Examining Determinants of Sport Event Attendance:

A Multilevel Analysis of a Major League Baseball Season

Abstract

Attendance data in sports leagues are organized at more than one level and thus are nested data with factors varying by individual games (e.g., single game attendance figure), which are nested within the factors varying by teams (e.g., local population and income level, stadium). Such a nested data structure requires a multilevel modeling approach for an accurate examination of attendance. Also, although the previous application of multilevel modeling to sport attendance research has been limited to the data aggregated and averaged by seasons or by teams, no multilevel modeling of attendance data at the individual game level is available. The uniqueness of the current study is its extension of the multilevel modeling approach by analyzing the audience data at the individual game level. Thus, this study examined the relationship between attendance determinants and single game attendance in a Major League Baseball (MLB) season by using multilevel modeling with 14 game level variables and 12 team level variables. Twelve predictors (e.g., home/visiting team playoff appearances, day of game, season progress, ticket price, stadium capacity, game uncertainty) ASIGNIFICANTLY ($p < .05$) influenced attendance.

Keywords: attendance; attendance determinants; MLB; multilevel modeling; hierarchical linear regression modeling

1. Introduction

The total revenues of the average Major League Baseball (MLB) team were $237 million in 2013, $262 million in 2014, and $300 million in 2017, which was comparable to that of teams in the NFL, and is the second highest gross of any professional sports league in the world (Gaines, 2014; "Major League Baseball," n.d.; "The business of baseball," n.d.). Because other revenue streams (e.g., television broadcasting rights, new media opportunities, sponsorship deals) have grown recently (Stewart, 2014), the percentage of MLB team revenues from ticket sales among total revenues has recently decreased from 38.2% in 2009 to 30.48% in 2014 ("Regular Season," n.d.). However, ticket sales are still the substantial revenue stream for each MLB team because, as noted by Stewart (2014), one of top four revenue sources for most professional sports teams and leagues is ticket sales.

In fact, ticket sales have been a main revenue source of revenues for professional sports, amateur sports, and mega sporting events (Stewart, 2014). Due to the importance of attendance to the bottom line in the sport industry, numerous studies (e.g., Hansen & Gauthier, 1989; McDonald & Rascher, 2000; Schofield, 1983; Wall & Myers, 1989; Zhang, Pease, Hui, & Michaud, 1995; Zhang & Smith, 1997) have been conducted to examine the attendance determinants for several sport leagues, organizations, and events. The focus of these attendance studies has ranged from examinations of economic factors (McDonald & Rascher, 2000; Wall & Myers, 1989; Zhang et al., 1995; Zhang & Smith, 1997) and spectator preferences (Hansen & Gauthier, 1989; McDonald & Rascher, 2000; Wall & Myers, 1989; Zhang & Smith, 1997) to investigations of game characteristics such as team quality, game uncertainty, and past team accomplishments (e.g., DeSchriver & Jensen, 2002; Lee & Fort, 2008) to the quality of sports facilities, such as the capacity, age, and amenities of stadiums (e.g., McEvoy, Nagel, DeSchriver, & Brown, 2005).

While gate receipts make up an important revenue stream for most spectator-based sport organizations, ticket sales for MLB teams are especially significant because the MLB revenue made up of gate receipts has always been higher than that of other sports. The average gate receipts of MLB teams in 2008 was $76 million per year, almost half as much as the average ticket sales of NFL teams (Vrooman, 2012). A major reason for this is that each MLB team plays 81 home games during one regular season, which is almost twice the number of home games in both the National Basketball Association (NBA) and the National Hockey League (NHL), and 10 times the amount played in the NFL. Because of this unusual MLB business situation, various studies have focused on MLB attendance in the context of factors such as star players and payroll distribution (Rivers & DeSchriver, 2002), location (Winfree, McCluskey, Mittelhammer, & Fort, 2004), and game uncertainty (Knowles, Sherony, & Haupert, 1992; Lee & Fort, 2008). The results of these studies have revealed several variables (e.g., average team payroll, past championships, season rank, distance between home and visiting teams) that significantly affect the attendance statistics of teams' individual games.

While the above attendance studies have contributed to the body of knowledge in this area by defining and testing the relationship between attendance and attendance determinants, such investigations did not apply multilevel models (MLM) also known as hierarchical linear models (HLM) or mixed models even though the attendance data are in the form of the nested data structure. In addition, although some previous studies (e.g., Ferreira & Bravo, 2007; Pecha & Crossan, 2009) have adopted hierarchical modeling to examine the determinants of attendance, these studies examined them but only at the season and team level, and not at the individual game level. Therefore, the purpose of the present study was to examine the MLB attendance determinants within the context of the variances of both the individual game level and the team level by using multilevel models. This was done by examining the data structure, the significant determinants, and the influence of each observed significant determinant on the single game attendance in an MLB regular season.

2. Attendance Determinants in Sporting Events

2.1. Review of Literature

Sporting event attendance accounts for revenues that come from gate receipts, parking fees, stadium concessions, etc. As such, the greater the attendance the more revenue will be realized by a given team or facility (Howard & Crompton, 2014). For this reason, the attendance demand of sporting events has been an interesting subject for researchers (e.g., Hansen & Gauthier, 1989; McDonald & Rascher, 2000; Wall & Myers, 1989; Zhang et al., 1995; Zhang & Smith, 1997). Many studies in this area have classified attendance determinants into either four (Schofield, 1983) or five (Borland & Macdonald, 2003) categories. While Schofield's classification highlighted demographic and economic factors, Borland and Macdonald's classification placed detailed emphasis on the viewing quality of sporting events. Because the present study pays more attention to the effects of demographic and economic factors on attendance, Schofield's attendance determinants categorization is more applicable for the current investigation. The four categories of attendance determinants are factors related to economics, demographics, game attractiveness, and residual preferences. Other researchers have also examined various attendance determinants based on these four categories (e.g., Ferreira & Bravo, 2007; Hansen & Gauthier, 1989; Zhang et al., 1995), with analyses ranging from sports game content and quality of viewing to economic conditions and demographical status.

