Rev Ind Organ (2008) 33:281–295
DOI 10.1007/s11151-008-9193-9

Attendance and the Uncertainty-of-Outcome Hypothesis in Baseball

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Published online: 1 November 2008

Abstract Sports offer interesting insights into demand due to the added twist of fan preferences for outcome uncertainty. We add to and amend previous work by analyzing the time series behavior of Major League Baseball attendance (1901–2003) using break point analysis, exploring a wide variety of measures of game uncertainty, playoff uncertainty, and consecutive season uncertainty. Only playoff uncertainty is statistically significant, and it is economically significant only for (1) truly ambitious intervention and (2) recent history. The policy implication is that actual league choices may be motivated by wealth redistribution rather than concerns over competitive balance.

Keywords Attendance · Outcome uncertainty · Break point analysis

JEL Classifications L83 · C22

1 Introduction

Demand analysis is an economics cornerstone, and professional sports offer a productive laboratory for assessing demand. In addition to determining the impact of the usual determinants of demand, the sports case includes an interesting twist: the "uncertainty-of-outcome" hypothesis (henceforth, the UOH). First detailed for baseball by

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Rottenberg (1956), later discussed for North American leagues more generally by Neale (1964) and Canes (1974), and initially by Sloane (1971) for world football, the UOH holds that fan demand is positively related to outcome uncertainty; fans prefer success for their home team but also prefer less predictable outcomes over more predictable ones. In this paper we assess a particular aspect of demand: the impact of outcome uncertainty on actual Major League Baseball (MLB) attendance.

Outcome uncertainty and competitive balance on the field, pitch, court, or ice are positively related; the more uncertain outcomes become, the greater is competitive balance in a league. The UOH implication is that declining competitive balance in a league causes fan interest in perennial losing teams to wane, threatening the economic viability of those teams. But also important is that even surviving teams might suffer reduced revenues as general interest in the sport declines. As Rottenberg originally pointed out, leagues have a vested interest in outcome uncertainty since it determines competitive balance, which is of vital importance to fans. And so there are policy implications in the relationship between outcome uncertainty and attendance.

In our opinion, past analysis of the UOH suffers in four ways, all of which we attempt to remedy. First, past work has failed to include all aspects of outcome uncertainty—at the game level, playoff determination level, and across seasons—relevant to the object of analysis. Second, there are measurement issues. Measurements of outcome uncertainty have failed to distinguish which type of outcome uncertainty is under analysis. Further, there is disagreement over which type of measurements are most useful for different purposes: just tracking the behavior of competitive balance over time, versus ascertaining the impact of outcome uncertainty on fan demand. Third, few demand studies account for the time series characteristics of attendance data beyond a correction for serial correlation or the inclusion of time trend dummy variables. Finally, there is little in the way of coherent, comprehensive policy statements in past work.

Our chosen case is MLB attendance at the annual league level. To us, three things are gained from league-level aggregation. First, the annual league level seems appropriate relative to the original Rottenberg discussion of the UOH and just why it is a *league*-level concern in the first place. Second, all three types of outcome uncertainty relate to aggregate league-level attendance. Finally, examining annual attendance data informs future analysis at the disaggregated level. Ignoring the time series behavior of attendance data can leave disaggregated approaches confronting spurious correlation problems if their analysis spans structural changes in the data. We stress that all analysis provides useful information; aggregated and disaggregated analyses are complementary.

The paper proceeds as follows. In Section 2, we lay out the model relating outcome uncertainty to attendance taking into account the possibility of break points in the attendance time series. We discuss the data and explore a wide variety of measures of the different types of outcome uncertainty and compare their veracity in attendance estimation. Estimated break points and outcome uncertainty effects on attendance are the focus of Section 3. We find no evidence supporting outcome uncertainty at either the game level or for consecutive seasons, but playoff uncertainty is statistically significant in both leagues. Section 4 is our assessment of the economic significance of our findings and their role in evaluating league policy toward outcome uncertainty.

The paper concludes in Section 5 with our suggestions for further theoretical and empirical research.

2 The Model and the Data

Since it is multi-faceted, Cairns (1987), following Sloane (1976), developed the following useful categorization of outcome uncertainty in their work on English football. Game uncertainty (GU) concerns the predictability of individual contests. Playoff uncertainty (PU) pertains to the closeness of championship races during the regular season. Consecutive season uncertainty (CSU) applies to the question of dynasties over time. We adopt these conventions in the rest of the paper.

