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Playoff Uncertainty and Pennant Races

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Abstract

Outcome uncertainty, a fundamental principle associated with Rottenberg, has many meanings in the sports economics literature. In this article, the authors consider a type of within-season uncertainty termed "playoff uncertainty" (PLU). As with any type of within-season uncertainty, this concept looks at how demanders respond to the probability that their team has a chance of winning over the course of the season. But more specifically, PLU focuses on whether attendance is affected by a team's chance of making the playoffs. Looking at attendance data on a monthly basis, the authors find that a tighter pennant race does enhance league-wide attendance, but only for those months toward the end of the season when the pennant race is heating up.

Keywords

monthly attendance, playoff uncertainty

In his seminal article "The Baseball Players' Labor Market," Simon Rottenberg (1956) lays out two very important theses: the invariance principle (IP) and the uncertainty of outcome hypothesis (UOH). While often overlooked in favor of the famous Coase Theorem (Coase, 1960), Rottenberg's IP preceded Coase by at least 4 years. His other major contribution, the UOH, has received much more attention in that it outlines the critical nature of a cooperative competition, such as a sports league. As Rottenberg puts it: "... no team can be successful unless its competitors

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also survive and prospers sufficiently so that the differences in the quality of play among teams are not 'too great.'" Given that the uncertainty of outcome is positively related to the demand for the entertainment provided by the sport, Rottenberg's UOH leads to the simple conclusion that leagues must promote competitive balance or face declining attendance.

But competitive balance has met with many meanings and interpretations in the literature. One line of literature looks at the individual games as the building block of competitive balance. Balance in this sense is interpreted in regards to the closeness between two opponents. In what Fort (2006) refers to as game uncertainty, the UOH here refers to the predictability of the outcome of a particular game. Game uncertainty, for example, dictates that leagues do not match professional teams against amateur teams.

Since the economic well-being of a league depends upon its ability to create and sustain league-wide interest, another interpretation of the UOH is uncertainty at a more aggregate level. One could classify uncertainty at the league level across two different time horizons: uncertainty within each season and uncertainty across consecutive seasons. Consecutive-season uncertainty (CSU) is concerned with the legitimacy of a league when fans believe that the ultimate outcome of a season-long competition is essentially predetermined. For example, consecutive-season balance deals with the possibly deleterious effect of perennial dynasties on the entertainment value of a league. In terms of measurement, analysts have used a variety of metrics to measure the distribution of success across seasons (see Butler, 1995; Fort & Lee, 2008; Hadley, Krautmann, & Ciecka, 2005; Humphreys, 2002; Krautmann & Hadley, 2006; Quirk & Fort, 1992).

Within-season uncertainty, on the other hand, is associated with how demand responds to success across teams within any one season. If the distribution of performances in a league is widely dispersed (i.e., a high variance) or bimodal (i.e., with contenders and non-contenders and no "middle class"), then mismatches will be frequent and the legitimacy of the league will be called into question.[1] The UOH applied here implies that to incite the interest of fans, teams must be viewed as sufficiently equal to make the race for the championship exciting. In terms of empirical analysis on this topic, this notion of game-match uncertainty (GMU) has been measured by a number of metrics (see Depken, 1999; Fort & Quirk, 1995; Humphreys, 2002; Lee, 2004; Quirk & Fort, 1992; Schmidt & Berri, 2001).

A recent extension of the concept of within-season uncertainty is concerned primarily with the closeness of the race for the playoffs or championship, with a narrower focus on the notion of playoff uncertainty (PLU; Lee, 2009; Lee & Fort, 2008). PLU is concerned with how attendance responds to the closeness of the race for the championship, particularly as it pertains to the degree to which runner-ups have a reasonable probability of catching the leaders by the end of the regular season. In Lee and Fort (2008), PLU was measured by the difference in win percentage between those Major League Baseball (MLB) teams making the playoffs and the nearest runner-ups. As defined by the closeness between the eventual division winner and the runner-ups, their study found that PLU does have a significant impact on annual attendance in MLB (although its economic significance was found to be rather weak).

With the number of teams in MLB admitted into the playoffs doubling in 1969, and then again in 1994, Lee (2009) looked at whether these structural changes affected PLU, and hence attendance. Lee used a more refined metric of PLU, which includes every member of the league (instead of just the first- and second-place teams), as well as allowed for more flexibility in terms of the manner in which the differences in win percentage affects PLU. Similar to the conclusions in Lee and Fort, he found that PLU does have a significantly positive effect on game attendance in MLB. In terms of the changes in the playoff structure in 1969 and 1994, Lee concluded that increasing the number of teams admitted into the playoffs resulted in a league-wide increase in total regular season attendance of about 150,000 to 250,000 fans per season.

Overall, the literature appears to agree with Rottenberg's UOH, although the manner in which competitive balance matters is subtle and complex. Game-match uncertainty surely affects demand, with PLU likely to be a critical aspect of this within-season uncertainty. What remains to be seen is whether PLU affects attendance over the entire season (beginning on Opening Day), or if this is really an end-of-season effect, effecting attendance primarily in the last phase of the season. In Lee's 2009 article, PLU was analyzed across the entire season, using annual attendance per game (APG) as the unit of observation. Thus his approach implicitly assumes that PLU is as important in April as it is in September. We intend to expand on Lee's prior article by looking at whether PLU has any effect on average APG but measured at different points across the season. We also present empirical evidence testing whether GMU and/or CSU are significant factors by considering all three types of uncertainty in the monthly attendance model. To our knowledge, there has been no previous analysis using monthly attendance data to gain a better understanding of how PLU affects demand. We suspect that the tightness of a playoff race affects attendance, but this effect is primarily felt toward the end of the season.