Because some studies (e.g., Ferreira & Bravo, 2007; Welki & Zlatoper, 1994) have regarded attendance behavior at sporting events as general purchasing behavior, a standard consumer theory model has been applied to the model of attendance demand at sporting events (Borland & Macdonald, 2003). Social economic variables such as price (Welki & Zlatoper, 1994), income level (Bird, 1982; Hansen & Gauthier, 1989), and population (Rivers & DeSchriver, 2002) have also been adopted to analyze the demand for attendance at sporting events. In particular, the elasticity of ticket prices is a typical determinant of attendance (e.g., Baimbridge, Cameron, & Dawson, 1995; Dobson & Goddard, 1995; Hynds & Smith, 1994), within the category of economic factors. Other economic indicators of the local area such as the existence of substitutes (e.g., Baade & Tiehen, 1990; Baimbridge et al., 1995) and average income level (e.g., Bird, 1982; Hansen & Gauthier, 1989) are also included in the category of economic factors.

The size and ethnic mix of the population are determinants of attendance that fall into the category of demographic factors. Because it is likely that more people attend games if they live near a stadium, numerous studies have investigated the influence of population size on attendance in MLB (Coates & Humphreys, 2007; Knowles et al., 1992; Lemke et al., 2010; McDonald & Rascher, 2000; McEvoy et al., 2005; Tainsky & Winfree, 2010), minor league baseball (Siegfried & Eisenberg, 1980), the NBA (Coates & Humphreys, 2007), and the Chilean national soccer tournaments (Ferreira & Bravo, 2007). Furthermore, some researchers have examined the significance of the ethnic mix of the population as one of the determinants of attendance at sporting events (e.g., Siegfried & Eisenberg, 1980).

In addition to the above determinants (e.g., ticket price, existence of substitutes, average income level, population) which are based on social and economic factors, the nature of the sporting events themselves affects the sports fans' attendance decisions. These aspects include team qualities (e.g., win-loss records, season standings, possibility for advancing to the playoffs), game uncertainty, existence of star players, rivalry games, and promotions (e.g., Carmichael, Millington, & Simmons, 1999; Hansen & Gauthier, 1989; Marcum & Greenstein, 1985; Welki & Zlatoper, 1994). There determinants significantly influence attendance and are included in the category of attractiveness factors.

While attractiveness factors are correlated to the contents of sporting events, the determinants in residual preference factors are linked to the comfort, convenience, and accessibility afforded to spectators. Weather, time and day of game, and stadium quality are included in the category of residual preference factors and significantly influence attendance across various sports (e.g., Ahn & Lee, 2014; Brewer & Pedersen, 2013; DeSchriver & Jensen, 2002; Hynds & Smith, 1994; Tainsky & Winfree, 2010). Also, Hansen and Gauthier (1989) noted that easy access and multiple means of access to a facility are significant residual preference factors that lead to increased attendance. However, the degree to which each determinant affects attendance depends on the type of sport, and the characteristics of the team and city. Because there are a variety of influences, it is necessary to examine the determinants of the specific sports league or events with a hierarchical analysis.

2.2. Limitations of Prior Research

For a long period of time, numerous studies (e.g., Hansen & Gauthier, 1989; Schofield, 1983; Zhang et al., 1995) have investigated diverse aspects (e.g., economic conditions, team qualities, stadium qualities) affecting attendance in a wide range of sports, from amateur to professional and from major professional sports leagues (e.g., English Premier League (EPL), La Liga, NFL, MLB, NBA) to professional sports in semi-periphery countries (e.g., Chilean soccer, Czech basketball). Overall, the studies have found that variables in four categories (i.e., economic, demographic, attractiveness, and residual preference factors) have an effect – positively or negatively – on attendance at sporting events.

While the studies have made significant contributions to the literature, they often have limitations. Most of the previous studies approached the subject by using models of a general linear regression model, an analysis of variance (ANOVA) model, or a multivariate analysis of variance (MANOVA) to examine the relationship between attendance and several determinants in four categories (e.g., Lemke et al., 2010; McDonald & Rascher, 2000; McEvoy et al., 2005; Welki & Zlatoper, 1994). Because the methodologies above are used to analyze attendance data without identifying the hierarchical features of the data, the analyses involved in these studies are unable to distinguish the effects of independent variables at different levels (e.g., game, team) (Snijders & Bosker, 2012). For instance, in the case of the attendance data of individual games, the seasonal average attendance level of each MLB team is different according to each team's features (i.e., the population and income level of the home city, the home team's popularity and its past achievements, and the quality of the home stadium), and these variables are defined as the team level variables. However, the team variables are ineffective in explaining any within-team variance (e.g., individual game attendance of a team). The game level variables (i.e., the winning percentages of the home team and the visiting team, the visiting team's popularity, the season's progress, and the day of a game) have different values for each individual game, and these variables affect individual game attendance. While the proportion of data variance in each level cannot be analyzed through general linear regression modelling, it can be explained through hierarchical linear regression modelling.

