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Team-Level Time Series Analysis in MLB, the NBA, and the NHL: Attendance and Outcome Uncertainty

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Abstract

We extend the attendance break point literature to the team level, addressing structural change and season aggregated outcome uncertainty for franchises in three of the four North American major leagues. We compare the larger variation at the team level with past time series analysis of league-level annual aggregate attendance. We also note that there is at best mixed evidence of outcome uncertainty impacts on team-level attendance. We discuss the implications for these findings with respect to future research that attempts to comprehensively estimate the demand for attendance.

Keywords

attendance, structural change, time series, uncertainty of outcome

This article extends inquiry into the time series behavior of U.S. major league sports team-level attendance and its relationship to Rottenberg's (1956) uncertainty of outcome hypothesis (henceforth, UOH). We address the relationship between the variation in attendance structural changes at the team level, compared to the league-level analysis in past work (Lee & Fort, 2008; Mills & Fort, 2014), and relate our findings to the broader literature on the UOH.

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The UOH has been central in the development of the economics of sport, particularly in the context of professional sports league demand and policy. Leagues often claim that outcome uncertainty, typically labeled competitive balance, is necessary in order to maintain interest among fans. However, empirical results on the influence of outcome uncertainty on attendance are mixed, leaving room for further empirical attention to this central issue.[1] Our work is therefore complementary to previous empirical analysis investigating the UOH in North America, which has overwhelmingly involved analysis of baseball attendance.[2]

In addition, very little exists on long-term *team-level* attendance time series.[3] Only Davis (2008) evaluated team-level attendance time series and only to control for break points in his subsequent-level data analysis.[4] Our more comprehensive treatment of team-level attendance series can inform league-level policy in diverse markets that may change dramatically over time as well as inform more comprehensive demand estimation with respect to the structure of both attendance and covariates in panel models. We apply what is commonly referred to as the Bai and Perron (BP) approach[5] in the sports economics literature to team-level attendance time series for teams that have existed, or did exist in the past, longer than 40 years in three major leagues—Major League Baseball (MLB), the National Basketball Association (NBA), and the National Hockey League (NHL). The prevalence of sellouts in the National Football League (NFL) precludes the use of the BP approach, as it is not well suited for censored data.

We stress that we analyze *attendance*, not *demand*, and there are two reasons for this. First, data on some important demand factors (especially ticket prices) are simply unavailable for such long periods of time. Second, the presence of sellouts in some cases suggests that the data on attendance may lie off of the demand curve. This problem with the BP approach is illustrated in a few more instances, less pervasive than in the omitted NFL case. Lastly, our level and trend changes estimated through the BP approach provide insight related to important structural impacts of covariates in demand analysis—such as championship appearances—some of which we note may be poorly specified in past work.

We compare our results with the past work at the league-level annual aggregate attendance and find a consistent but richer explanation in the case of World War I (WWI) and World War II (WWII) as well as the Great Depression. Further, previous league-level work found break points for three episodes of labor unrest and two expansion episodes. There were also team-level shifts at the same juncture, but team-level attendance shifts and subsequent trends are not always in the same directions. However, for the few NHL teams with break points coinciding with a league merger, shifts and subsequent trends largely matched the behavior of the league-level aggregate break point found earlier. Finally, past MLB league-level attendance analysis speculated that a break in 1987 might signal a relationship to the performance enhancing drug era, but attendance at only one team among the few with breaks at the same time supports that view.

We also find little overall evidence of any UOH impact on attendance. What there is differs both across leagues and across teams within leagues. In addition, what there is does not appear to be significant economically speaking in terms of revenues associated with changes in outcome uncertainty. Thus, our work adds to the mixed results on the impact of outcome uncertainty cited above.

The article proceeds as follows. In the second section, we briefly reprise the BP approach and present the data. Our basic findings with respect to stationarity with and without endogenously specified break points appear in the third section, in addition to the full estimation of structural changes and competitive balance impacts for each team in each league. These are more thoroughly discussed in the fourth section.[6] Finally, the fifth section rounds out the article with conclusions and suggestions for future work.

Data and Method

Description of Data

We evaluate 29 MLB teams (the earliest series starting in 1903), 13 NBA teams (the earliest series starting in 1945-1946), and 11 NHL teams (the earliest series starting in 1952-1953) that either have been, or were, in existence for over 40 seasons.[7] Our intention was to extend the data as far as possible as of this writing which is 2012 for MLB but 2010-2011 for the NBA and 2011-2012 for the NHL due to lockouts that complicate the final two seasons in the possible series for both of these leagues. The series length requirement is used in an effort to avoid detrimental impacts on the size and power of the break point statistical tests. The majority of our data come from standard sources for sports economics.[8]

