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An Examination of the Effects of the Recent Economic Crisis on Major League Baseball (MLB)
Attendance Demand

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November 3, 2011

Abstract

We investigate the effects of the recent economic crisis on Major League Baseball (MLB) attendance during the 2008 and 2009 seasons. To elaborately capture the impact of economic circumstances, we adopt the composite index of coincident indicators released by Federal Reserve Bank of Philadelphia. Major advantages of the coincident indexes are the ability to specify monthly changes in state economic conditions as well as combining the information from several economic indicators. The estimates for the coincident indicators suggests the economic downturn drives a fall in attendance of about 6%, compared to the reported decline of 6.77%. The success of the composite index in explaining the impact of the recent economic crisis on attendance in MLB suggests the indicator is a viable proxy for income in game attendance demand studies.

KEYWORDS: composite index of coincident indicators, economic downturn, attendance, MLB

An Examination of the Effects of the Recent Economic Crisis on Major League Baseball (MLB) Attendance Demand

Major League Baseball (MLB) attendance in 2009 was about 6.77% below what it was in 2008 (30,338 per game for 2009 compared to 32,543 for 2008) (Brown, 2009), and 2008 was down slightly compared to 2007. The drop between 2008 and 2009 was the largest single-season loss in attendance since 1952, excluding years involving a work stoppage (Nightengale, 2009). More specifically, 22 of the 30 clubs experienced a decline in attendance, including four teams' attendance decreasing more than 20%. The Florida Marlins, Kansas City Royals, and Texas Rangers were the only teams able to boast 10% or greater increases in attendance (Brown, 2009).

The surprisingly large drop in attendance may be attributable to the recent economic crisis, the beginning of which was set at December 2007 by the National Bureau of Economic Research. In fact, MLB announced that "because of the economy, this year's (2009) total is 6.6 percent less than last year's total, but is actually only 5.2 percent lower when accounting for the reduced capacities of the two new ballparks in New York" (MLB.com, 2009, n. p.). It is certainly a possibility that the state of the economy in 2009 led to reduced attendance. Widespread unemployment and reduced incomes mean tighter budget constraints causing consumers to alter their spending patterns. Consumers may reduce the quantity of sporting events attended in response to the economic crisis both because their financial status is precarious and for psychological reasons. The psychological impact of the crisis may lead to a decrease in expenditures regardless of the consumers' actual financial status (Katona, 1974). This first contribution of this paper is that it empirically assesses the impact of the recent economic crisis on the radical decline in attendance between the 2008 and 2009 seasons. The key problem in this study is how best to represent the economic conditions in our analysis. The ideal economic

indicators would vary daily and by city, but such data do not exist. The second contribution of this paper is to utilize “coincident indicators”, produced by the Federal Reserve Bank of Philadelphia, reflecting the macroeconomic health of a given state in each month. These indicators reflect an improvement over the literature in which income per capita for a specific year is used to capture the role of consumer income in the determination of ticket demand.

The first section of the paper discusses what economic indicators should be used and why they are useful in measuring the effects of the recent economic crisis on MLB attendance demand. In the second section, the attendance demand model is presented along with descriptions of other explanatory variables. Finally, the last section discusses the empirical results, conclusions, and recommendations for future research.

Economic indicators

The Great Depression inspired economists to search for ways to detect or predict economic cycles (Conference Board, 2001). As an initial effort of gauging economic cycles, Arthur Burns and Wesley Mitchell of the National Bureau of Economic Research (NBER) developed a list of leading, coincident, and lagging indicators of economic activity in the United States as part of the NBER research program on business cycles (Stock & Watson, 1989). In their book, *“Measuring Business Cycles”*, they described the business cycles as “consist[ing] of expansions occurring at about the same time in many economic activities, followed by similarly general recessions, contractions, and revivals which merge into the expansion phase of the next cycle” (Burns & Mitchell, 1946, p.3). This early research was represented as the beginning of the study of the business cycle measured by the combination of various economic indicators (Stock & Watson, 1989). Further, the NBER and Geoffrey Moore contributed to much of the following development of this “indicator approach” in the 1950s and 1960s. Their work on economic

indicators has led many governmental and private institutions in the U.S. to construct composite indexes of leading, coincident, and lagging indicators of economic activity. For example, the U.S. Department of Commerce and, more recently, some regional U.S. Federal Reserve Banks have released composite indexes of economic indicators by month (Crone, 1994).