Because of the statistical limitations of previous non-multilevel modelling studies in terms of their explaining the different effects by attendance determinants at each level (Snijders & Bosker, 2012), scholars such as Ferreira and Brave (2007) and Pecha and Crossan (2009) have examined seasonal average attendance by using hierarchical modeling that distinguished between season level and team level. For example, Ferreira and Bravo (2007) analyzed the attendance determinants of Chilean national soccer tournaments using the data from 18 teams over 12 years. Likewise, Pecha and Crossan (2009) investigated the attendance statistics of 18 Czech basketball teams over 10 years. However, both studies only examined team-level variables (e.g., population, income level, stadium capacity) by seasons, and did not extend to individual game level variables (e.g., visiting team's quality, game uncertainty, visiting team's popularity). Also, because they were focused on relatively minor sports leagues in terms of their market values and league revenues, the current study sought to address these areas by introducing and analyzing a new level of analysis (single game level) within multilevel modeling and by focusing on a major professional sport league. Therefore, the present study introduced the individual game level and investigated the demand for MLB attendance using multilevel modeling based on attendance data from each single game (game level) as well as from each of the 30 MLB teams (team level).

Based upon prior literature of attendance demand in sporting events, the current study sought to answer the following research questions:

RQ1: What is the data structure of single game attendance in an MLB regular season?

RQ2: What are the significant determinants in the major categories (i.e., economic, demographic, attractiveness, and residual preferences) of single game attendance in an MLB regular season?

RQ3: How much do the observed significant determinants of the suggested final model explain the game attendance variance within the individual teams and between the teams?

3. Methodology

To investigate the data structure of MLB attendance and the relationship between the attendance determinants and the actual attendance, this study employed each game's attendance during the 2014 regular season (N=2430) as the dependent variable – from ESPN ("MLB Attendance," 2016) – for 30 MLB teams. Also, a total of 14 independent variables were defined as game level variables while 12 variables were used in this study as team level variables.

3.1. Game Level Predictors

The home team quality (*HTQ*) and visiting team quality (*VTQ*) were game-level predictors and as such were calculated using the percentage of games won during the previous season (2013) and the current season (2014) prior to game *i* (Tainsky & McEvoy, 2012).

$$TQ_{ij} = \{Win\%_{j(2013)} \times [162 - (Progress_{ij} - 1)] + Win\%_{ij(2014)} \times (Progress_{ij} - 1)\} /162$$

When, i: i^{th} home game of team j ($i = 1,\ldots,81$)

j: team j ($j = 1,\ldots,30$)

$Win\%_{j(2013)}$: team j's winning percentage in the 2013 season

$Win\%_{ij(2014)}$: team j's winning percentage prior to game i in the 2014 season

$Progress_{ij}$: team *j's* number of games that have been played, including game i

In addition, the following equation of match uncertainty (*Uncertainty*) was from Bill James' baseball game uncertainty (Tainsky & McEvoy, 2012) and calculated using the *HTQ* and *VTQ*:

$$Uncertainty_i = |0.5 - C_i|$$

where,

$$C_i = (HTQ_i - HTQ_iVTQ_i)/[(HTQ_i + VTQ_i) - 2HTQ_iVTQ_i]$$

Moreover, the payroll average of the home and visiting teams (from "MLB salaries," 2016), in terms of home team and visiting team attractiveness, were adopted as independent variables. Also, the variables related to the visiting teams (i.e., *VT_Payroll*, *VT_FinalRank*, *VT_Age*, *VT_Champs*, *VT_StarPlayers*, and *VT_Playoff*) were applied as game level variables because those variables changed the value and affected attendance at individual game *i*. Further, the home team's number of games behind the division leader (*GB*) was included as a game level variable. If the game was played between local or divisional rivals, it was considered a rival game (*Rival*). In addition, whether or not the game is played on a weekend was a game level independent variable. If the game was played on a Friday, Saturday or Sunday, it was regarded as weekend game (*Weekend*), and had a value of "1." If not, its value was "0." The season's progress (n=1, 2,…, 162) as it pertained to each team was also employed as a game level predictor with regard to MLB attendance, and the season's progress (*Progress*) would indicate how many games had been played during the 2014 season, including the game *i*. In addition, the square of the progress ($Progress^2$) was adopted as a quadratic term of the season's progress.

3.2. Team Level Predictors

Economic variables (i.e., median household income, number of other professional teams in the same area, and average ticket price in each team's home city), demographic variables (i.e., population size of home city), attractiveness variables (i.e., home team's average payroll, final season rank, age, number of championships won, number of star players and playoff appearances), and residual preferences variables (i.e., capacity and age of stadium) were applied in this study as team-level independent variables because each variable above had same value during the season.

Among the team level independent variables, ticket price (*Ticket*) referred to the 2014 MLB Fan Cost Index of the *Team Marketing Report* (2014). The data related to population (*Population*) and median household income (*Income*) were taken from the 2014 U.S. Census Bureau (2015) and the Canada Census ("Population," 2015) of cities in which the stadium of each MLB team is located. In the case of the Minnesota Twins and the Tampa Bay Rays, because St. Paul is close to Minneapolis and Tampa is near St. Petersburg, this study measured the two teams' fan bases by taking the sum of the two neighboring cities' populations, and their respective populations' weighted average incomes. In addition, the average of 2014 exchange rates between US dollar and Canadian dollar ("Yearly Average Rates," n.d.) was reflected in the stated income of Toronto. Also, the number of other professional sports teams in the home city, including local MLB rival teams, served to measure the variable of competition (*ProTeams*).