Past attendance analysis is plagued by a variety of weaknesses. First, past work has failed to include all aspects of outcome uncertainty—GU, PU, and CSU—relevant to the object of analysis. Fort (2006) details how this specification error leaves past analysis of the UOH for North American leagues prone to bias in coefficient estimates. And most of these past works pass judgment on "outcome uncertainty" in general without careful attention to whether the object of analysis is GU, PU, or CSU.

The second weakness in past work on the UOH is in terms of measurement. Each type of uncertainty may matter to fans and measurements of each type of uncertainty depend on the object of analysis. For example, if the object of analysis is game-by-game outcomes, one way to measure GU is by the relative winning percentages of the two teams up to game time or by prior odds from betting markets. But an aggregate measure would be needed for the analysis of annual attendance time series. Disagreements over how to measure outcome uncertainty have failed to distinguish which type of outcome uncertainty is under analysis: GU, PU, or CSU (Eckard 2001a,b, 2003; Humphreys 2002, 2003; Zimbalist 2002). There also is the question of which type of measurements are most useful for different purposes: just tracking the behavior of competitive balance over time, versus ascertaining the impact of outcome uncertainty on fan demand (Fort and Maxcy 2003; Zimbalist 2003; Dawson and Downward 2005).

As a third weakness, only a few North American league attendance studies account for the time series characteristics of attendance data beyond a correction for serial correlation or the inclusion of time trend dummy variables (Schmidt 2001; Schmidt and Berri 2001, 2002, 2003, 2004; Fort and Lee 2006). Using European football, Davies et al. (1995) were the first to show that ignoring time series behavior in sports data could lead to spurious correlations posing special problems for demand analysis and policy prescriptions. Again for world football, Jones et al. (2000) extended these observations. We remedy all three of these shortcomings in the model that follows.

On these same MLB attendance data, Schmidt and Berri (2001) failed to reject non-stationary attendance after ordinary unit root testing and used the first-difference approach in their analysis of attendance. If y_t is the time series, where $t = 1, \ldots, T$ indexes the time series length, then the first-difference series $y_{t+1} - y_t$, $t = 1, \ldots, T$, is invariably stationary. But this first-difference approach creates some problems for the usual economic interpretations (e.g., there is no longer any elasticity interpretation).

Fort and Lee (2006) test the same data for unit root with endogenous break points in the attendance time series and find that the series is stationary with break points.

This suggests applying the methods of Perron (1989); Bai and Perron (1998, 2003), henceforth the BP method, to pin down the break points more specifically. The BP method helps identify stationary periods for attendance regressions using level data. This method also has the advantage of allowing for elasticity calculations that are lost using the first-difference approach.

Lee and Fort (2005) detail the BP method in their application to MLB competitive balance time series, and there is no need for a reprise here. But their analysis does detect break points in the *competitive balance* time series for 1926 and 1957 in the American League (AL) and for 1912, 1926, and 1933 in the National League (NL). None of these break points coincide with the break points we discover below in the *attendance* time series, but we still utilize a one-step procedure, including our measures of GU, PU, and CSU in the break point analysis. It may well be the case that outcome uncertainty as we measure it is one of the determinants of the attendance break points in the first place.

In addition, examination of the attendance data suggests that there may be scale effects tied to expansion in the number of teams in a league. While attendance invariably grows anyway with population, some of the increases occurring with expansion in the number of teams in a league are quite large (e.g., 12.8 million for the 1993 NL expansion; 6.8 million for the 1998 NL expansion). Since this type of increase in attendance with expansion exists, despite what may be happening with other variables, we measure attendance on a league average-attendance-per-game basis. The AL and NL are analyzed separately since measures of competitive balance, for example, are generated from intra-league play for nearly the entire sample.

There is some work suggesting that work stoppages may play a role in the attendance time series (Schmidt and Berri 2002, 2004; Coates and Harrison 2005). The only stoppages of consequence that actually reduced the number of regular season games in MLB were the player strikes of 1981 and 1994–1995. While the evidence is that strikes have significant but short-lived impacts on attendance, these short-term impacts may falsely influence our break point estimation aimed at detecting longer-term structural changes.