Model

In this article, we look at whether PLU has a season-long effect on attendance or just a boost in attendance arising toward the end of the season when the pennant race is tight. To achieve this end, we use monthly data on APG in MLB over the 50 years associated with the 1957-2006 seasons.[2] The months included in this study are April through September.[3]

We also consider the other types of uncertainty in our monthly attendance model. In this analysis, we measure GMU using the tail-likelihood metric (TL) proposed by Lee (2004), where a larger value of TL corresponds to greater balance with respect to GMU. For CSU, we utilize the competitive balance ratio (CBR) devised by Humphreys (2002), defined as the ratio of between-season variation to within-season variation. A larger value of CBR corresponds to greater balance with respect to CSU.[4]

For PLU, we begin by recognizing Cairns's (1987) argument that two factors relevant to determining the closeness of a pennant race are games back (GB) in a baseball league together with the number of games played. Lee and Fort (2008) used this basis to form an aggregate, within-season measure of PLU, which represented the average difference in wins between division winners and runner-ups (as well as between a wild-card team and the next-best trailing team). In this regard, their measure implicitly assumed that the PLU of the entire league is completely determined by the contest between just two teams: the eventual winner and the runner-up.

Recently, Lee (2009) developed a more complete measure that includes other desirable qualities of a metric used to measure the degree of PLU. First, for PLU to adequately measure league-wide uncertainty, this metric should consider the games back of every member team in the league. That is, even if the top two teams are in a tight race to advance, the degree of competitiveness can nonetheless be low if all of the other teams in the division fall out of playoff contention early in the season. Alternatively, these top two teams could be in a relatively loose pennant race (e.g., the runner-up is, say, five games back), but the league-wide competitiveness could still be quite high if the other teams still have a "reasonable" chance of catching the division winner before the season ends. Therefore, it is important that our metric allow for teams throughout the standings to have an influence on the league-wide PLU. Second, we should allow for nonlinearity in the relationship between GB and PLU since it is reasonable to assume that the impact of a one-unit difference in GB between top contending teams is different than a one-unit difference between last place teams. To this end, we use a normal probability density function to model the uncertainty of a "trailing team" (i.e., a team that trails behind the division-leading team) making the playoffs. The appeal of this assumption is that allows: (a) the PLU of a team to be highest when its GB is close to zero;[5] (b) a one-unit increase or decrease in GB will have an insignificant impact on PLU for those teams toward the bottom of the standings; and (c) the PLU difference between zero and one GB is smaller than that between, for example, three and four GB because the teams that are zero and one GB remain playoff hopefuls until almost the last game of the regular season. Finally, since PLU can differ when the total number of games in a regular season differs, another desirable property of this metric is that it takes into account the number of regular-season games.

Our PLU measure is given by:

$$\mathrm{PLU} = \frac{1}{N}\sum_{i=1}^{N} f\left(\mathrm{GB}_i \cdot \frac{162}{G}\right), \tag{1}$$

where f is a normal density function with a mean of zero and variance of six, GB_i is either the smaller GB of a team i wins behind the division winner or a wild-card

Table 1. Augmented Dickey-Fuller (ADF) Unit Root Tests

Month	League	ADF (*p*) With Only a Constant	ADF (*p*) With a Constant and Trend
April	AL	−0.510 (0)	−3.431 (0)
	NL	−1.346 (0)	−3.685* (0)
May	AL	−0.450 (1)	−4.097* (0)
	NL	−1.632 (0)	−5.773* (1)
June	AL	−0.681 (0)	−2.995 (0)
	NL	−0.340 (2)	−5.122* (1)
July	AL	−1.215 (0)	−3.711* (0)
	NL	−1.346 (0)	−5.207* (1)
August	AL	−0.848 (0)	−3.006 (0)
	NL	−0.645 (2)	−5.602* (1)
September	AL	−0.294 (0)	−2.675 (0)
	NL	0.448 (3)	−4.376* (0)
All periods	AL	−0.375 (6)	−2.607 (6)
	NL	−0.838 (6)	−4.339* (6)

Note. p = the number of lags.
* Significant at the 95% critical level.

winner, G is the number of regular-season games for each team, and N is the number of teams other than division winners in a league. The $(162/G)$ implies that this measure set a basis of the 162 games that is actual number of games in 2006. It reflects the fact that one game back has different effect on PLU when total numbers of regular season games per team are different.[6] Note that this metric increases as competitive balance improves.

In order to estimate the attendance function in MLB over the 50-year time period, a number of time-series issues must first be addressed. The first empirical issue typically encountered with time-series data is the problem associated with nonstationarity. As shown by Dickey and Fuller (1979), data characterized by a unit root can result in serious errors in inference. To this end, we begin by conducting an Augmented Dickey-Fuller (ADF) test on monthly APG, for both the American League (AL) and the National League (NL). These results are presented below in Table 1, where the number of lags (ρ) is determined by minimizing the Schwartz-Bayesian criterion. In the case of a model with only a constant, the ADF tests result in a failure to reject the null hypothesis of a unit root for all months in both the AL and the NL. The results are somewhat more scattered when we consider the case of the ADF tests with a constant and a linear trend. In the AL, we cannot reject the unit root in the months of April, June, August, and September. In the NL, on the other hand, we reject the null for all months.