Lastly, the age (*STD_Age*) and capacity (*STD_Capacity*) variables were indicative of how many years had passed since a given stadium was built, and how many people the stadium could accommodate. This data came from stadium information found on the official MLB website. Table 1 shows a summary of the variables that are employed in this study.

3.3. Data Analysis

Before analyzing the data via multilevel modeling, the variables were centered using the grand mean of each predictor for the convenient interpretation of parameters. The scale of home and visiting teams' final rank were reversed from 1-to-5 to 5-to-1 during the process of grand mean centering. In case of binary predictors (i.e., *Rival*, *VT_Playoff*, *HT_Playoff*, and *Weekend*), the data centering was not applied.

{Insert Table 1 about here}

Based on these collected and grand-centered data, the null model of two levels was generated. In addition, the variance results of this null model described each variance caused by game level and team level, and were used to determine the data variance structure of single game attendance in an MLB regular season. After the analysis of the data structure, the two-level model was constructed to examine the relationship between the MLB regular season attendance demand and the determinants in the four categories. Further, several predictors were included in the null model of two-level for decomposing the variance within and between MLB teams. The 14 independent variables in game level, and the 12 predictors in team level were applied to the full model. Most variables were regarded as a linear term, and one quadratic effect for progress ($Progress^2$) was included. The full model was suggested below:

Game Level: $$Att_{ij} = \beta_{0\cdot j} + \beta_{1\cdot j}(HTQ_{ij}) + \beta_{2\cdot j}(VTQ_{ij}) + \beta_{3\cdot j}(Uncertainty_{ij}) + \beta_{4\cdot j}(VT\_Payroll_{ij}) + \beta_{5\cdot j}(VT\_FinalRank_{ij}) + \beta_{6\cdot j}(VT\_Playoff_{ij}) + \beta_{7\cdot j}(VT\_StarPlayers_{ij}) + \beta_{8\cdot j}(VT\_Age_{ij}) + \beta_{9\cdot j}(VT\_Champs_{ij}) + \beta_{10\cdot j}(GB_{ij}) + \beta_{11\cdot j}(Rival_{ij}) + \beta_{12\cdot j}(Weekend_{ij}) + \beta_{13\cdot j}(Progress_{ij}) + \beta_{14\cdot j}(Progress_{ij}^2) + R_{ij}$$

Team level: $\beta_{0\cdot j} = \gamma_{0\cdot 0} + \gamma_{0\cdot 1}(HT\_Payroll._{j}) + \gamma_{0\cdot 2}(HT\_FinalRank._{j}) + \gamma_{0\cdot 3}(HT\_Playoff._{j}) + \gamma_{0\cdot 4}(HT\_StarPlayers._{j}) + \gamma_{0\cdot 5}(HT\_Age._{j}) + \gamma_{0\cdot 6}(HT\_Champs._{j}) + \gamma_{0\cdot 7}(STD\_Age._{j}) + \gamma_{0\cdot 8}(STD\_Capacity._{j}) + \gamma_{0\cdot 9}(Ticket._{j}) + \gamma_{0\cdot 10}(Income._{j}) + \gamma_{0\cdot 11}(ProTeams._{j}) + \gamma_{0\cdot 12}(Population._{j}) + U_{oj}$

$\beta_{k\cdot j} = \gamma_{k\cdot 0}$ (When *k*= 1, …, 14)

When, *i*: *i*th home game of team *j* (*i* = 1,…,81)

j: team *j* (*j* = 1,…,30)

σ^2 : within group variance (R_{ij})

τ_0^2 : between group variance (U_{0j})

In addition, the final model was suggested through -2 log likelihood ratio tests for fixed effects. Finally, as the suggested model satisfied the assumptions of the hierarchical linear model (i.e., the normal distribution of residuals by game level predictors, and the normal distribution of team level residuals for random coefficients), it became the final model. Also, the data analyses noted above were conducted using SAS 9.4.

4. Results

The descriptive statistics of variables in this study are detailed in Table 2. Because the attendance of the first game of a doubleheader was not provided with the ESPN data (“MLB Attendance,” 2016), a total of nine data points associated with the dependent variable (attendance) were missing. In addition, the team average of player’s payroll, team age, and championships were $3,892,357, 83 years, and 3.6 championships, respectively. Further, 48.5% of games played during the 2014 MLB regular season were played on Friday, Saturday, or Sunday, and 12.5% of games were local or divisional rivalry games. Also, a total of 10 teams among the 30 MLB teams advanced to the postseason because the wild card teams of each league increased to two from the 2012 season. Thus, the percentage of playoff appearances became 33.3%.

{Insert Table 2 about here}

These collected data were analyzed via multilevel modeling, and Table 3 shows the results of the null model, full model, and final model. In the null model, the residual (R_{ij}) is the random effect of individual game *i*, which indicates the variance of game level, and U_{0j} is the random effect of team *j*, which shows the variance of team level. The intraclass correlation (ICC) describes the proportion of variance explained by group difference, and the ICC of the null model in this study was calculated as 56.4%. This finding reveals that over half of the variance in each single game's attendance could be attributed to between-team differences, and the remainder of the variance (43.6%) lies within the team (between single games). This result also shows the need for using multilevel modeling in the analysis of the data for each game's attendance because more than half of the variance was caused by team differences.