However, accounting for work stoppages is somewhat problematic. Dummy variables for strikes cannot be used in the BP method. The BP method divides the sample into two sub-samples in order to estimate break points so that, in some cases, dummy variables could be equal to zero or one for all observations in these sub-samples. We account for work stoppages by simply using the mean difference of APG between strike years and regular seasons as the dependent variable during strike years.

We apply the BP method to these adjusted league average annual attendance data, allowing both levels and trends to change (Perron 1989). The attendance regression results with breaks are from the following regression, 1901–2003:

$$\mathrm{LAPG}'_t = z_t\beta_i + x_t\gamma + \varepsilon_t, \quad t = T_{i-1}+1, \ldots, T_i, \quad i = 1, \ldots, m+1.$$

LAPG'_t is league average attendance per game (adjusted for strikes as described previously) in year t, i indexes the ith regime, and the indices $(T_1, \ldots, T_m)$ are treated as the unknown break points. For example, we find that there are four breaks in the AL (1918, 1945, 1962, and 1987) but in this case i = 1,…, 5: (1901, 1918), (1919, 1945), (1946, 1962), (1963, 1987), (1988, 2003). z_t is a (q × 1) dimensional covariate with coefficients β_i subject to change over time: essentially the constant and a trend. x_t is a (p × 1) covariate comprised of our outcome uncertainty variables: GU_t, PU_t, and CSU_t. Ours is a partial structural change model since the parameter vector γ is not subject to change. When $p = 0$, this model is a pure structural change model where all the coefficients are subject to change. Perron's GAUSS code was used to estimate the break points.

Ours is clearly not a structural model since it uses time trends and break points without independent variables to capture aggregate-level demand determinants. There are no league-level aggregate variables for income, ticket price, and substitutes (e.g., the rise of TV, then cable TV, then other electronic media; alternative sports leagues). Neither do we attempt to incorporate stadium amenities or technology in general.

Partly, this is due to data limitations. Our sample covers more than 100 years. A consistently measured income series is surely problematic over the sample period, and we know that there are no ticket price data over this entire period (let alone a consistently measured series!). These data issues are further magnified by aggregation. For example, income would need to be aggregated across dramatically different cities, and seat prices would need to be aggregated across both different seat types and different stadium locations. But another reason for the parsimony is that a "structural" approach has its own estimation issues. Some of the independent variable time series must be non-stationary even if we consider break points in them. Then the analysis would require the first-difference approach and co-integration investigations.

In light of these issues, given that we include a trend variable, we assume that our break points, and interactions of break points and time trend, explain the average movement of attendance in order to focus on the effects of outcome uncertainty on league-level attendance. Break points should be picking up whether structural changes really did matter in fundamental ways to league-level attendance.

In addition, our approach does have the following two things to recommend it. First, differenced variables limit interpretation, precluding the usual discussion of elasticities. Our approach generates elasticities, allowing us to discuss statistical significance *and economic significance* for policy purposes. Second (looking a bit ahead), our goodness-of-fit statistic is large as typifies time series modeling. This means that there is little in the way of *added explanation* that can come from the structural approach. This suggests that *if the trend is capturing these structural issues*, then the significance of the trend would just be transferred to the significance of the structural variables (if we could get them) with little impact on other estimates.

With respect to the specification of outcome uncertainty, Fort (2006) reviews all of the different ways that GU, PU, and CSU have been measured. In order to determine which variables best capture PU, GU, or CSU, we estimated our model with an exhaustive comparison of PU, GU, and CSU specifications to determine which outcome uncertainty measurements generated the best fit. Results available upon request suggested the following variables (descriptive statistics for the dependent and independent variables are all in Table 1):

For GU, we are interested in capturing how close the games were during the regular season. A tried and true approach in the sports economics literature is to examine the dispersion of winning percentages at the end of the regular season. The more evenly