Of the leading, lagging, or coincident indicators, the most useful for the study of baseball attendance is the index of coincident indicators. The three indexes have different attributes and are used differently. The composite index of leading indicators is used to attempt to judge or predict the future state of the economy. Thus, this index may be helpful for investors and businesses to make more-informed decisions about what is ahead by forecasting the state of the economy (Yamarone, 2004). Second, the composite index of lagging indicators is used as an after-the-fact way to confirm economists' assessment of current economic conditions (Conference Board, 2001). Therefore, its primary use is to confirm the direction of the economy indicated from the leading and coincident indexes. Meanwhile, the composite index of coincident indicators is designed to measure current economic conditions; that is, the coincident indicators provide a description of the actual circumstances that consumers face at a point in time. Of these three composite indexes of economic indicators, Crone (1994) claimed the composite index of coincident indicators is the most important index for dating business cycles. He stated that 18 of 22 business-cycle turning points in the U.S. economy over a period of 45 years closely corresponded with the index of coincident indicators. In other words, the composite index of coincident indicators is an excellent benchmark for assessing the current pace of economic activity (Yamarone, 2004). Therefore, the composite index of coincident indicators is the best of the business cycle indicators to use as a determinant of attendance demand.

Composite index of coincident indicators

As mentioned above, two different coincident indexes have been released by the U.S. Department of Commerce and some regional U.S. Federal Reserve Banks. The index released by the Commerce Department (now published by the Conference Board) consists of four monthly data series – 1) the number of jobs in nonagricultural establishments, 2) personal incomes, less transfer payments adjusted for inflation, 3) the index of industrial production, and 4) manufacturing and trade sales adjusted for inflation (Crone, 1994). The Commerce Department's index is calculated based on month-to-month percent changes for each of these four series. The changes are standardized based on the long-run average absolute monthly change in the series; “this preliminary index is adjusted to grow over time at the same rate as real gross national product and is set to 100 in 1982” (Crone, 1994, p. 21). However, there is a primary issue about the methods used by the Commerce Department--the index is not derived from a formal mathematic or statistical model (Stock & Watson, 1989). More specifically, the same weight is assigned to each indicator in forming the composite index. It is unlikely that each indicator can equally reflect the overall state of the economy. For example, some indicators like the total number of jobs may better reflect the overall state of the economy than other indicators like manufacturing and trade sales (Crone, 1994).

In contrast with the traditional Commerce Department methodology, several procedures have been proposed to aid in the dating of recessions and expansions by using techniques based on econometric and time series analysis (Crone, 1994). Stock and Watson (1991) developed a probabilistic state space model based on time-series econometric techniques to estimate a latent process; this estimation is used as a coincident indicator of the economic activity. Their approach was based on the common movements across several economic data series best measuring the business cycles. Unlike the Commerce Department methodology, their methodology assigned the

different weights determined by the degree of common movement in the indicators (Crone, 1994).

The Stock and Watson national index used the same data series as the Department of Commerce except for the number of nonagricultural jobs. Instead of the number of nonagricultural jobs, they used employee hours in nonagricultural jobs since economic output depends not only on how long they work but also on how many people are working (Crone, 1994). Their national index demonstrated the index tracks the official business cycles closer than the method used by the Department of Commerce. However, the Stock and Watson index is not available at the state level, indicating the inability of the index for measuring the regional economy (Crone & Clayton-Matthews, 2005). Accordingly, Crone and his colleagues of the Federal Reserve Bank of Philadelphia developed a new coincident index for each of the 50 states in order to describe recent economic trends at the state level.