A few teams still had a few game-level attendance reports consecutively missing.[9] For those single missing years for each team, we interpolated between the team average attendance per game (TAPG) for the year before and year just following the missing data point. In those years with more than 15 game attendance reports available, we take the average attendance of these games as TAPG for that team in the given season. If less than 15 games are reported, we use a linear interpolation for the seasons in question using nearby data points.[10]

Finally, for the annual team-level attendance, Schmidt and Berri (2002, 2004) and Coates and Harrison (2005) find that strikes and lockouts may impact attendance. We handle strikes and lockouts using our interpolation method (1972, 1981, 1994, and 1995 for MLB; 1994-1995 and 2004-2005 for NHL; and 1998-1999 for NBA) similarly to Lee and Fort (2008; henceforth LF08) and Mills and Fort (2014, henceforth MF14), avoiding problems they detail for the BP approach caused by indicator variables.

Method: Unit Root Testing

A first best practice for time series is ordinary unit root testing with trend variables of nonstationary behavior. If nonstationary behavior is rejected, level-data practitioners may proceed to use the entire time series. However, if ordinary unit root tests fail to reject nonstationary behavior, further insight can be gained about the behavior of the time series using unit root tests with endogenously specified structural breaks.

We first test each team-level attendance series against the null of a unit root using the augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests with both a constant and a trend variable. The lags were determined by minimization of the Bayesian information criterion for the ADF test and by the truncation suggested by Newey and West (1994) for the PP test. Unit roots were further analyzed using the generalized least squares Dickey–Fuller test as described in Elliott, Rothenberg, and Stock (1996). Subsequently, for all series, the two-break minimum Lagrange Multiplier (LM) unit root test is employed (Lee & Strazicich, 2001, 2003, 2004).[11] This is followed by an LM test allowing for only a single break for attendance series where unit root presence is not rejected with the two-break test. We subject all series to tests both with and without breaks for robustness, even for those series that were found to be stationary without breaks, as standard Dickey–Fuller tests can lead to spurious rejections in the case where breaks occur early in the series (Leybourne, Mills, & Newbold, 1998).

If the one or two-break LM tests reject the presence of a unit root, we proceed with applying the BP approach to evaluate the size and statistical significance of breaks in the data. In estimating our BP regressions, we include covariates measuring team quality and UOH measures to simultaneously estimate both breaks and coefficients on these covariates. Finally, if the unit root test with endogenously specified break points fails to reject the presence of a unit root, data transformation such as taking first differences may be required in order to perform additional regression analysis. We leave this for future work.

Method: The BP Approach

For the BP approach, we follow LF08 and MF14 by including team win percent ($W\%$)[12] to ensure that large breaks are not the result of improvements in regular season performance. We note that uncertainty over game outcomes may be different from uncertainty over playoff races. Separately, dynasties—or the propensity for teams to excel across seasons—may identify an additional way in which balance and uncertainty plays out in leagues. Therefore, we measure outcome uncertainty in three ways to ensure the various realizations are captured in our estimations, as first noted in LF08. *Game uncertainty* (GU = *TL*) is measured using the tail likelihood measure employed in both LF08 and MF14, *playoff uncertainty* is measured with the *PLU* measure from Krautmann, Lee, and Quinn (2011; also used in MF14), and *consecutive season uncertainty* (CSU) is captured as in LF08 and MF14 using the 3-year average win percentage correlation (CSU = *Corr3*).[13]

The team-level attendance regression and estimated breaks come from the following model:

$$\mathrm{TAPG}_{ft} = \boldsymbol{z}_{ft}\beta_{ft} + \boldsymbol{x}_{ft}\gamma_{ft} + u_{ft},\ t = T_i + 1, \ldots, T_i; i = 1, \ldots, m + 1. \quad (1)$$

TAPG_{ft} is team average attendance per game in year t for franchise f, i indexes the ith regime, u_{ft} identifies the error term, and the indices $(T_1, \ldots, T_m)$ are treated as the unknown break points. In this expression, $\boldsymbol{x}_t(p \times 1)$ and $z_t(q \times 1)$ are vectors of covariates and β_{ft} and γ_{ft} are the corresponding vectors of coefficients. As in LF08 and MF14, we estimate a model for franchise attendance to evaluate the multifaceted nature of competitive balance: *TL*, *PLU*, and *Corr3*.[14] Statistical significance of break point locations and magnitudes are tested for within the BP procedure simultaneously as the regression model is estimated. The model is described as follows:

$$z_t = \{1,\ t\}, \quad x_t = \{TL,\ PLU,\ Corr3,\ W\%\}, \quad \text{and } (q = 2; p = 4), \quad (2)$$

where $z_t = 1$ indicating mean shifts in the attendance series and t represents a simple time trend. The coefficient estimates for z_t are allowed to vary across regimes; however, team quality and UOH measure regressors are estimated without coefficients changes across break point regimes.