Table 1 Descriptive statistics, 1901–2003

Variable	Min	Max	Median	Average	Std. Dev.
AL					
LAPG′	3,067	30,366	12,313	13,270	7,859
TL (GU)	0.0003	1.621	0.068	0.167	0.239
WinDiff (PU)	0.004	0.128	0.042	0.046	0.031
Corr (CSU)	−0.197	0.942	0.618	0.564	0.245
CBR	0.338	0.899	0.619	0.608	0.114
NL					
LAPG′	2,701	32,532	13,928	13,836	8,420
TL (GU)	0.0001	2.421	0.091	0.211	0.350
WinDiff (PU)	0.006	0.198	0.034	0.043	0.032
Corr (CSU)	−0.536	0.958	0.614	0.533	0.320
CBR	0.310	0.927	0.595	0.611	0.138

matched the teams were during the season, the more "tightly bunched" would have been the team winning percentages at the end of the season. We employ a measure of dispersion used to great success in other work. The "tail likelihood" (TL) from Fort and Quirk (1995), also examined by Lee (2004), utilizes data for the teams in the upper and lower tails of the winning percentage distribution. If TL increases, the tails of the distribution are moving closer to the league average winning percentage of 0.500, and GU within the season has increased. The superiority of TL to other measures suggests that fans are sensitive to changes in the relative extremes of the winning percent distribution rather than to changes around winning percents of 0.500. TL would probably fall to another competitor like game odds in the game-by-game team level analysis of GU, but the object of analysis here is annual league average-attendance-per-game, and something like TL is as disaggregated as possible.

As for PU, the idea is to capture the level of contention for final annual outcomes. Prior to 1969, there were no divisions in either the AL or the NL. For this time period, we use the difference in winning percentages between first and second place finishers in each league. From 1969–1972, each league was divided into two divisions. For this period, we use the *average* difference in winning percentages between division winners and runner-ups. For the three-division modern format started in 1973, we also add the winning percentage difference between wild-card teams and the next best team to the calculation of the average. We refer to this PU measure generically across all periods as "WinDiff." If WinDiff *decreases*, division races are relatively more likely to be tight, and PU has increased.

For our CSU measure, we are interested in the occurrence of dynasties; if the same teams are champions year after year, outcome uncertainty has decreased on this dimension. The subsidiary regressions suggested a measure similar to one devised by Butler (1995). The correlation between (a) each team's winning percentage in this season and (b) the same team's average winning percentage over the last three seasons (Corr) increases with consecutive season dominance. So, if Corr increases, the same teams dominate over time, with declining year-to-year CSU.

A measurement of outcome uncertainty currently of interest in the sports literature is Humphreys (2003) "Competitive Balance Ratio," or CBR, a measure composed of both average within-season variation and between-season variation in winning percentages. We include it in our model analysis in order to assess its empirical affects compared to our other measures. Doing so also adds to the assessment of the veracity of our approach. By its nature, Humphreys' CBR combines elements of both GU and CSU, so that it is included in regression analysis only with our chosen PU variable.

As a final note, it is important to observe that MLB teams typically do not price their tickets to fill their stadiums so there are nearly no sell-outs and, consequently, no truncation issues. For example (demonstration available upon request to the authors), in 1900, NL average attendance per game was around 3,214 while average capacity was 13,725. So the occupancy rate averaged about 23%. In 2007, the NL average occupancy was about 75%. This suggests that attendance and demand are at least closely related without need for a truncated dependent variable approach that would be required if occupancy rates were closer to 100%.

3 Break Points and Outcome Uncertainty Results

The regression results for our model in Table 2, for the AL and NL, suggest that there is much to recommend the approach. Coefficient signs and significance are generally as expected for the outcome uncertainty variables. Further, the usual goodness-of-fit statistics suggest that the regressions are solid.

The actual statistical testing methodology used to uncover break points in the attendance data are detailed elsewhere (Fort and Lee 2006). For the sake of brevity, the break point test results for the model specified in the last section are available upon request but not presented here. Those results suggest the four breaks for the AL—1918, 1945, 1962, and 1987 and the three for the NL—1918, 1945, and 1967—shown in Table 2. It is easier to discuss these break points using the fitted values of LAPG_t' in Fig. 1 for our interpretations. Using the coefficient estimates on the trend variables in Table 2 to interpret changes before and after the break points is straightforward. But it is not so easy to see what happens with the coefficient estimates of intercepts. The intercept estimates are single-season values for the first season in the sample, 1901, but not when a season occurs during a break point.

