead to additional time-variant determinants being omitted. A longitudinal study covering data from multiple years could reveal any shifts in preference for both broadcasters and viewers and help achieve a deeper understanding of the decision-making process. Second, because we used average ratings at the national level, we were unable to examine the fluctuations in ratings throughout each game. Nor was it possible to understand the specific media consumption patterns of local TV audiences. The use of minute-by-minute data, as well as data separated by local media markets, could help researchers uncover changing patterns of viewership throughout the game and audience behaviors in relation to their geographical location.

Note

1. The population of Korea was approximately 52 million in 2019 (http://www.kostat.go.kr).

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