Further, based on the null model, the full model was constructed by applying 14 game level and 12 team level variables to the null model. Per the results of the full model, each insignificant variable was examined by the likelihood ratio tests for fixed effects to determine if the variable should remain in the final model. In addition, the five game level variables (i.e., *HTQ*, *VTQ*, *VT_StarPlayers*, *VT_Age*, and *Rival*) and the nine team level variables (i.e., *HT_Payroll*, *HT_FinalRank*, *HT_StarPlayers*, *HT_Age*, *HT_Champs*, *STD_Age*, *Income*, *ProTeams, and Population,*) were excluded from the final model by the results of the likelihood ratio tests. Because the results of the likelihood ratio tests for *HT_Playoff* and *Ticket* showed that the model with both variables was statistically different from the model excluding them, both variables were kept in the final model and were significant variables in predicting the MLB attendance.

Also, the suggested final model satisfied the assumptions of the hierarchical linear model such as the normal distribution of residuals by game level predictors, and the normal distribution of team level residuals for random coefficients. In addition, the results of the final model show that the nine game level variables (i.e., *Uncertainty*, *VT_Payroll*, *VT_FinalRank*, *VT_Playoff*, *VT_Champs*, *GB*, *Weekend*, *Progress*, and $Progress^2$), and the three team level predictors (i.e., *HT_Playoff*, *STD_Capacity*, and *Ticket*) significantly influenced each single game's attendance during the 2014 MLB regular season. The value of Bill James' baseball game uncertainty (Tainsky & McEvoy, 2012), which was adopted in this study, is zero when the qualities of home and visiting teams are the same, and it will be greater if the difference between the teams' qualities is greater. Thus, the negative estimated parameter of game uncertainty means that the attendance demand of games between teams that have relatively similar qualities was higher than that of games between qualitatively different teams ($\gamma_{3 \cdot 0}$ = -5636.3, t = -2.37, p < .05).

Furthermore, the results of the final model confirmed that the visiting team's average payroll ($\gamma_{4 \cdot 0}$ = 0.0005, t = 5.72, p < .001) and number of championships ($\gamma_{9 \cdot 0}$ = 186.8, t = 7.28, p < .001) served as means of attraction that increased the likelihood of fans attending a given game. While the final rank of the visiting team ($\gamma_{5 \cdot 0}$ = 467.0, t = 3.71, p < .001) positively influenced the attendance of each single game, the effect of the home team's final rank was not significant. In addition, whether the visiting team ($\gamma_{6 \cdot 0}$ = -1052.0, t = -2.83, p < .05) advances to the playoffs or not, and the home team's number of games behind ($\gamma_{10\cdot 0}$ = -234.2, *t* = -8.17, *p* < .001), both notably influenced attendance.

The results of the final model also revealed that the attendance of a weekend game was higher than that of a weekday game ($\gamma_{12\cdot 0}$ = 5574.7, *t* = 25.86, *p* < .001). In addition, the attendance had gradually increased as the regular season proceeds ($\gamma_{13\cdot 0}$ = 62.53, *t* = 6.57, *p* < .001). However, this increasing rate by *Progress* was reduced by the quadratic term, $Progress^2$ ($\gamma_{14\cdot 0}$ = -0.23, *t* = -4.08, *p* < .001).

With regard to the team level predictors, if the home team advances to the playoffs, the average home attendance would increase by 5952 ($\gamma_{0\cdot 3}$ = 5952.2, *t* = 4.73, *p* < .001). Also, ticket price ($\gamma_{0\cdot 9}$ = 409.0, *t* = 4.89, *p* < .001) was a significant team level predictor regarding 2014 MLB regular season attendance. The result of estimated parameter of stadium capacity ($\gamma_{0\cdot 8}$ = 0.776, *t* = 5.73, *p* < .001) shows that a team would had more spectators per game by 776 if the team played at a stadium with a capacity of at least 1,000 more seats than the average capacity of MLB stadiums.

{Insert Table 3 about here}

Moreover, R^2 measures were adopted for checking the global fit of the final model. The final model's variances of within team (σ^2 = 28,058,066) and between teams (τ_0^2 = 15,736,205) were reduced from the null model. Based on these values, R_1^2 and R_2^2 were measured, and R_1^2 indicates that the proportional reduction of prediction error is 52.8%. Further, R_2^2 shows that the proportional reduction of prediction error for MLB attendance is 69.3% if game *i* is fixed and team *j* is randomly chosen.

5. Discussion

This study used multilevel modeling to analyze the data structure of single game attendance (confirming the nesting of the data) and investigate the attendance in the 2014 MLB regular season by using attendance determinants found to be significant in previous research (e.g., Borland & Macdonald, 2003; DeSchriver & Jensen, 2002). Per the results of intraclass correlation (ICC), the nested or hierarchical data structure was found and thus confirmed the necessity of using multilevel analysis. Furthermore, from the results of the multilevel modeling, the findings support significant implications with regard to various theoretical and practical perspectives. Also, the results answer the research questions pertinent to the significance of and relationships that exist among various determinants related to the visiting team's quality and popularity (i.e., visiting team's final rank, playoff, payroll, and championships), the possibility of the home team's ability to advance to the playoffs (i.e., home team's playoff appearances and games behind), game uncertainty, average ticket price, stadium capacity, and seasonal progress.