In Fig. 1, attendance was roughly equal and stable in the two leagues to 1918, typically between 4,000 and 5,000 per game. After a significant upward jump, coincident with the end of World War I, the same was true until 1945 in both leagues at around 7,000 per game. The truly massive upward jump in 1945 (approximately doubling attendance per game in both leagues), of course, coincides with the end of World War II. But an interesting divergence occurred after the shared 1945 break point. NL attendance gently increased, but AL attendance declined – the only prolonged decline observed over the entire sample period. The AL decline was truly precipitous at the break point in 1962, after which attendance rebounded at the highest rate of increase in the sample. The NL enjoyed a trend increase only at its final detected break point in 1967. While NL attendance per game has continued its increase since 1967, AL

Table 2 BP attendance estimation results, AL and NL

Regime	Variables	AL		NL	
		Coefficient (t-value)	Coefficient (t-value)	Coefficient (t-value)	Coefficient (t-value)
(1901, 1918)	Intercept	6,094* (7.92)	4,307* (3.27)	7,002* (6.50)	6,110* (5.61)
	Trend Slope	−64 (−0.85)	−90 (−1.06)	−153*** (−1.63)	−188*** (−1.80)
(1919, 1945)	Intercept	8,101* (8.00)	5,921* (3.92)	7,131* (6.16)	5,806* (3.88)
	Trend Slope	−1 (−0.04)	14 (0.41)	26 (0.071)	34 (0.90)
(1946, 1962)	Intercept	25,201* (7.91)	21,767* (5.45)		
	Trend Slope	−204** (−3.23)	−173** (2.37)		
(1963, 1987)	Intercept	−20, 431* (−6.22)	−19, 414* (−7.87)		
	Trend Slope	518* (14.57)	484* (14.35)		
(1988, 2003)	Intercept	18,850* (2.85)	15,243** (2.20)		
	Trend Slope	101 (1.41)	118 (1.65)		
(1946, 1967)	Intercept			9,115* (3.32)	7,587* (2.62)
	Trend Slope			117** (2.33)	128** (2.52)
(1968, 2003)	Intercept			−12, 878* (−6.22)	−13, 237* (−6.62)
	Trend Slope			447* (17.74)	443* (17.70)
	TL	−36 (−0.52)		189 (0.36)	
	PU	−7, 586*** (−1.73)	−8, 695** (−2.02)	−17, 940* (−3.08)	−17, 860* (−3.10)
	Corr	−555 (−0.84)		−421 (−0.80)	
	CBR		2,596 (1.57)		1,521 (1.10)
	R-squared	0.977	0.976	0.971	0.971

Dependent variable: LAPG′
* Significant at the 99% critical level
** Significant at the 95% critical level
*** Significant at the 90% critical level

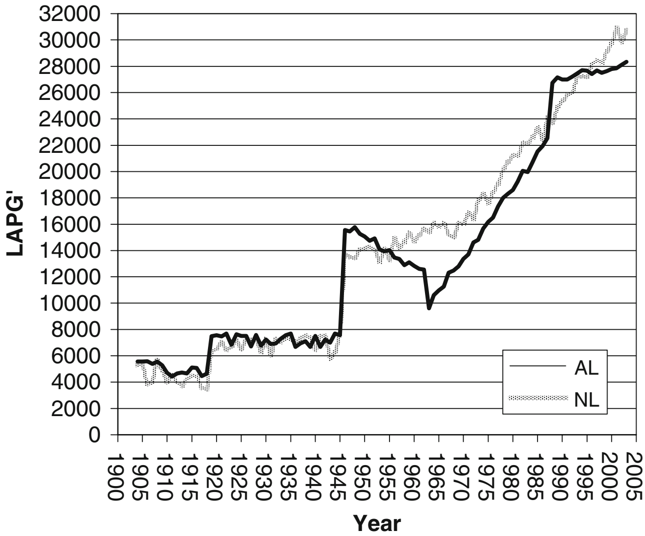

Fig. 1 Fitted LAPG'_t, AL and NL

attendance leveled off after 1987. In the very few most recent years in the sample, it appears that the NL is leaving the AL behind.

Turning to the UOH, statistically significant evidence in Table 2 is found only for PU (measured by WinDiff) in both leagues but not for either GU or CSU in either league. The sign on PU is as expected: A decline in WinDiff increases PU, indicating greater outcome uncertainty, and attendance increases in both leagues as a result. Use of Humphreys' CBR, rather than separate variables to capture GU and CSU, makes the PU impacts that much larger (and the impacts of a few of the break points that much smaller) with nearly no change in R^2 for the AL. Nearly nothing changes in the NL, including R^2, using CBR. To the extent that CBR might confound GU and CSU, using separate variables probably allows a more precise estimation of the impacts of the break points. We restrict the rest of our discussion to the results in Table 2 without CBR.