Standard unit root tests of APG data can be misleading when structural breaks are ignored (Fort & Lee, 2006; Lee & Strazicich, 2003; Perron, 1989). Lee and Strazicich (2003) proposed a minimum LM unit-root test for stationarity when there are

Table 2. Minimum LM Unit Root Tests With Endogenous Breaks

Variable	League	$\hat{k}$	Test Statistic
April	AL	3	−6.971*
	NL	8	−6.387*
May	AL	8	−7.316*
	NL	8	−6.927*
June	AL	3	−7.052*
	NL	8	−6.220*
July	AL	3	−6.435*
	NL	0	−5.857*
August	AL	0	−7.361*
	NL	8	−6.042*
September	AL	0	−6.933*
	NL	8	−7.325*
All period	AL	6	−6.563*
	NL	7	−7.906*

Note. $\hat{k}$ is the optimal number of lagged first-difference terms included in the unit root test to correct for serial correlation. See Table 2 in Lee and Strazicich (2003) for critical values.
* Significant at the 95% critical level.

endogenous breaks in the data.[7] Table 2 presents the results of the unit root test with endogenous breaks on each month and for each league. In contrast to the earlier results without breaks, we find that the unit root test with endogenous breaks concludes that the monthly APG data are stationary for both AL and NL. That is, Table 2 shows that all test statistics are significant at a reasonable level of significance. As such, we reject the null hypothesis of a unit root and proceed to the primary issue of whether PLU is an important factor in determining APG.

To assure the robustness of our analysis, we take two different approaches to testing the role of competitive balance in monthly APG data. One approach is to model APG at a disaggregated level (Disaggregate Approach), which estimates six separate regressions, one for each month of the season. The other approach (Aggregate Approach) uses a balanced panel data set of all months across the entire 50-year period. For the Aggregate Approach, we use dummy variables to measure monthly effects in a balanced panel data set of 300 observations (i.e., 50 years $\times$ 6 months). For the Disaggregate Approach, on the other hand, six regressions are run on yearly data that are disaggregated into each of the 6 months. While this disaggregated model cannot compare APG across months, it does solve possible stationarity problems in the time series by allowing for endogenous break points in the data.[8]

Disaggregate Approach

There have been two different approaches to empirically analyze league-wide attendance. One is a structural equation model that includes a number of typical demand shifters (e.g., price, income, etc.) along with league-specific characteristics (e.g., competitive balance, superstar effects, etc.). The alternative is to find structural breaks in the attendance time-series data, and then assume that different constants and the trend coefficients explain average variation in attendance. We are forced to adopt this latter approach primarily because of nonstationarity issues in the explanatory variables. For example, the typical explanatory variables in a demand estimation would include some measure of aggregate income and ticket prices, along with average metro population of all host cities' in the United States. If the time-series data of price, income, population are nonstationary (as they almost certainly are), then we would have introduced inconsistency into our model even though the dependent variable is stationary (with breaks). While traditional nonstationarity solutions, such as first differencing the exogenous variables, might provide a solution to the problem but it would greatly complicate the computation and interpretation of the estimates (e.g., elasticities).

As such, we avoid such difficulties by estimating the variations in APG using structural break models using trend and CB variables.[9] Once the break points are identified, the attendance equation with structural breaks is then estimated by:

$$\mathrm{APG}_t = \sum_{j=1}^{m+1} \beta_j Z_{jt} + \alpha_1 \mathrm{PLU}_t + \alpha_2 \mathrm{GU}_t + \alpha_3 \mathrm{CSU}_t + u_t. \quad (2)$$

Since the linear regression equation has m breaks, this results in $(m+1)$ regimes or eras. The first segment on the right-hand side shows that within each of these $(m+1)$ regimes, Z_{jt} consists of a constant and a trend variable. Because the parameter vector α is not subject to change, this is called a "partial structural change" model.

Table 3 presents the estimated break points using the monthly attendance data. In the AL, we find two breaks for the months of April, June, July, and September and three breaks for the month of May and August. In the NL, we find two breaks for the months of April and September and one break for the month of June; and we find no break for the months of May, July, and August.[10] The structural break model, developed by Bai and Perron (1998, 2003), is used here primarily because it gives reasonably good explanatory power. As our interest is primarily in looking at the relationship between attendance and CB, such a modeling approach is appropriate.

Table 4 reports the results of this estimation for the AL; a similar set of estimates are reported in Table 5 for the NL. Table 4 presents the regression estimates of the coefficients on each regime-specific constant and trend, along with the three competitive balance variables: PLU, TL, and CBR. Since the break analysis presented in Table 3 shows a number of different month-specific regimes, Table 4 gives the monthly estimates for the AL within each regime. For example, in the month of April, Regime #1 corresponds to the 1957-1974 era; Regime #2 corresponds to the 1975-1994 era; and Regime #3 represents the 1995-2006 era. The estimate on the trend within each regime indicates the growth in monthly APG during that era. For

Table 3. Break Points Estimation (Using Monthly Data)

League Regime	American League					
	April	May	June	July	August	September
Break 1	1974 (1972, 1975)[a]	1965 (1963, 1968)	1976 (1974, 1977)	1963 (1961, 1968)	1976 (1974, 1979)	1976 (1974, 1977)
Break 2	1994 (1993, 1996)	1986 (1984, 1987)	1994 (1992, 1996)	1987 (1986, 1988)	1986 (1984, 1992)	1989 (1986, 1990)
Break 3		1994 (1992, 1995)			1994 (1992, 1996)	

League Regime	National League					
	April	May	June	July	August	September
Break 1	1975 (1973, 1980)[a]	–	1963 (1961, 1964)			1964 (1962, 1965)
Break 2	1992 (1991, 1993)					1992 (1988, 1993)

[a] The 90% confidence interval for the break point.

example, the slope coefficient for April in Regime #2 implies that APG rose by 713 annually between 1975 and 1994.[11]

We can draw a number of conclusions about monthly APG in the AL from Table 4. For all months, the positive coefficient on the trend slope in Regime #2 suggests that APG increased grew each year from the 1970s to the mid-1990s. In contrast, there was not any significant growth in APG before the 1970s; and with the exception of June, there has not been any significant growth after the mid-1990s.

To visualize the meaning of these shifts at each break point, Figure 1 displays the time trend in the fitted versus actual attendance for each of the 6 months. For the AL, APG was essentially flat up until the mid-1970s. From the mid-1970s until the mid-1990s, attendance rose by roughly 500 fans per game. After the mid-1990s, however, APG flattened out again. These results are suggestive that perhaps fans of AL teams have not fully forgiven MLB for the cancellation of the World Series in 1994.