The coincident indexes for the 50 states are comprised of four state-level indicators to summarize current economic conditions in a single statistic. The four state-level variables in each coincident index are 1) nonagricultural payroll employment, 2) unemployment rate, 3) average hours worked in manufacturing, and 4) real wage and salary disbursements (Crone & Clayton-Matthews, 2005). Nonagricultural payroll employment is intended to reflect actual changes in hiring and firing for the individual states by month. This is considered the most reliable employment series published for the all the states.

The unemployment rate produced by the Bureau of Labor Statistics is utilizes the current population survey, the payroll employment survey, state population estimates, and unemployment claims. While Stock and Watson's national index and the Conference Board's index include industrial production, the coincident index for the 50 states uses average hours

worked in manufacturing due to the unavailability of comparable measure of industrial output at the state level (Crone & Clayton-Matthew, 2005). Finally, while the Bureau of Economic Analysis releases personal income and its components at the state level on a quarterly basis, the major component of personal income, real wage and salary disbursements, are included in the state index. The quarterly wage and salary disbursements produced by the BEA are adjusted by lagging the structure in the measurement equation for this variable to obtain the monthly data (Crone & Clayton-Matthew, 2005).

Usefulness of the composite index of coincident indicators for the 50 states

Consumer income is a determinant of demand and is commonly accounted for in the literature on attendance demand by income per capita measured at the metropolitan level. One problem with income per capita at the metropolitan level is that it is an annually reported variable so that it will not vary over the season. Moreover, as a measure of the financial situation of fans, income also may be lacking as it is only one of many alternative factors reflecting those circumstances. However, the use of a single economic indicator may lead to a different estimation of economic conditions because the indicators do not move together perfectly. In other words, one indicator may be showing a decline in economic conditions but another may show an improvement. For example, the unemployment rate may be increasing at the same time job levels are rising (Crone, 1994). In the literature, income is often found not to be a significant determinant of attendance, possibly because of the lack of variation over the league's season or because it is not a good measure of the purchasing power and economic circumstances of the fans. The coincident indexes have an advantage over income per capita because they vary by month within the season and because they combine information from several indicators so they can better reflect the current economic conditions. The coincident indexes do suffer from the

disadvantage that they cover an entire state rather than the metropolitan area. If the economic circumstances of the city from which a team draws its fans do not correspond well to the circumstances of the entire state, then the coincident indicator may be a poor variable to capture the influence of income on demand.

The Attendance Model

Attendance demand, like all demand, has well-known theoretical determinants. Among these determinants are income of the consumers, prices of tickets and of other goods and services, and preferences. The difficulty in estimating the demand equation is how to control for these theoretically relevant factors with the sort of data that exists. For example, it is difficult to control for preferences because there is no clearly defined or observable way to measure them. Consequently, variables like educational attainment, racial composition, marital status, and age are used as proxy variables for preferences. In the sports context, fan loyalty is also important. In the current context, none of these variables will vary meaningfully over the course of a baseball season, especially from one game to the next. For this reason, city or team fixed effects are used to capture the influence of these time-invariant factors. Consequently, our regression model incorporates the current economic condition indicator as well as the most widely used demand determinants as follows:

$$\begin{aligned}
 AttenPct_{ijt} = & \delta_i + \beta_1 Econcon_{ijt} + \beta_2 HomeWin_{ijt} + \beta_3 OppWin_{ijt} + \beta_4 MarchGB_{ijt} + \beta_5 AprGB_{ijt} \\
 & + \beta_6 MayGB_{ijt} + \beta_7 JuneGB_{ijt} + \beta_8 JulyGB_{ijt} + \beta_9 AugGB_{ijt} + \beta_{10} SepGB_{ijt} + \beta_{11} OctGB_{ijt} \\
 & + \beta_{12} PlayoffApp_{ijt-1} + \beta_{13} HomeStar_{ijt} + \beta_{14} OppStar_{ijt} + \beta_{15} Interleague_{ijt} \\
 & + \beta_{16} Weekend_{ijt} + \beta_{17} Apr_{ijt} + \beta_{18} May_{ijt} + \beta_{19} June_{ijt} + \beta_{20} July_{ijt} + \beta_{21} August_{it} \\
 & + \beta_{22} September_{ijt} + \beta_{23} October_{ijt} + \beta_{24} AvgTicket_{ijt} + \mu_{ijt}
 \end{aligned}$$