If WinDiff declines by a unit, our results show that LAPG increases by 7,586 fans and 17,940 fans in the AL and NL, respectively. The significance level of the effects is higher in the NL than in the AL, and the decade-by-decade examination of PU in Table 3 suggests why this might be so. Over the entire 1901–2003 period, PU has been 90 percent lower in the AL than in the NL. Further, the AL has had less PU than the NL in every decade since the 1920s. Baseball aficionados will recognize that the New York Giants dominated everything in the NL prior to the 1920s. Assessment of the economic significance of these results leads into the discussion of policy implications to which we now turn.

4 Economic Significance and Policy Implications

As noted in the introduction, past work fails to state policy implications in a coherent fashion. A league is actually composed of the individual owners of the teams in

Table 3 Playoff uncertainty (WinDiff) by Decade, AL and NL

Decade	AL Ave.	NL Ave.	Ave. Diff.	Ave. % Diff.
1900s	0.027	0.082	−0.054	−48.2%
1910s	0.051	0.062	−0.010	−14.6%
1920s	0.050	0.032	0.019	152.8%
1930s	0.072	0.029	0.043	204.2%
1940s	0.045	0.043	0.002	128.1%
1950s	0.040	0.038	0.002	128.5%
1960s	0.047	0.030	0.018	155.1%
1970s	0.043	0.040	0.003	61.7%
1980s	0.035	0.038	−0.003	65.7%
1990s	0.045	0.038	0.008	41.2%
1990a	0.039	0.035	0.005	62.7%
1990b	0.051	0.039	0.012	38.0%
2000s	0.042	0.044	−0.002	119.3%
1901–2003	0.046	0.043	0.003	90.0%

the league. All leagues have at one time or another justified business decisions and demands in collective bargaining with reference to the state of competitive balance in their league. For our particular example, during labor negotiations in 2000, MLB sounded a stern warning about the lack of balance in playoff participation and outcomes (Levin et al. 2000). Of course, actions to enhance balance also have wealth distributional consequences so it is difficult to ascertain actual intent; is the league's aim enhanced competitive balance or wealth redistribution? From this perspective, just knowing whether or not competitive balance actually is important to fans helps sort out the issue. We have found this to be the case for PU, statistically, but the remaining question is whether PU is important economically speaking.

Economic significance, accompanying statistical significance, would lend a note of sincerity to owner claims that their favored policy interventions will enhance competitive balance. After all, there would be something significant for owners resulting from enhanced balance. But if PU effects are *economically* insignificant, even if they are *statistically* significant, then such claims ring hollow; other reasons for owner actions should be sought, and economists are naturally inclined to look toward wealth redistribution explanations.

We assess the economic significance of PU for MLB in 1950 and 2003. These are indicator years that are chosen because they have different season lengths and available supporting financial data. That we can even make calculations that generate insights about the magnitude of PU effects is one of the strengths of the BP method compared to the first-difference approach.

It is perhaps more intuitive to address the impacts of PU (a decrease in our WinDiff variable) in terms of a league management variable rather than, say, attendance elasticity with respect to PU (also reported in Table 4). WinDiff lends itself naturally to the gap between first and second place finishers as a management objective. We char-

Table 4 Economic significance of improved playoff uncertainty, 1950 and 2003

	1950		2003	
	AL	NL	AL	NL
Home Games[a]	616	616	1,134	1,296
LAPG[b]	13,423	13,416	28,119	29,571
PU[c]	0.040	0.038	0.042	0.044
Coeff. Est.[d]	−7,586	−17,940	−7,586	−17,940
Elasticity[e]	0.023	0.051	0.011	0.027
Incremental Approach				
Incremental Factor[f]	15.0	15.8	14.3	13.6
ΔLAPG[g]	46.3	108.1	44.2	108.6
%ΔLAPG[h]	0.34%	0.81%	0.16%	0.37%
Rev. per Attend.[i]	$1.44	$1.52	$37.98	$36.45
ΔAttend. Rev.[j]	$41,070	$101,216	$1,903,664	$5,130,177
ΔNon-Attend. Rev.[k]	–	–	$1.92 mil.	$4.88 mil.
ΔAll Rev.[l]	$41,070	$101,216	$3.82 mil.	$10.01 mil.
League Revenues[m]	$16,338,920	$15,696,562	$1.855 bil.	$2.023 bil.
Ambitious Approach				
PU in Games[n]	6.2	5.9	6.5	6.8