Turning to NL, Table 5 reports the results of the attendance estimation. Given that Table 3 showed that there were no break points in the NL for the months of May, July, and August, the estimate of the trend in these three months imply that APG grew by roughly 300 fans each year across the entire 50-year period. For the months of April and September, however, we found that growth in APG was primarily confined to the mid-1970s to the mid-1990s. Figure 2 displays the time trend in the fitted versus actual attendance for each of the 6 months.

Having controlled for the impact on APG of the other competitive balance variables (TL and CBR), Tables 4 and 5 both show that the coefficient on PLU is statistically significant only in the month of September. That is, the only month in which we find attendance affected by PLU is at the end of the season. Furthermore,

Table 4. Disaggregated Attendance per Game (American League)

Regime		April	May	June	July	August	September
Regime 1	Intercept	14.154 (9.41)**	16.171 (12.12)**	17.644 (13.30)**	20.502 (11.12**	18.496 (10.65)**	11.420 (7.37)**
	Trend slope	−0.087 (−1.13)	−0.174 (−1.24)	0.032 (0.57)	0.039 (0.12)	0.006 (0.08)	−0.088 (−1.29)
Regime 2	Intercept	1.448 (0.85)	12.125 (6.67)**	8.945 (4.78)**	15.471 (7.29)**	16.307 (3.49)**	1.266 (0.41)
	Trend slope	0.713 (11.16)**	0.428 (11.20)**	0.641 (9.70)**	0.500 (9.72)**	0.352 (1.95)*	0.616 (5.27)**
Regime 3	Intercept	26.408 (2.61)**	−1.107 (−0.19)	14.933 (1.78)*	38.508 (7.26)**	10.583 (1.27)	20.707 (3.57)**
	Trend slope	0.003 (0.01)	0.900 (5.39)**	0.381 (2.24)**	−0.089 (−0.93)	0.643 (2.67)**	0.129 (1.15)
Regime 4	Intercept		26.474(3.36)**			23.741 (2.16)**	
	Trend slope		0.079 (0.50)			0.193 (0.87)	
	PLU	−14.506 (−0.41)	−12.550 (−0.43)	−44.230 (−1.03)	−22.610 (−0.51)	−39.229 (−0.91)	77.116 (1.95)*
	TL	0.450 (0.58)	0.396 (0.62)	0.721 (1.05)	1.196 (1.23)	0.714 (0.74)	0.460 (0.51)
	CBR	−1.512 (−0.49)	−5.842 (−2.33)**	−2.560 (−0.99)	−5.767 (−1.72)*	−3.426 (−1.01)	−0.811 (−0.27)
	R^2	.963	.973	.969	.919	.940	.967

Note. Attendance per game is measured in thousands.
* Significant at 10% level.
** Significant at 5% level.

Table 5. Disaggregated Attendance per Game (National League)

Regime		April	May	June	July	August	September
Regime 1	Intercept	15.981 (6.63)**	10.639 (5.96)**	16.594 (7.22)**	16.319 (9.03)**	11.747 (6.29)**	17.398 (5.81)**
	Trend slope	−0.139 (−1.99)*	0.303 (11.24)**	−0.490 (−1.48)	0.335 (12.29)**	0.282 (10.01)**	−0.834 (−2.84)**
Regime 2	Intercept	13.057 (5.02)**		11.939 (7.13)**			8.975 (4.37)**
	Trend slope	0.251 (2.49)**		0.341 (10.31)**			0.356 (5.28)**
Regime 3	Intercept	41.381 (4.21)**					18.903 (1.66)
	Trend slope	−0.382 (−1.97)*					0.221 (1.01)
	PLU	−33.776 (−0.99)	−30.095 (−0.81)	−8.670 (−0.25)	−33.777 (−0.90)	47.394 (1.22)	162.837 (4.12)**
,	TL	1.431 (2.28)**	0.503 (0.75)	0.309 (0.48)	−0.513 (−0.76)	−0.018 (−0.03)	−1.245 (−1.77)*
	CBR	2.841 (0.79)	5.246 (1.82)*	5.423 (1.89)*	3.324 (1.14)	7.638 (2.54)**	−2.145 (−0.50)
	R^2	.912	.859	.901	.862	.853	.924

Note. Attendance per game is measured in thousands.
* Significant at 10% level.
** Significant at 5% level.