where i indicates team, j indexes games, and t indexes the season, β s are parameters to be estimated, δ represents the fixed effect parameter for each team, and μ is the error term. The variables used in the analysis are described below.

Dependent variable (*AttenPct*)

Because stadiums have widely varying seating capacities, we use each MLB team's game-by-game attendance as a percentage of stadium capacity as our dependent variable. It is common in the literature to use stadium capacity as an explanatory variable in the attendance equation, but our approach means we do not need to do that as a control for stadium size. Moreover, seating capacity is not rightly a determinant of demand so its inclusion in a demand equation is problematic. Whether the dependent variable is actual attendance or the share of capacity, the value is limited on the up side. Attendance cannot exceed capacity, and the percentage of capacity cannot exceed 100%. In fact, during the 2008 and 2009 seasons, a total of 524 out of 4696 games were sold out, representing approximately 12.6% of our sample. Consequently, we estimate the model using a censored regression technique. The existence of censored observations constrained by stadium capacity results in parameter estimates that are biased and inconsistent (Meehan, Nelson & Richardson, 2007) leading us to use censored regression to estimate the model.

Explanatory variables

Economic conditions (Econcon). The coincident index of economic indicators for the 50 states released by Federal Reserve Bank of Philadelphia is used to reflect economic conditions during each month of the 2008 and 2009 seasons. There may be an issue for teams such as the Phillies, Mets, and Yankees, whose territories cover multiple states. Thus, we performed pairwise correlations for the coincident index for the state pairs, using the data from 2006 to the

present. All of the correlations are positive and statistically significant and most are in the .9 and above range. Consequently, we feel comfortable linking a team to the coincident index of economic indicators for the state in which its stadium is located. Because of the unavailability of the index for Washington D.C., the index for the state of Maryland was coded for the Washington Nationals.

Rottenberg (1956) hypothesized that attendance will be affected by the quality of the home team and the uncertainty of the outcome of the game. These variables can be measured in several ways. Our variables are described below:

Game uncertainty (HomeWin and OppWin). Winning percentages of the home and visiting teams prior to the game are used to capture game uncertainty of outcome in this study. Coates and Humphreys (2010) used these winning percentages as indicators of the game uncertainty of the outcome, along with betting line information in NFL. As Coates and Humphreys (2010) mentioned, these winning percentages also capture the quality of the teams.

Rottenberg (1956) suggested attendance would be greatest at games between evenly matched teams, all else constant. However, evidence from Forrest, et al. (2005), Buraimo and Simmons (2008), and Coates and Humphreys (2010) who use betting line information to measure the expected closeness of games, in Football Association games in England and the National Football League, respectively, found home attendance rises as the home team becomes a greater favorite.

Playoff uncertainty (monthsGB). The measure of the playoff uncertainty assumes where a game is significant in determining promotion or relegation, or for participation in the playoffs or a wildcard race, then fans are more attracted to the game, resulting in higher attendance (Borland & Macdonald, 2003). To measure this, the month dummy variables are included and then the

interaction of the month and the number of games behind the division leader was added. Without the month dummy variables, the interaction variable is likely picking up mostly the month effect, especially early in the season.