[a] (8 teams) × (77 home games), both leagues 1950; (14 AL teams) x (81 home games) and (16 NL teams) (81 home games), 2003
[b] Decade average LAPG′
[c] Decade average PU from Table 4
[d] Estimated coefficient on PU from Table 2
[e] (Coeff. Est.) × [(PU)/LAPG′]
[f] %ΔPU required to decrease gap between 1st and 2nd place by one game. Example: AL, 1950. Decade average WinDiff of 0.040 (Table 3) yields average difference between the winner and the runner-up (154 games/season): $0.040 \times 154 = 6.2$ games. Closing the gap by one game to 5.2 games implies WinDiff $=$ 0.034 Rather than a 1 percent reduction in WinDiff to calculate the usual elasticity measure, a reduction in WinDiff of $\frac{0.040-0.034}{0.040} \times 100 = 15.0$ percent would close the gap between first and second place by one game. This is the "Incremental Factor" reported in Table 4
[g] (Incremental Factor) × (Elasticity) × (0.01) × (LAPG′)
[h] ΔLAPG′/LAPG′
[i] 1950: U.S. House of Representatives (1957). 2003: Team Marketing (2007)
[j] (Rev. per Attend.) × (ΔLAPG′) × (Home Games)
[k] (Non-attendance revenue) × (ΔLAPG′); 2003 non-attendance revenue calculated from Forbes.com as follows. AL: Revenue from all sources = $1.86 billion; Attendance-related = $650 million; Non-attendance related (difference) = $1.20 billion; NL: Revenue from all sources = $2.02 billion; Attendance-related = $701 million; Non-attendance related (difference) = $1.32 billion
[l] (ΔAttend. Rev.) + (ΔNon-Attend. Rev.)
[m] See note 9
[n] (PU) × (Season Length); Season Length 1950 = 154; 2003 = 162

acterize this objective under two scenarios. The "Incremental Approach" reduces the gap by a single game while the "Ambitious Approach" eliminates the gap completely. Example calculations are shown in the notes to Table 4.

Table 4 tells a decidedly clear story for the Incremental Approach. For either league in either year, reducing the gap between first and second place by one game leads to an increase in LAPG of less than 1 percent (%ΔLAPG row in Table 4). For the earlier year 1950, where TV revenues are really unimportant compared to gate revenues and attendance-related spending (parking, concessions, memorabilia), the impacts are about 0.25% and 0.64% of total league revenues for the AL and NL, respectively.

For the later year 2003, since TV revenues are much more important, viewer responses to PU would also be important. Since we don't model viewer responses, and nothing in the literature is helpful on this dimension, for a reference point we assume viewers respond with the same estimated coefficient as do attendees in our model. The calculation of changes in non-attendance revenue (ΔNon-Attend. Rev. row in Table 4) is also detailed in the notes to Table 4. Essentially (ΔAll Rev row in Table 4), these additional values double the economic significance of PU but, even then, the impacts are still only about 0.21% and 0.49% of total league revenues for the AL and NL, respectively. While a subjective observation to be sure, the incremental approach earns amounts that seem trivially small.

The economic significance of the ambitious approach in Table 4 is, of course, larger (simply multiply the incremental results by the PU in Games row, Table 4). The impacts are only about 1.6% and 3.8% of total league revenues for the AL and NL, respectively, for the 1950 example. For 2003, we find the impacts are about 1.4% and 3.3% of total league revenues for the AL and NL, respectively. Again, while a subjective claim, these amounts are still relatively small.

Of course, the added fans in our attendance analysis would be *at least* as happy as their spending indicates since consumers' surpluses remain. And the actual impacts would not be evenly distributed across the league so that team impacts for even a single-game improvement in PU would be larger still for those teams actually in contention. In addition, if profit margins are narrow in MLB, then even modest increases in attendance might yield quite significant increases in profits (since marginal costs are likely to be quite low). But, overall, the assessment here suggests that only an ambitious approach to playoff uncertainty in 2003 has any chance of being judged as economically significant.