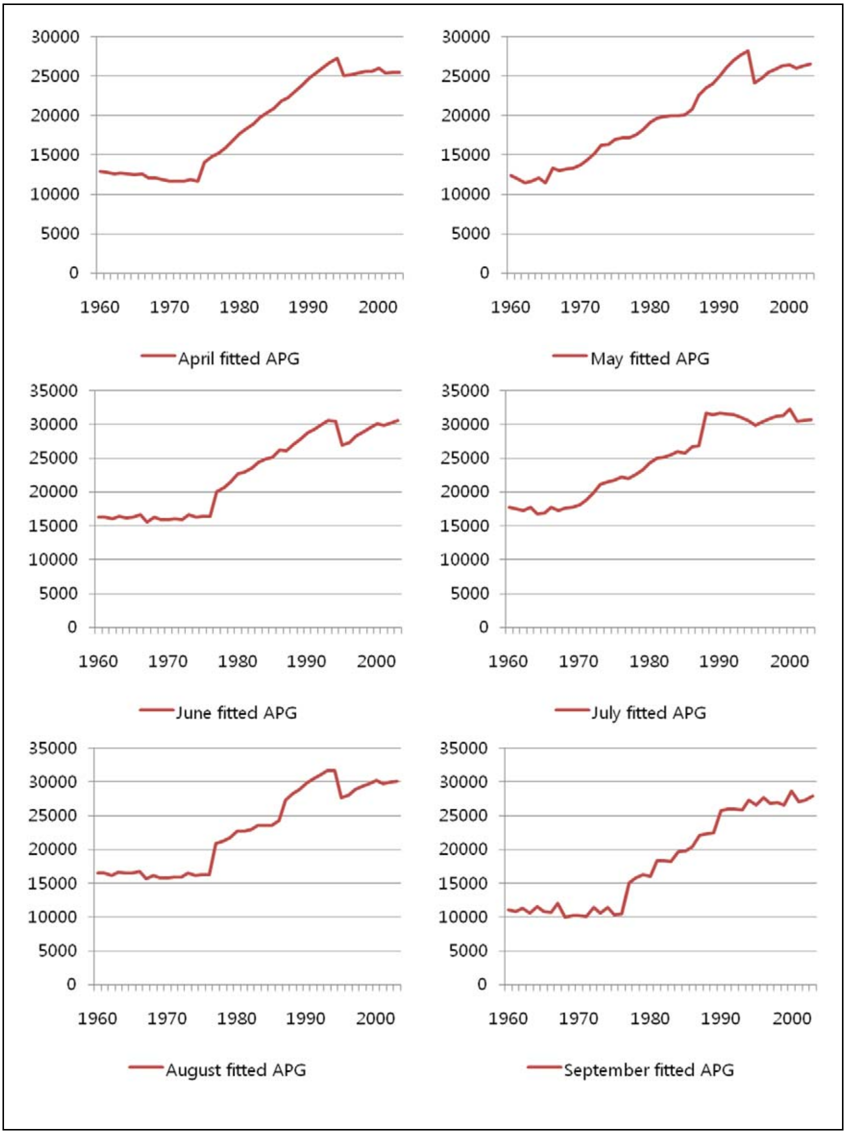

Figure 1. Fitted and actual APG by month: AL. AL = American League; APG = attendance per game.

the economic impact of PLU is more than twice as strong in the NL as it is in the AL—a result that is consistent with the conclusions presented in Lee and Fort (2008) and Lee (2009).

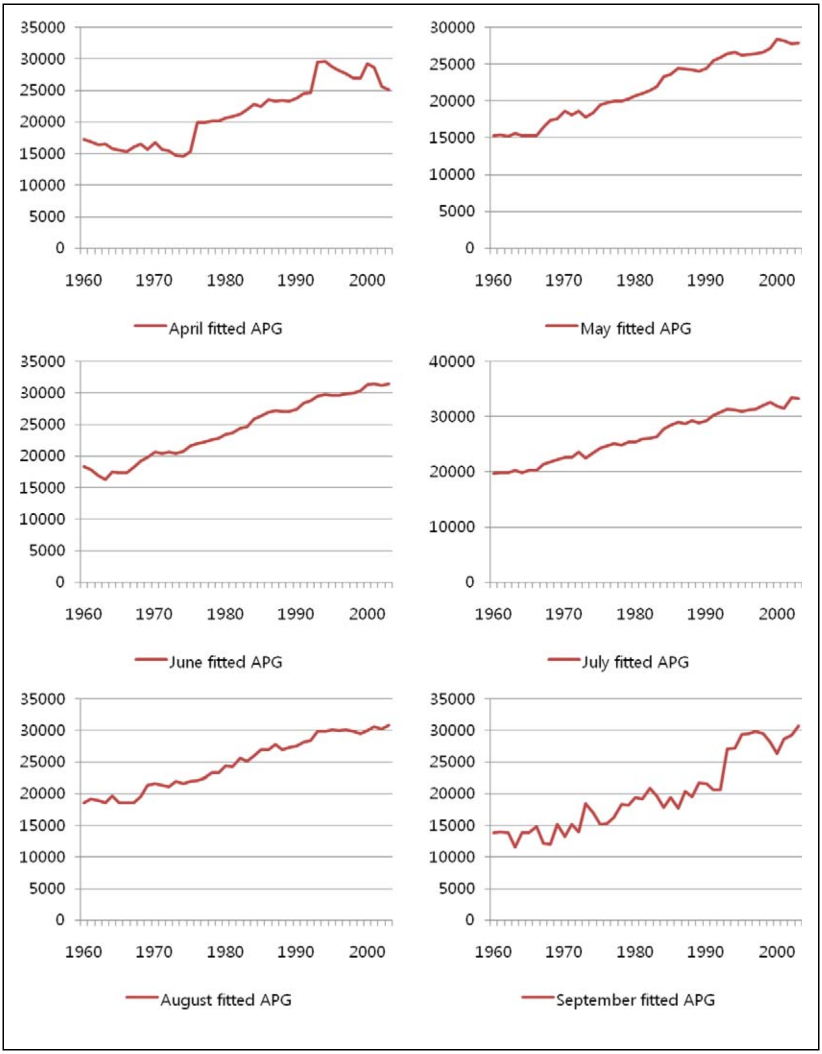

Figure 2. Fitted and actual APG by month: NL. APG = attendance per game; NL = National League.