We estimate our models with variance estimations that are homogeneous across breaks using the trimming parameter $\varepsilon = 0.10$. Although the notation above could indicate the use of a panel model, in this case, the BP approach is performed separately for each franchise due to limitations in the method and to evaluate the heterogeneous impacts of covariates and differences in structural changes at the team level.[15]

Results and Discussion

Tests for Unit Roots

We found five franchises stationary without breaks: Chicago Cubs, Detroit, and Pittsburgh in MLB; Los Angeles Lakers in the NBA; and Philadelphia in the NHL.[16] Since there is a chance for spurious rejection of the unit root (Leybourne et al., 1998), we continue to include these teams when testing stationarity with breaks and ensure robust rejection prior to subjecting attendance series to structural change model estimation.

We proceed with the two-break LM test and, for those not rejected with the two-break test, we employ the one-break LM test as in MF14.[17] Interestingly, we find only four of the five franchises that were stationary without breaks were also stationary with breaks. The cumulative results lead us to include these four as we move on to the BP approach. Our test results fail to reject that five MLB franchise attendance series, three NBA franchise series, and two NHL franchise series are nonstationary once breaks are considered for the series.[18] The teams exhibiting nonstationary attendance series would require alternative treatment, for example, taking first differences. Thus, we proceed to the BP approach on 44 teams for which the presence of a unit root was rejected: 24 in MLB (Table 1), 10 in the NBA (Table 2), and 10 in the NHL (Table 3).

Structural Changes

Tables 1–3 summarize the results of the break tests and show confidence intervals for those breaks for each team. While it is possible to tell the direction of shifts and trends, if any, associated with break points from the model coefficients, it is much easier to show them visually.[19] Figure 1 shows the fitted TAPG series and sketches in the break points and trends for three selected franchises, one from each league, strictly for illustration—Boston in MLB, New York in the NBA, and Montreal in the NHL.[20]

We adopt the following shorthand for describing break points: In the pair (S, T), S = (+, 0, −) corresponds to a shift upward, a break but no shift, and a downward shift, respectively; T = (+, 0, −) corresponds to a positive subsequent trend, no trend, and a negative trend, respectively. For example, from Table 1 and Figure 1, there were three break points for the Boston Red Sox (MLB)—1923 (+, +), 1945 (+, −), and 1966 (+, +). The relative sizes of these three shifts and trends can be seen in Figure 1.

Literature Comparison: Team-Level Variation Versus League-Level Variation

In Table 4, we group our findings on structural breaks to match others in the literature in order to compare the insights from team-level and league-level aggregate analysis. Given the starting point of the different leagues, only MLB teams should be expected to have attendance changes associated with World Wars or the Great Depression.[21] Over the course of these events, MLB was comprised of the same 16 teams and 14 are in our sample.

For WWI, there was a (+, 0) alteration found in the previous work on aggregate league-level MLB attendance. However, only four breaks occur at the team level, three exhibiting (+, +) and the other (−, +). By and large, the post-WWI impact was in just a few MLB cities and not even for all teams in a given city, that is, there is a shift for the Braves in Boston but not the Red Sox and for Brooklyn but not the Giants in New York. Partly, all of this variation could just be due to WWI being very close to the beginning of the data set and limitations in the BP approach associated with breaks near either end point of a time series.

Turning to WWII, the league-level finding in past work was a (+, −) alteration. In this case, the team-level results fit hand in glove and pervasively. All but the Philadelphia Athletics exhibited statistically significant structural change associated with the end of WWII; however, it is important to note that there was a large, short-term post-WWII change that was not sustained enough to warrant a structural change to be estimated. This is likely due to the large drop shortly before the team left Philadelphia, which took place not long after WWII. The dominant pattern was

Table 1. MLB Franchise Estimated Break Dates for TAPG.