The first determinant, the home team's quality (e.g., winning percentage, final standing), is an important factor that can lead to increased attendance (e.g., DeSchriver & Jensen, 2002; Tainsky & Winfree, 2010; Welki & Zlatoper, 1994). Biner (2009) indicated that a home team's high quality, such as its winning percentage, contributes more to increased attendance at home games than does the quality of the visiting team. However, several studies have also analyzed the positive influence of the visiting team's quality and popularity (e.g., winning percentage, star players, payroll, championships) on attendance (e.g., Lemke et al., 2010; Meehan, Nelson, & Richardson, 2007). In the present study, the importance of the visiting's attractiveness was confirmed, while the home team's quality was found to contribute insignificantly to increases in attendance during the 2014 MLB regular season. It could be postulated that some relatively unpopular teams (e.g., Pittsburgh Pirates, Kansas City Royals, Oakland Athletics) would influence such results. According to The Harris Poll (2015), the Pirates, Royals, and Athletics were ranked 19, 22, and 23, respectively, with regard to the average ranking of relative popularity among the 30 MLB teams from 2003 to 2015. Even though these teams advanced to the 2014 MLB postseason (and the Royals eventually won the World Series in 2015), their individual team's seasonal average attendance was less than the 2014 MLB average attendance per game.

In addition, six teams among the 14 teams that maintained a winning percentage of over .500 at the end of the season, failed to achieve attendance numbers greater than the average attendance per game during the 2014 MLB regular season. Because some teams have weak spectator mobilizing power even though they have had successful seasons, the effect of some home teams' quality and popularity on attendance would be underestimated with regard to the 2014 MLB regular season. Nevertheless, the home team advancing to the postseason plays a role in increasing attendance. Although three teams that advanced to the playoffs failed to maintain their home game attendance over the average of MLB attendance, the other seven teams maintained attendance number above the average. Moreover, five of the teams to advance to the playoffs (i.e., the Los Angeles Dodgers, St. Louis Cardinals, San Francisco Giants, Los Angeles Angels, and Detroit Tigers) maintained attendance numbers that ranked among the top seven of the average attendance table.

In addition to the home team's quality and popularity, the indicator of the possibility of advancing to the playoffs, which is represented by the home team's number of games behind the division leader, significantly influenced attendance in the present study. Rivers and DeSchriver (2002) described the variable of games behind as the specific measurement of a baseball team's success in the season, while other sports leagues have focused on winning percentage (e.g., NFL) or points system (e.g., NHL, Major League Soccer, European soccer leagues). While the variable of games behind in the Rivers and DeSchriver study was not a significant predictor of seasonal average attendance, the present study shows the variable of games behind at each single game is an important factor in predicting the attendance of each single game. The results regarding the home team's playoff appearances and games behind suggest that these variables would effectively stimulate more sports fans to visit their home team's games.

In several studies (e.g., Borland & Macdonald, 2003; Ferreira & Bravo, 2007), the stadium capacity has been introduced as one of the viewing quality variables because it indicates the crowdedness of a stadium. The age of a stadium has also been regarded as a significant predictor of attendance because a new stadium would likely have more spectator-friendly amenities (Ahn & Lee, 2014; Coates & Humphreys, 2007; DeSchriver & Jensen, 2002; McEvoy et al., 2005; Rivers & DeSchriver, 2002; Tainsky & Winfree, 2010; Welki & Zlatoper, 1994). While the studies of Baade and Tiehen (1990) and McDonald and Rascher (2000) showed that stadium capacity was an insignificant or conditional predictor of attendance, it was an important variable related to increased attendance in the study of Ferreira and Bravo (2007). The present study also found that stadium capacity had a positive influence on attendance during the 2014 MLB regular season.

However, the current study revealed that the age of a stadium is an insignificant predictor of MLB attendance. This result conflicts with the findings of studies conducted by Ahn and Lee (2014) and Coates and Humphreys (2007); those studies determined that new stadiums are more attractive to spectators than old stadiums. A few historic stadiums, such as Fenway Park and Wrigley Field, might account for the different findings. According to Coates and Humphreys, the novelty effect of MLB stadiums gradually decreases, and it becomes zero once a stadium is about 68 years old, at which time the influence of stadium age on attendance changes positively to increase attendance. Because the current study did not adopt this historical effect, the variable of stadium age insignificantly affected attendance during the 2014 MLB regular season.

This study's results regarding ticket price are also intriguing. In general, low prices encourage an increase in consumer demand and thus increase consumers' likelihood of purchasing products (Alexander, 2001). Several studies have proven that this microeconomic price theory is able to apply to various sports leagues such as the English soccer league (e.g., Dobson & Goddard, 1995), English cricket (Hynds & Smith, 1994), the NFL (Welki & Zlatoper, 1994), and the MLB (Coates & Humphreys, 2007). However, some studies (e.g., Baimbridge et al., 1995) have produced different results, which have to do with the positive price elasticity in English rugby and soccer.

However, some scholars (e.g., Fort, 2004) have posited that the ticket price in sport is in the inelastic range of the attendance demand. Even though the current study found the positive estimate of average ticket price in the 2014 MLB regular season, future studies that focus on ticket prices should examine the reasons for this positive estimate because the cause and effect relationship between attendance demand and ticket price is indistinct. For example, in the timeframe examined with the current study, the three teams with the highest average ticket prices were the Boston Red Sox, New York Yankees, and Chicago Cubs. Based on the average popularity ranking at the same time as revealed by The Harris Poll (2015), these teams were among the top four in terms of popularity. Therefore, it is conceivable then that higher ticket prices result from a greater attendance demand with regard to the home games for these popular teams. Furthermore, there has been a tendency in ticket sales and operations to move away from fixed ticket pricing toward more of a dynamic and hierarchical ticket pricing structure according seat location, the day the game takes place, and the popularity of the visiting team. Such an approach leads to a large variation in ticket prices, even at the same game. While this pricing pattern satisfies the demand of various consumer classes, this approach makes it difficult to examine the effect of ticket prices. In addition, most teams make a dedicated and focused attempt to increase season ticket sales in order to stabilize their seasonal revenue, and to allow season ticket holders to resell their tickets through secondary markets facilitated by entities such as StubHub and Vivid Seats. This means that sports fans are able to purchase tickets at a price that is more or less the price than the official price. As such, a limitation of the current study involves the need to understand the influence of the average ticket price on the attendance in the 2014 MLB season, and more detailed studies regarding the relationship among actual ticket price, attendance demand, and attendance are necessary in the future.