Team performance (PlayoffApp). It is reasonable that fans' expectations for the coming year and the decision to buy season tickets could depend on the last season's performance. To reflect these fans' expectations, a number of attendance studies used last season's appearance in the playoffs (Coates & Harrison, 2005; Coates & Humphreys, 2005; Meehan et al., 2007; Noll, 1974; Rivers & Deschriver, 2002). This variable is measured as a dummy variable for whether the home team appeared in the playoffs in the last season.

Interleague Play (Interleague). Since its inception in 1997, Interleague Play has contributed to an increase in the MLB attendance. According to Brown (2009), Interleague Play has drawn an average of 33,260 fans per game, compared to the intraleague average of 29,706 fans per game during the same span. This figure indicated that Interleague Play attracted 12.0 percent more fans than intraleague games. Therefore, a number of attendance demand studies have included the effect of Interleague matchups (Boyd & Krebiel, 2006; Butler, 2002; Meehan et al., 2007). A dummy variable was used to measure the effect of interleague play on attendance by coding 1 if the home team played against another league's team and 0 otherwise.

New stadium (Novelty). A large body of attendance research has demonstrated a positive effect of a new stadium on attendance (e.g., Borland & McDonald, 2003; Coates & Humphreys, 2005; McEvoy, Nagel, & DeSchriver, 2005; Noll, 1974; Zygmunt & Leadley, 2005). During the 2008 and 2009 seasons, the Washington Nationals played at a new stadium both years, and the New York Yankees and Mets played at a new stadium in 2009. To capture the novelty effect, the

analysis included a dummy variable that takes value 1 when playing at the new stadium and 0 otherwise.

Star player (HomeStar and OppStar). Team composition plays a fundamental role in facilitating fan support (Brandes, Frank, & Nuesch, 2008). Recent studies on attendance demand clearly indicated that star players contribute to driving attendance demand (Berri & Schmidt, 2006). To assess the impact of popularity of star players on attendance, the number of previous season All-Stars until mid-season of the current year, and current season All-Stars for the second half of the season were coded for both home and visiting teams.

Schedule (Weekend). To control for when the game is played, several studies have included the weekday and weekend variables. For example, the games played on Friday, Saturday, and Sunday took the value of 1 and 0 otherwise (Boyd & Krehbiel, 2006; Bruggink & Eaton, 1996; DeSchriver, 2007; Garcia & Rodriguez, 2001; Hill et al., 1982; Knowles, Sherony, & Hauptert, 1992). Consistent with previous studies, this study included the Weekend in order to control for the effects of the schedule.

Average ticket price (AvgTicket). Ticket (or admission) price has been used in almost all attendance demand models in MLB (Coates & Humphreys, 2007). Consistent with demand theory, it is assumed that as price increases game attendance should decrease. Thus, it is expected that the coefficient on the ticket price variable will be negative and significant.

Data were collected for every regular season game for the 29 MLB teams based in the United States. The composite index of coincident indicators is not available for the Toronto Blue Jays. The sample contains 4,696 games during the two seasons, but two of these are dropped because they were played in Japan. Multiple resources were used to collect the data such as Baseball-Reference.com, ESPN.com, and the Federal Reserve Bank of Philadelphia's website.

Descriptive statistics for the variables used in the regression equation are presented in Table 1. Home attendance as a percentage of stadium capacity was 71.33% on average, with a standard deviation of 22.44. The mean Econ for the states where the teams are located was 159.36 with a standard deviation of 17.99. The index declines over the sample period for all of the states, though to varying degrees. Figure 1 displays the index for each state for each month. Arizona, home to the Arizona Diamondbacks, had the highest of the composite index of economic indicators, while Michigan (home of the Detroit Tigers) had the lowest index. Michigan's index changed the most, New York's changed the least.

Empirical Results and Discussion

(Figure 1 inserted) (Table 1 inserted)

Table 2 reports regression results from the censored regression analysis with the team fixed effects. The censored regression model was found to be significant with a log-likelihood statistic of -17056.90.