This brings us to the policy implications of these calculations. As Rottenberg (1956), Neale (1964), Sloane (1971), Canes (1974) argued long ago, leagues like MLB have a vested interest in managing competitive balance as long as it matters to fans. And we find that playoff uncertainty does matter to fans. However, the only chance that *economic impacts* on MLB might be worth mentioning is for the complete removal of any gap at all between first and second place finishers and only for recent times (2003 versus 1950). Playoff uncertainty is statistically significant for attendance, but economic significance is more questionable.

This subjective conclusion lends a note of insincerity to MLB claims that its policy aims include the pursuit of greater competitive balance in the name of fan and, eventually, league welfare. Unless MLB ambitiously guarantees *complete* playoff uncertainty, there really isn't much economic return in it for the owners in the league.

This suggests that an alternative focus for future research is in-depth analysis of the wealth redistribution consequences of league choices among owners, players, and fans. If playoff uncertainty pursuits matter significantly to fans, but with little economic consequence to league owners, then understanding owner preferences for the form and structure of revenue sharing probably lies in the wealth that they transfer from players to owners, and from larger-revenue owners to smaller-revenue owners, rather than with fan demands for more competitive balance.

5 Conclusions and Suggestions for Further Research

We estimate the impact of outcome uncertainty on the time series behavior of MLB league average attendance per game, 1901–2003, accounting for the time series behavior of attendance using break point analysis. We are careful to measure all three types of potential competitive balance impacts on attendance—game uncertainty, playoff uncertainty, and consecutive season uncertainty. The aim is to help inform theoretical, empirical, and policy work on the relationship between outcome uncertainty and attendance.

Our results suggest that there are break points in the attendance time series in 1918, 1945, 1962, and 1987 in the AL and in 1918, 1945, and 1967 in the NL. The first two break points, common to both leagues, correspond to post-war attendance rebounds. The remaining behavior of the attendance time series warrants further investigation.

Of the three competitive balance elements, we find that only playoff uncertainty has statistically detectable impacts on league average attendance per game. Playoff uncertainty increases attendance in the both the AL and NL (significantly more so in the latter). However, further investigation of attendance and revenue impacts from our estimates suggests that economic impacts are quite small even if the gap between first and second place finishers were completely eliminated. And even then this would only be true for more recent times (2003 in our calculations). This suggests that league policy choices ostensibly aimed at satisfying fan demands for competitive balance may, instead, be motivated by wealth redistribution.

As for suggestions for future research, the bulk of past *theoretical* work focuses on game uncertainty (see the reviews in Fort and Quirk 1995, and more generally for world sports in Szymanski 2003). Only (Whitney 1988, 1993) pursued the idea that fans care primarily about playoff uncertainty, and our empirical results suggest his is a fruitful line of endeavor. But this must be a careful conclusion. Only one sport, Major League Baseball, has been analyzed. And it is possible that game uncertainty and consecutive season uncertainty have been managed so carefully and correctly by MLB that not enough variation exists in the data to detect its impact on attendance.

As for the conclusions for *empirical* research, results of the BP method suggest that past work on MLB attendance estimation that spanned the break points discovered in this paper may suffer spurious correlation problems. Schmidt and Berri (2001) measured game uncertainty with the Gini coefficient on winning percentages with a 1903–1998 sample that spans all break points in both leagues. This measure was statistically significant in their attendance estimation for both the American and National Leagues. Our findings suggest that ignoring break points and including only a variable that measures game uncertainty in their analysis, without a playoff uncertainty variable, could be responsible for their findings.

On a final research note, ours is an analysis at the league level. Attention to the role of outcome uncertainty at a more disaggregated level with a different focus should provide important complementary insight. Our results aid disaggregated approaches (but do not replace them) by making sure that they proceed under the knowledge that there are break points in the data. Interestingly, past works on baseball attendance demand using disaggregated, level data all skate cleanly between the break points we find here, avoiding the spurious correlation problems that would have arisen had they used data sets spanning these break points (Demmert 1973; Noll 1974; Hunt and Lewis 1976; Baade and Tiehen 1990; Domazlicky and Kerr 1990).

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