Aggregate Approach

An alternative approach of studying whether competitive balance affects attendance is achieved by aggregating together the 6 monthly observations across the 50 years into a large panel data set of 300 observations. In this model, we use monthly dummy variables to test for differences in attendance across the season. Since the Bai/Perron technique does not permit the inclusion of dummy variables, we cannot derive the endogenous breaks as was done in the Disaggregate Approach above. As such, we assume that the same breaks Lee (2009) found in annual data apply to the monthly data used here. For the AL, these breaks are in 1970 (i.e., Regime #1 corresponds to 1957-1970) and 1990 (i.e., Regime #2 corresponds to 1970-1990). For the NL, Lee found just one break in 1976 (i.e., Regime #1 corresponds to 1957-1976). For the Aggregate Approach, the APG for each league is estimated by the following model:

$$\begin{aligned} \mathrm{APG}_t = \alpha + \gamma T_t + \sum_{j=1}^{m+1} \beta_j \,\mathrm{REGIME} + \sum_{j=1}^{m+1} \delta_j \,(\mathrm{REGIME} \times T_t) \\ + \sum_{j=1}^{3} \phi_j \,\mathrm{CB}_{jt} + \sum_{k=1}^{5} \phi_k \,\mathrm{MONTH}_{kt} + \sum_{j=1}^{3}\sum_{k=1}^{5} \eta_{jk} \,(\mathrm{MONTH}_{kt} \times \mathrm{CB}_{jt}) + \varepsilon_t. \end{aligned} \tag{3}$$

In Equation (3), REGIME are dummy variables that separate the data according to the structural breaks found in Lee (2009); MONTH are five dummy variables for the months of May through September (April is the default month); CB is a vector of the competitive balance variables (CB1 = PLU, CB2 = TL, and CB3 = CBR); T is a simple annual trend variable; and ε is a stochastic error term.

Pretest procedures led to estimating Equation (3) as an ARMA (2, 1) process. Table 6 presents the estimated coefficients for the AL, while Table 7 presents the estimates for the NL.[12] The first three columns (Models 1–3) present the results of the attendance equation with only one type of the competitive balance variable included. In Model 4, all three competitive balance variables are included. Not surprising, Tables 6 and 7 implies that attendance in both leagues is greatest in June through August.

In terms of the competitive balance variables, Tables 6 and 7 show that within-season uncertainty (as measured by TL) is not a significant factor influencing attendance in either league (the exception is the month of September in the NL). While consecutive-season uncertainty (as measured by CBR) is insignificant across all months in the AL, CBR is significant in 3 of the 6 months for the NL.

The results in Tables 6 and 7 are consistent with those found in the Disaggregated Approach above. That is, we find that PLU affects attendance in both leagues, but only in the month of September.[13] That is, the coefficient on SEPT × PLU is significantly positive in both leagues, implying that September attendance is most strongly increased when the league is experiencing the greatest degree of PLU. These results suggest that the playoff-uncertainty effect found in Lee (2009) is primarily an end of the season effect.

While the regression coefficients on the September cross-terms are statistically significant, the interesting question remains as to its economic significance. To interpret the economic impact of PLU in the month of September, we begin by noting that the PLU metric increased by 50% from about 0.02 to 0.03 across the sample period

Table 6. Aggregated Model of APG (American League)

Variable	Model 1	Model 2	Model 3	Model 4
Constant	13.028 (11.49)**	12.803 (13.08)**	13.184 (7.44)**	13.180 (7.01)**
TIME	−0.112 (−1.02)	−0.084 (−0.84)	−0.077 (−0.68)	−0.110 (−0.90)
D1970	−11.429 (−6.39)**	−11.057 (−6.81)**	−11.067 (−6.66)**	−11.652 (−6.31)**
D1970 × TIME	0.782 (6.09)**	0.754 (6.47)**	0.755 (6.17)**	0.795 (5.92)**
D1990	21.221 (6.11)**	26.666 (6.51)**	27.719 (5.93)**	28.033 (5.65)**
D1990 × TIME	−0.591 (−6.31)**	−0.730 (−6.66)**	−0.757 (−6.02)**	−0.770 (−5.72)**
MAY	0.540 (1.04)	0.676 (1.86)*	2.547 (1.71)*	2.613 (1.76)*
JUNE	4.140 (7.06)**	3.966 (9.81)**	5.629 (3.44)**	5.635 (3.42)**
JULY	5.736 (9.43)**	5.553 (13.34)**	6.385 (3.79)**	6.428 (3.78)**
AUG	4.196 (6.92)**	4.125 (9.93)**	4.670 (2.85)**	4.584 (2.78)**
SEP	−1.893 (−3.25)**	−0.910 (−2.31)**	−3.070 (−2.00)**	−3.319 (−2.15)**
PLU	3.261 (0.11)			10.628 (0.30)
MAY × PLU	16.114 (0.49)			24.176 (0.61)
JUNE × PLU	−19.933 (−0.54)			−11.741 (−0.27)
JULY × PLU	−16.808 (−0.43)			−13.909 (−0.30)
AUGUST × PLU	−11.164 (−0.29)			−8.409 (−0.18)
SEPT × PLU	92.412 (2.34)**			81.888 (1.76)*
TL		−0.306 (−0.42)		−0.422 (−0.50)
MAY × TL		0.390 (0.46)		0.456 (0.47)
JUNE × TL		−0.200 (−0.21)		0.167 (0.15)
JULY × TL		−0.267 (−0.27)		0.495 (0.44)
AUGUST × TL		−0.235 (−0.23)		−0.137 (−0.12)
SEPT × TL		0.791 (0.79)		−0.463 (−0.40)
CBR			−0.982 (−0.33)	−0.417 (−0.13)
MAY × CBR			−2.730 (−1.19)	−3.580 (−1.48)
JUNE × CBR			−2.696 (−1.07)	−2.528 (−0.94)
JULY × CBR			−1.168 (−0.45)	−1.175 (−0.42)
AUGUST × CBR			−0.962 (−0.38)	−0.579 (−0.21)
SEPT × CBR			3.800 (1.60)	2.662 (1.03)
AR(1)	1.044 (4.26)**	0.984 (3.52)**	0.972 (3.69)**	1.001 (3.84)**
AR(2)	−0.182 (−1.24)	−0.149 (−0.96)	−0.139 (−0.93)	−0.157 (−1.01)
MA(1)	−0.630 (−2.72)**	−0.598 (−2.24)**	−0.585 (−2.31)**	−0.593 (−2.38)**
R^2	.957	.955	.957	.959
D-W statistic	1.992	1.997	1.989	1.997
# observations	300	300	300	300

Note. Model estimated is ARMA(2,1).
* Significant at 10% level.
** Significant at 5% level.