The coefficient on the coincident indicator variable Econ is significant and positive, as expected. This clearly indicates that healthier economic conditions are associated with higher attendance. Thus, the decrease in the composite index between 2008 and 2009, representing the recent economic downturn throughout the whole economy, influenced a decrease in attendance between the 2008 and the 2009 seasons. The estimated regression coefficient of 0.35 appears small. However, at the mean values of attendance percentage and Econ, the coefficient estimate implies an elasticity of 0.78. In other words, a one percent increase in Econ, the coincident indicator, implies a 0.78 percent increase in attendance. For the period of our data, the average decline in Econ is over 7.7%, suggesting a rough impact of the economic decline on attendance

from the start of 2008 until the end of 2009 of about 6%, very nearly the 6.77% reported decline mentioned in the introduction.

The following variables are used to capture the importance of competitive balance and the uncertainty of outcome hypotheses. For game uncertainty, the coefficients on the home (HomeWin) and visiting team's (OppWin) current winning percentage to date variables are statistically significant and positive. This result supports the idea that fans are eager to see good teams play, regardless of whether it is the visiting team (Coates & Humphreys, 2011). Thus, fans consider the quality of both home and visiting teams for attendance. For playoff uncertainty, the coefficients on the playoff uncertainty variables before the month of August (MarchGB, AprGB, MayGB, JunGB, and JulyGB) were found to be insignificant while the variables since the month of August (AugGB, SepGB, and OctGB) were significant and negative. This has two important implications. One defines when fans start to recognize playoff contention and the other is when the effect of the division leader on attendance is more prominent than other months. Indeed, the results are consistent with Noll's (1974) judgment on when the contention, or race, for playoff spots begins. Specifically, he judged the playoff contention as if the second-place team averaged five games or fewer behind the leader between August 1 and the end of the season.

The significant negative coefficients on the month dummy variables indicated average attendance is lower in other months relative to average attendance at games in March, the omitted month in the regression. There are very few games played in March, 15 out of 4,696, and two of those were played in Japan. These March games are, of course, "Opening Day" games for the home teams and, therefore, have unusually high attendance. It is, therefore, not surprising that average attendance in other months is lower than in March. More importantly, consider the pattern in the coefficients on the month dummy variables. As the weather heats up

through spring and into summer, and kids get out of school, average attendance is rising – the negative month coefficients move toward zero – until July. Average attendance starts to decline again through August and September, until it jumps up substantially in October. Not much should be made of this increase in October, however, as there are only 56 games played in October in the data compared to between 700 and 825 games each month from April through September.

Surprisingly, the PlayoffApp had a negative impact on attendance. The negative impact of the PlayoffApp may be explained with two features of the teams that appeared in the 2007 and 2008 Playoffs. One feature is that several teams that appeared in previous playoffs showed poor performance in that year. For example, the Cleveland Indians and the Colorado Rockies appeared in the 2007 playoffs but performed poorly in the 2008 season, resulting in a decrease in attendance. The Chicago White Sox and the Milwaukee Brewers appeared in the 2008 Playoffs and also performed poorly in the 2009 season, resulting in a decrease in attendance. If one includes interactions between the playoff appearance dummy and the month of the season dummies (excluding an October interaction), those interactions are each individually statistically significant, and negative, while the playoff appearance dummy is positive and statistically significant. (These results are available upon request.) This relates to a second possible explanation for the negative coefficient on the playoff appearance variable; several teams' continued dominance may result in fans losing interest, particularly early in the season. Eckard (2001) found a significant decrease in attendance when a team is on a run of dominance. Thus, the appearances of several dominant teams in the 2007 and/or 2008 Playoffs such as the New York Yankees, the Los Angeles Angels, the Chicago Cubs, the Boston Red Sox, and the Los Angeles Dodgers may generate the possible loss of fan interest, or not produce additional interest

in the team, resulting in lower early-season attendance. The estimated coefficients on the playoff appearance month interactions suggest that interest, in the form of attendance, rises slowly throughout the season for the teams that repeatedly contend for the playoffs.