In addition to these theoretical implications, the feasible and practical implications for increasing MLB attendance can be suggested based on the results in this study. This is particularly true with regard to findings pertaining to various visiting teams' quality and popularity variables, such as average payroll, final ranking, number of championships, and playoff appearances, and how these influence attendance. However, the MLB senior vice president of scheduling and club relations is responsible for 2,430 regular season MLB games (Zahneis, 2012). Further, the teams' league, divisions, and local rivals are reflected in their schedules. Because MLB teams do not have the authority to select visiting teams, home teams should encourage their fans to attend games even when the teams playing are relatively unpopular or poor performers. For instance, various promotions and games-related events could help these unpopular teams to increase the game attendance. Also, teams need to encourage their fans to purchase season tickets or certain packages to bundle some of these weaker teams.

In addition, several teams (e.g., Minnesota Twins, Miami Marlins, New York Mets, Washington Nationals) moved into new stadiums in the previous 10 years. Although the effect of stadium novelty on attendance was insignificant in this study, a stadium's capacity proved to be a significant variable with regard to increased attendance during the 2014 MLB regular season. If some MLB teams plan to move to new stadiums in the future, the size of stadium should be something strongly considered. Also, it may be necessary to conduct studies related to the optimal capacity of a stadium not only MLB teams but also for other professional sports teams.

While this study focused on analyzing the relationship between the well-known attendance determinants and each single game attendance of the 2014 MLB regular season using a multilevel analysis, more specific determinants were not adopted. For example, ticket prices that differ based on seating sections are more reliable than average ticket prices when we are trying to better understand sports fans' drive purchasing tickets. Although the rate of seasonal ticket sales would influence attendance, it was not adopted in this study. In addition, the distribution of the home team's and visiting team's payroll would be useful to researchers looking to better understand a team's popularity with regard to variables associated with average payroll.

In addition, this study adopted only the age and capacity of the stadium, and whether or not the game was played on a weekend. However, game time and weather conditions during a game have proven to be significant variables in several studies (e.g., Hynds & Smith, 1994; Lemke et al., 2010; Marcum & Greenstein, 1985). Further, previous research has revealed – and most observers would acknowledge – that a game's starting pitchers also influence attendance

(McDonald & Rascher, 2000). The distribution of the home team's and the visiting team's payroll would be also useful when assessing a team's popularity via the variable of average payroll. Moreover, because the number of wild card teams in each league has been extended to two since the 2012 MLB season, the influence of this extension on attendance is worth investigating, and the comparison analysis of games behind effects between before and after this wild card team extension might be at the center of future study.

Lastly, the current study investigated only one MLB regular season. The investigation of multi-season data would be possible to understand the seasonal differences and the influence of MLB attendance determinants in a cross-sectional aspect. However, the results of a multi-year study could not explain specific phenomena (e.g., when a lower-rated team makes the playoffs). For instance, based on The Harris Poll in 2015, the favorite baseball teams (i.e., Royals, Athletics, Pirates, Orioles, Angles, and Nationals) were in the lower ranks among the 30 teams even though all of them made the playoffs in the 2014 season. Because the results of the 2014 MLB regular season were unusual, the attendance data pertaining to the current study's investigation of the 2014 season are unique and needed to be examined (just as data across multiple seasons have been examined). However, the analysis multi-season attendance data is still necessary for future research to examine which attendance determinants have generally influenced actual attendance in the MLB seasons.

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Table 1

Variable Descriptions of MLB Attendance Demand

Symbol	Description	Source
Dependent Variable		
Att_{ij}	Team *j*'s attendance of game *i*	
(Game level) Independent Variables		
HTQ_{ij}	Home team's winning percentage prior to game *i*	DeSchriver & Jensen (2002)
VTQ_{ij}	Visiting team's winning percentage prior to game *i*	Welki & Zlatoper (1994)
$Uncertainty_{ij}$	Bill James's baseball game uncertainty	Tainsky & McEvoy (2012)
$VT\_Payroll_{ij}$	Average payroll of visiting team	Rivers & DeSchriver (2002)
$VT\_FinalRank_{ij}$	Visiting team's final rank in the season	Baade & Tiehen (1990)
$VT\_Playoff_{ij}$	Dummy of visiting team playoff appearance	Rivers & DeSchriver (2002)
$VT\_StarPlayers_{ij}$	Visiting team's number of star players	Meehan et al. (2007)
VT_Age_{ij}	Visiting team's age	Coates & Harrison (2005)
VT_Champs_{ij}	Visiting team's number of previous Championships	Ferreira & Bravo (2007)
GB_{ij}	Home team's number of games behind	Rivers & DeSchriver (2002)
$Rival_{ij}$	Dummy of local or divisional rivalry games	Welki & Zlatoper (1994)
$Weekend_{ij}$	Dummy of weekend games (from Friday to Sunday)	McDonald & Rascher (2000)
$Progress_{ij}$	Number of games that have been played, including game *i*	Welki & Zlatoper (1994)
(Team level) Independent Variables		
$HT\_Payroll._j$	Average payroll of home team *j*	Rivers & DeSchriver (2002)
$HT\_FinalRank._j$	Home team *j*'s final rank in the season	Baade & Tiehen (1990)
$HT\_Playoff_{ij}$	Dummy of home team *j*'s playoff appearance	Rivers & DeSchriver (2002)
$HT\_StarPlayers_{ij}$	Home team *j*'s number of star players	Meehan et al. (2007)
$HT\_Age._j$	Home team *j*'s age	Coates & Harrison (2005)
$HT\_Champs._j$	Home team *j*'s number of previous championships	Ferreira & Bravo (2007)
$STD\_Age._j$	Stadium age of home team *j*	McDonald & Rascher (2000)
$STD\_Capacity._j$	Stadium capacity of home team *j*	McDonald & Rascher (2000)
$Ticket._j$	Average ticket price	Baade & Tiehen (1990)
$Income._j$	Median household income for city	Baade & Tiehen (1990)
$ProTeams._j$	Number of other professional teams in same area	Baade & Tiehen (1990)
$Population._j$	Population of city	Baade & Tiehen (1990)