(see Figure 3). Using Model 4 in the AL, this increase in PLU of +0.01 over the 50-year period, coupled with the coefficient on SEPT × PLU of 81.888, implies (.01) × (81.888) = .819 thousand (or about 800) additional fans per home game in September (over the default month of April). A similar calculation for the NL yields an additional 1,582 fans per home game associated with the 50% increase in PLU over the sample period. Assuming 12 home games per team during September, these estimates correspond to 137,592 extra fans in AL parks and 303,744 more fans in

Table 7. Aggregated Model of APG (National League)

Variable	Model 1	Model 2	Model 3	Model 4
Constant	15.421 (13.19)**	15.465 (13.76)**	10.189 (4.32)**	10.656 (4.23)**
TIME	0.084 (1.04)	0.078 (0.93)	0.099 (1.19)	0.099 (1.14)
D1976	−3.051 (−1.62)	−2.727 (−1.31)	−2.215 (−1.06)	−2.750 (−1.26)
D1976 × TIME	0.274 (2.90)**	0.273 (2.70)**	0.228 (2.22)**	0.241 (2.25)**
MAY	0.546 (0.90)	0.220 (0.53)	2.784 (1.54)	3.198 (1.75)*
JUNE	3.114 (4.71)**	2.830 (6.38)**	4.449 (2.31)**	4.554 (2.32)**
JULY	4.927 (7.17)**	4.681 (10.24)**	7.909 (4.03)**	8.058 (4.00)**
AUG	2.666 (3.86)**	3.339 (7.41)**	5.530 (2.87)**	4.538 (2.29)**
SEP	−4.213 (−6.28)**	−2.133 (−4.98)**	1.889 (1.02)	−1.205 (−0.63)
PLU	4.845 (0.15)			16.844 (0.48)
MAY × PLU	−32.535 (−0.90)			−29.103 (−0.74)
JUNE × PLU	−20.931 (−0.54)			−17.956 (−0.42)
JULY × PLU	−23.954 (−0.59)			−26.559 (−0.59)
AUGUST × PLU	32.685 (0.79)			42.030 (0.91)
SEPT × PLU	178.658 (4.40)**			158.234 (3.47)**
TL		−0.172 (−0.27)		−0.637 (−1.00)
MAY × TL		−0.203 (−0.29)		0.092 (0.14)
JUNE × TL		0.209 (0.27)		0.462 (0.63)
JULY × TL		−0.003 (−0.00)		0.413 (0.54)
AUGUST × TL		−0.229 (−0.29)		−0.111 (−0.14)
SEPT × TL		1.457 (1.92)*		1.215 (1.64)*
CBR			7.948 (2.43)**	7.324 (2.22)**
MAY × CBR			−3.972 (−1.49)	−4.004 (−1.59)
JUNE × CBR			−2.303 (−0.81)	−2.327 (−0.86)
JULY × CBR			−4.848 (−1.67)*	−4.734 (−1.70)*
AUGUST × CBR			−3.413 (−1.20)	−2.762 (−1.01)
SEPT × CBR			−5.207 (−1.89)*	−4.692 (−1.80)*
AR(1)	0.816 (3.25)**	0.806 (3.09)**	0.819 (3.29)**	0.807 (2.99)**
AR(2)	−0.015 (−0.10)	−0.012 (−0.07)	−0.016 (−0.10)	−0.004 (−0.03)
MA(1)	−0.394 (−1.62)	−0.409 (−1.62)	−0.435 (−1.81)*	−0.373 (−1.42)
R^2	0.911	0.901	0.901	0.915
D-W statistic	1.989	1.977	1.972	1.973
# Observations	300	300	300	300

Note. Model estimated is ARMA(2,1).
* Significant at 10% level.
** Significant at 5% level.

NL parks during September. In the word of elasticity, the attendance in September increase by 0.63% (NL) and 1.32% with respect to the doubling of the PLU.

The economic significance of this difference might be assessed by a simple "back-of-the-envelope" calculation. For 2008, the average MLB Fan Cost Index value is $192 for a family of four, which translates into an average of about $50 in revenue per MLB attendee (Team Marketing Report, 2010). We will assume that the marginal revenue is equal to the average revenue per fan here. Should MLB implement changes that would result in an increase in the PLUs for each league from the current value of approximately 0.02–0.03, our analysis above indicates that the

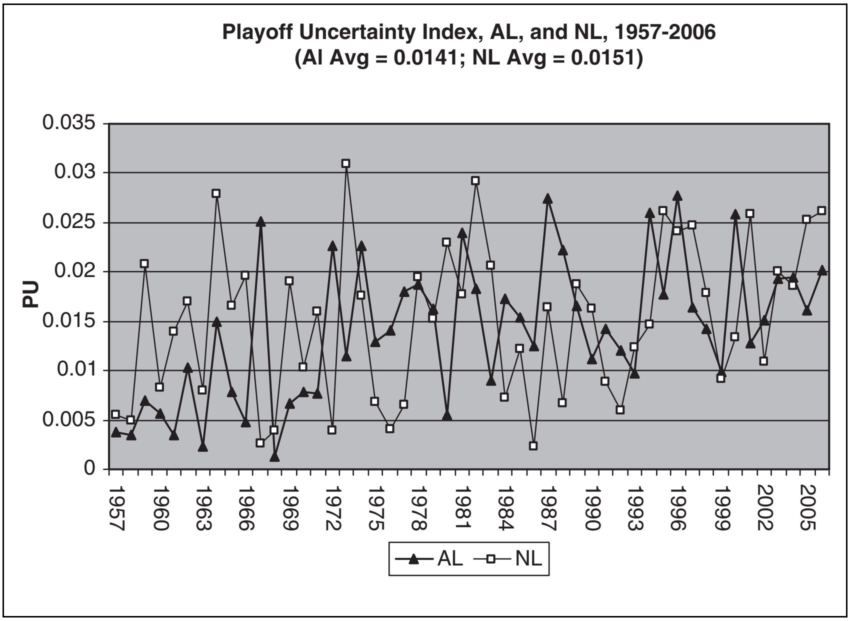

Figure 3. Playoff uncertainty metric: 1957-2006. AL = American League; NL = National League.