The estimated coefficients on the all-star variables for home (HomeStar) and visiting teams (OppStar) were significant and positive. What this result reveals is that home spectators are interested in seeing both the home teams' and visiting teams' star players. Visiting teams' star players' scarcity value (produced by less opportunity of seeing them) is one possible explanation for the positive association with attendance. Berri and Schmidt (2006) document the impact of star players from the visiting team on attendance in the NBA.

The Novelty effect was positive and statistically significant despite only three teams playing at a new stadium during the time span used. The coefficients on the weekend and the interleague variables are also significant and strongly positive, as expected. These results are consistent with findings of previous attendance studies.

Finally, the AvgTicket was found to be negative and statistically significant. The negative sign on this variable indicates that higher ticket prices are associated with lower attendance, as implied by demand theory. The estimated absolute value of ticket price elasticity ($.04 < 1$) supports the idea that attendance demand is price inelastic.

Conclusion and Limitations

Using 4,696 games during the 2008 and 2009 seasons, the main focus of the proposed study was to investigate the effect of the recent economic crisis on attendance in MLB. The empirical evidence from the study indicates the recent economic crisis contributed to a decline in MLB attendance over the period 2008 through 2009; deteriorating economic circumstances explain a decline of about 6% compared to the reported decline of 6.77%.

The success of the composite index of coincident indicators in explaining the impact of the recent economic crisis on attendance in MLB suggests the indicator is a viable proxy for income in game attendance demand studies.

There are several limitations to this study that need to be discussed:

One limitation is the lack of weather data in the model. Past attendance models have measured the effect of weather on daily attendance, but we have not included that in the current analysis. Two approaches are common in the attendance demand studies. The first approach is concerned with the temperature for the day of the game. For example, as continuous variables, the average of the daily low and high temperature (Meehan, Nelson, & Richardson, 2007) and the temperature reported during the game (Bruggink & Eaton, 1996; Paul, Paul, & Yelencsics, 2008) were used. Meanwhile, Butler (2002) used two dummy variables; one is a dummy variable equal to 1 if game temperature is less than 55° F; the other is a dummy variable equal to 1 if game temperature is greater than 94°F. The second approach concerns rain. Meehan, Nelson, and Richardson (2007) used the number of inches of rain for a given day, while DeSchrive (2007) and Butler (2002) included a dummy variable to indicate whether the game was played during rainy weather conditions. These different approaches to measurement of weather conditions have generated contradictory results. Researchers should therefore address more accurate methods that can be employed to assess the impact of weather conditions. Omitting weather should not alter our results regarding the coincident indicator, however, as it is highly unlikely that daily weather and monthly coincident indicator are highly correlated.

A second limitation of the current study is the measure of the playoff uncertainty, measured as the interaction of the number of games behind the division leader and the month dummy variables. By using the month dummy variables, we addressed how contention for

playoff qualification was defined. Yet, there are still two matters to consider in using this method. One is its inability to capture whether teams are out of playoff contention and the other is the need to capture the effect of the wild-card system. For example, a team a given number of games behind the divisional leader can still be in the wild-card race, and that may keep its fans keep more interested in September games. Thus, future research is required to address these matters.

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Table 1. *Descriptive statistics for the variables to predict MLB attendance demand during the 2008 and 2009 seasons (N = 4694)*