Note. *i*: home game *i* (*i*=1,…,81); *j*: team *j* in MLB (*j*=1,…,30)

Table 2

Descriptive Statistics of MLB 2014

Variable	N	Mean	Std. Dev.	Min	Max
Dependent Variable					
Attendance	2421	30,458	9,626	8,848	53,500
(Game level) Independent Variables					
Home Team (HT) Quality	2430	0.502	0.061	0.311386	0.616141
Visiting Team (VT) Quality	2430	0.503	0.061	0.308756	0.615226
Game Uncertainty	2430	0.072	0.051	0.000116	0.272243
VT Payroll	2430	3,982,357	1,524,056	1,606,636	8,031,948
VT Final Rank	2430	2.97	1.43	1	5
VT Playoff	2430	0.33	0.47	0	1
VT Star Players	2430	2.07	1.32	0	6
VT Team Age	2430	83.07	43.38	16	138
VT Championships	2430	3.63	5.21	0	27
HT Games Behind	2430	6.33	6.64	0	37
Rival Game	2430	0.13	0.33	0	1
Weekend	2430	0.49	0.50	0	1
Season Progress	2430	81.51	46.78	1	162
(Team level) Independent Variables					
HT Payroll	2430	3,982,357	1,524,056	1,606,636	8,031,948
HT Final Rank	2430	2.97	1.43	1	5
HT Playoff	2430	0.33	0.47	0	1
HT Star Players	2430	2.07	1.32	0	6
HT Team Age	2430	83.07	43.38	16	138
HT Championships	2430	3.63	5.21	0	27
Stadium Age	2430	23.33	24.74	0	102
Stadium Capacity	2430	43,152	5,170	31,042	56,000
Ave. Ticket Price	2430	27.93	8.77	16.37	52.32
Median Household Income	2430	48198	12192	26095	78378
Professional Teams	2430	2.70	1.39	1	6
Population	2430	1,544,316	2,066,530	298,041	8,495,194

Note. This table is the descriptive statistics results of data before the grand mean centering.

Table 3

Results of Null Model, Full Model, and Final Model

	Null Model (ML)		**Full Model (ML)**		**Final Model (ML)**	
Fixed Effect	Estimate	(SE)	Estimate	(SE)	Estimate	(SE)
Intercept	** 30437	(1326.6)	** 23258	(1347.5)	** 23005	(966.6)
(Game level) Independent Variables						
HTQ			322.3	(4870.0)		
VTQ			992.97	(2542.3)		
Uncertainty			* -5687.8	(2462.5)	* -5636.3	(2381.4)
VT_Payroll			** 0.0005	(0.0001)	** 0.0005	(0.0001)
VT_FinalRank			** 476.8	(136.8)	** 467.0	(126.0)
VT_Playoff			* -1219.0	(405.9)	* -1052.0	(372.3)
VT_StarPlayers			18.71	(91.81)		
VT_Age			4.68	(3.14)		
VT_Champs			** 159.8	(28.83)	** 186.8	(25.65)
GB			** -235.1	(31.91)	** -234.2	(28.66)
Rival			632.1	(340.8)		
Weekend			** 5580.0	(215.3)	** 5574.7	(215.6)
Progress			** 63.18	(9.56)	** 62.53	(9.51)
Progress^2			** -0.230	(0.056)	** -0.228	(0.056)
(Team level) Independent Variables						
HT_Payroll			0.00091	(0.00074)		
HT_FinalRank			-586.6	(1018.6)		
HT_Playoff			5074.4	(3303.0)	** 5952.2	(1568.7)
HT_StarPlayers			122.9	(614.6)		
HT_Age			11.42	(20.37)		
HT_Champs			190.0	(218.8)		
STD_Age			-9.66	(35.99)		
STD_Capacity			** 0.625	(0.184)	** 0.776	(0.142)
Ticket			240.5	(133.1)	** 409.0	(83.7)
Income			-0.00065	(0.00063)		
ProTeams			0.0585	(0.0640)		
Population			684.5	(789.4)		
Random Effect						
Residual (σ^2)	40451108	(1.17E+6)	27981885	(8.09E+5)	28059066	(8.11E+5)
τ_0^2	52297105	(1.36E+7)	13167639	(3.49E+6)	15736205	(4.14E+6)
-2 Log Likelihood	49415.5		48493.4		48505.2	

Note. Standard errors are in parentheses. * p<.05 and ** p<.001