tighter pennant races would result in approximately \$6.8 million in marginal gate revenues across all AL teams and approximately \$15.2 million in marginal gate revenues across all NL teams. If TV viewers respond to this increased competition with the same estimated coefficient as do attendees in this attendance model, then MLB's marginal increase in total revenues due to PLU increasing from .02 to .03 would be about \$31.5 million per year.[14] Given that total MLB revenues in 2008 were about \$6 billion, this \$31.5 million increase amounts to only about a 0.5% increase in league revenues. That is, while our empirical results imply that the effect of PLU on attendance is statistically significant, its economic impact is somewhat trivial.

Concluding Remarks

The UOH is one of the most accepted theories in sports economics. In this article, we look at that type of within-season uncertainty known as PLU, which proposes that demand is directly affected by the likelihood that all teams stands a chance of making the playoffs. We analyzed the monthly attendance data to gain a better understanding of how PLU affects attendance, an approach not seen previously in the sports economics literature. Our empirical finding suggests that the only month in which attendance is affected by PLU is the month of September. These results should be interpreted as complementing the prior literature that has studied within-season uncertainty using annual attendance data.

We do not discuss the possible causes of specific break points since the main focus of this study is to test the UOH with monthly attendance data. In the future, however, it would be worth studying why the two leagues have such a large disparity in the number of breaks and where the break points occur. One possible explanation of why the AL has several structural breaks, and the NL has few, may come from the theory of habitual consumption. If NL teams tend to have fans with stronger habit persistence in attendance than AL teams (e.g., the Chicago Cubs vs. the Chicago White Sox), then we would expect the temporal variation in attendance of NL teams to be smoother. While this is just speculation (since we do not have any empirical evidence that NL teams have stronger habitual attendance), we leave this issue for further study.

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Notes

1. Quirk and Fort (1992) argued that the demise of the All American Football Conference, which ultimately merged with the National Football Conference, was due to the lack of intraseasonal balance.
2. The information used here was obtained free of charge from and is copyrighted by Retrosheet. Interested parties may contact Retrosheet at www.retrosheet.org.
3. There were a few regular-season games played in March and October, but these games were omitted from the sample. Sellouts should not be a problem here as they are not common in Major League Baseball. In addition, the analysis looks at average, league-wide attendance per game, so sellouts are not relevant.
4. The other common within-season metric, the ratio of the standard deviation of actual win percentage to the "idealized" standard deviation (Fort & Quirk, 1995), is calculated under the assumption all individual league teams have equal strength. The TL metric,

on the other hand, is the sum of the densities of the winning percentages of a certain percentage of the top and bottom teams in a league with an "idealized" normal distribution. Therefore, TL is sensitive to changes in the relative extreme of the win percentage distribution but insensitive to the changes of win percentage of teams in the middle.

5. When GB = 0, the team is a joint division winner based on its regular-season record but is considered the runner-up based on other contingent rules. Therefore, its probability to advance to the playoff at the end of the regular season is almost .5 (the highest uncertainty).
6. Suppose there are two cases of 100 and 200 regular-season games that are played during the same time span. And consider that a team is 10 games back in August 1 in both cases. Clearly playoff uncertainty for this team is lower in the first case (100 games) than the second case (200 games) since not many games left for catch-up in the first case.
7. This minimum LM unit root test, assuming two breaks, is outlined as follows. To endogenously determine the location of two breaks, a grid search is employed to find where the test statistic is minimized. At each combination of break points in the time interval [$0.1T$, $0.9T$], where T is the sample size, Lee and Strazicich used Perron's (1989) "general-to-specific" procedure to determine k (i.e., the number of lagged first-difference terms to correct for serial correlation). The Perron procedure is as follows. Start with an upper bound for k: $k_{\max}$. If the last included lag is significant, choose $k = k_{\max}$. If not significant, then reduce k by 1 until the last lag becomes significant. If no lags are significant, set $k = 0$.
8. Since the aggregate approach cannot endogenously determine the breaks in the data, we assume that the same breaks in the annual data (found in Fort & Lee, 2006) apply to monthly data.
9. See Lee and Fort (2008) for further discussion of this methodology.
10. Both AL and NL have identical structural breaks at 1974-1976 and 1992-1994 in April, but two leagues have large disparity in number of breaks and break points in other months. While these two break points have obvious structural interpretation (i.e., the advent of free agency and the lockout/strike of 1994), these other break points are more difficult to explain. One possible explanation for the differences between the months and leagues is due to habitual behavior. If fans of NL teams have stronger habit persistence than the fans of AL teams (e.g., Chicago Cubs vs. the White Sox), then NL teams would have fewer break points and at different points in time.
11. The dependent variable, APG, is measured in thousands.
12. Pretest procedures led to the ARMA (2, 1) model specification for both leagues. But given the possibility that fans of NL teams react differently than fans in the AL, we estimated Equation (3) separately for the two leagues.
13. In fact, the monthly effect on APG of PLU is ($\varphi + \eta_k \times \text{MONTH}_k$); but given that φ is small and highly insignificant, the coefficient η_k essentially captures the effect of PLU on a monthly basis.
14. We use the Fan Cost Index of about \$50 per ticket as an estimate of the marginal (local) revenue of each of the additional ticket sold as a result of the improvement in PLU (Team Marketing Report, 2010). The present value of this \$31.5 million increase, over a 20-year period and discounted at 5%, amounts to nearly \$400 million.

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