| Variable | Mean | SD | Minimum | Maximum |
|-----------------|--------|-------|---------|---------|
| AttendancePct | 71.34 | 22.44 | 21.00 | 100.00 |
| Econcon | 159.36 | 17.99 | 112.86 | 226.08 |
| Interleague | 0.10 | 0.30 | 0.00 | 1.00 |
| HomeWin | 49.97 | 9.81 | 0.00 | 100.00 |
| OppWin | 50.12 | 10.04 | 0.00 | 100.00 |
| PlayoffApp | 0.29 | 0.46 | 0.00 | 1.00 |
| HomeAllstar | 2.25 | 1.47 | 1.00 | 8.00 |
| OppAllstar | 2.18 | 1.44 | 1.00 | 8.00 |
| Weekend | 0.48 | 0.50 | 0.00 | 1.00 |
| AvgTicket | 26.10 | 10.20 | 14.31 | 72.97 |
| Novelty | 0.05 | 0.22 | 0.00 | 1.00 |
| MarchGameBehind | 0.00 | 0.04 | -0.50 | 1.50 |
| April | 0.15 | 0.36 | 0.00 | 1.00 |
| AprGameBehind | 0.29 | 1.17 | -6.50 | 9.50 |
| May | 0.18 | 0.38 | 0.00 | 1.00 |
| MayGamebehind | 0.59 | 2.14 | -8.50 | 14.00 |
| June | 0.16 | 0.37 | 0.00 | 1.00 |
| JunGamebehind | 0.81 | 2.86 | -9.50 | 18.50 |
| July | 0.16 | 0.37 | 0.00 | 1.00 |
| JulyGamebehind | 0.90 | 3.45 | -10.00 | 27.00 |
| August | 0.17 | 0.38 | 0.00 | 1.00 |
| AugGamebehind | 1.42 | 5.12 | -18.00 | 31.50 |
| September | 0.16 | 0.37 | 0.00 | 1.00 |
| SepGamebehind | 1.75 | 6.21 | -21.00 | 41.00 |
| October | 0.01 | 0.11 | 0.00 | 1.00 |
| OctGamebehind | 0.11 | 1.64 | -8.50 | 40.00 |

Table 2. *Summary of Regression Analysis for Variables Predicting MLB Attendance*

| Variables | Coefficient | Std. Error | t-stat | P-value |
|-----------------|-------------|------------|--------|---------|
| Econcon | 0.35 | 0.04 | 9.42 | 0.00 |
| Interleague | 8.14 | 0.88 | 9.24 | 0.00 |
| HomeWin | 0.12 | 0.04 | 3.23 | 0.00 |
| OppWin | 0.10 | 0.02 | 4.07 | 0.00 |
| PlayoffApp | -3.64 | 0.78 | -4.66 | 0.00 |
| HomeAllstar | 0.73 | 0.23 | 3.21 | 0.00 |
| OppAllstar | 2.11 | 0.15 | 14.16 | 0.00 |
| Weekend | 13.57 | 0.41 | 32.71 | 0.00 |
| AvgTicket | -0.12 | 0.06 | -2.08 | 0.04 |
| Novelty | 6.36 | 1.39 | 4.56 | 0.00 |
| MarchGameBehind | 4.10 | 5.85 | 0.70 | 0.48 |
| April | -44.09 | 5.85 | -7.53 | 0.00 |
| AprGameBehind | -0.22 | 0.27 | -0.83 | 0.41 |
| May | -42.73 | 5.86 | -7.29 | 0.00 |
| MayGamebehind | -0.10 | 0.14 | -0.73 | 0.47 |
| June | -41.46 | 5.90 | -7.03 | 0.00 |
| JunGamebehind | -0.07 | 0.11 | -0.66 | 0.51 |
| July | -34.38 | 5.88 | -5.84 | 0.00 |
| JulyGamebehind | -0.20 | 0.09 | -2.34 | 0.02 |
| August | -35.13 | 5.88 | -5.98 | 0.00 |
| AugGamebehind | -0.23 | 0.06 | -3.85 | 0.00 |
| September | -37.93 | 5.88 | -6.45 | 0.00 |
| SepGamebehind | -0.34 | 0.05 | -6.85 | 0.00 |
| October | -29.10 | 6.44 | -4.52 | 0.00 |
| OctGamebehind | -0.89 | 0.17 | -5.24 | 0.00 |

The model also includes home team dummy variables.

Figure 1. The composite index of coincident indicators for the 50 states during the 2008 and 2009 seasons