Team	T_1	T_2	T_3	T_4	T_5	Team	T_1	T_2	T_3	T_4	T_5
Baltimore Orioles	1974	1991	1996	2001		Milwaukee Brewers	1984	2000			
	[73, 75]	[90, 92]	[93, 98]	[00, 03]			[83, 87]	[99, 01]			
Boston Red Sox	1923	1945	1966			New York Giants	1945				
	[22, 25]	[44, 46]	[65, 67]				[43, 46]				
Brooklyn Dodgers	1918	1931	1945			New York Mets	1984	1990	2006		
	[17, 19]	[30, 32]	[43, 46]				[83, 85]	[89, 91]	[04, 07]		
Boston Braves	1909	1918	1933	1945		Oakland Athletics	1994	2002			
	[08, 10]	[17, 19]	[32, 36]	[43, 46]			[93, 98]	[00, 03]			
Chicago Cubs	1921	1931	1945	1968	1983	Philadelphia Athletics	1913	1922	1935	1949	
	[20, 23]	[30, 32]	[43, 46]	[67, 69]	[82, 86]		[11, 14]	[21, 23]	[34, 37]	[48, 50]	
Chicago White Sox	1945	1972				Philadelphia Phillies	1931	1945	1970	1996	
	[43, 46]	[71, 73]					[28, 32]	[43, 46]	[69, 71]	[94, 97]	
Cincinnati Reds	1945	1969	1980	1993		Pittsburgh Pirates	1917	1927	1946	1961	
	[43, 46]	[68, 70]	[79, 81]	[92, 95]			[16, 21]	[26, 28]	[44, 47]	[60, 62]	
Cleveland Indians	1946	1956	1983	2002		San Diego Padres	1987	2008			
	[44, 47]	[55, 57]	[82, 84]	[01, 04]			[84, 88]	[07, 09]			
Detroit Tigers	1945	1966	1989			San Francisco Giants	1977	1999			
	[43, 46]	[65, 68]	[82, 90]				[76, 78]	[98, 00]			
Houston Astros	1970	1998				St. Louis Cardinals	1945	1964	1984		
	[69, 74]	[93, 99]					[44, 46]	[62, 65]	[83, 85]		
Kansas City Royals	1977	1993				Texas Rangers	1975	1985	2001	2007	
	[75, 78]	[92, 94]					[74, 75]	[84, 87]	[00, 02]	[06, 08]	
Los Angeles Dodgers	1976					Washington Senators	1911	1918	1931	1945	1958
	[75, 78]						[9, 19]	[17, 19]	[30, 32]	[44, 46]	[56, 58]

Note. Brackets denote 90% confidence interval for break date. Nonstationary: Atlanta Braves, Cleveland Indians, Los Angeles Angels, Minnesota Twins, and New York Yankees. TAPG = team average attendance per game; MLB = Major League Baseball.

Table 2. NBA Franchise Estimated Break Dates for TAPG.

Team	T_1	T_2	T_3	T_4	T_5
Atlanta Hawks	1979	1988			
	[77, 80]	[87, 91]			
Boston Celtics	1978	1994			
	[77, 79]	[92, 95]			
Cleveland Cavaliers	1976	1995			
	[75, 77]	[94, 96]			
Detroit Pistons	1980	1987	2001		
	[79, 81]	[86, 88]	[00, 02]		
Houston Rockets	1983				
	[82, 84]				
New York Knicks	1960	1968	1977	1984	
	[57, 61]	[67, 69]	[75, 78]	[83, 85]	
Philadelphia 76ers	1981	1995	2000		
	[79, 82]	[94, 98]	[99, 01]		
Phoenix Suns	1991	2000			
	[90, 92]	[99, 01]			
Portland Trailblazers	1975	1982	1987	1994	2002
	[74, 76]	[81, 84]	[86, 89]	[93, 95]	[01, 03]
Seattle Supersonics	1977	1986	1997		
	[76, 78]	[85, 87]	[96, 98]		

Note. Brackets denote 90% confidence interval for break date. Year listed is year that season started or was originally scheduled to start. The Boston Celtics had missing/limited attendance data treated as stated in the text, 1977-1978. Nonstationary: Chicago Bulls and Milwaukee Bucks.

(+, −) with the other two (+, 0). Both the previous league-level and our team-level analyses support a postwar jump and then rebound back to the usual level and trend.

The team-level results here, coincident with the Great Depression, offer structural changes that were not found at the league-level aggregate in past work. Five teams had a (−, +) structural change just before or toward the beginning of the Great Depression in 1927-1933. Generally, the shift detected indicates that the depression hit attendance in these cities hard and then attendance rebounded in the following trend. While there is some evidence in the attendance time series that there was some negative effect near these dates in the American League (MF14), these changes were apparently not large enough to warrant an estimated break in the aggregate. As industrial cities were hit the hardest by the Great Depression, it is not surprising to see cities like Pittsburgh in this group. However, the omission of Cleveland and Detroit is curious, as is the exclusion of the Chicago White Sox, despite an apparent downward shift for the Cubs in the same city.[22]

League labor unrest episodes are also in Table 4. First, for the MLB strike episode that spanned the 1994 and 1995 seasons, league-level annual aggregate attendance

Table 3. NHL Franchise Estimated Break Dates for TAPG.

Team	T_1	T_2	T_3	T_4
Boston Bruins	1975	1999		
	[74, 76]	[97, 02]		
Detroit Red Wings	1974	1989		
	[71, 75]	[88, 90]		
Los Angeles Kings	1988	2000	2007	
	[85, 89]	[99, 03]	[06, 09]	
Montreal Canadiens	1967	1974	1995	
	[66, 68]	[72, 75]	[94, 96]	
New York Rangers	1975	1991		
	[74, 76]	[90, 92]		
Philadelphia Flyers	1972	1995		
	[71, 73]	[94, 96]		
St. Louis Blues	1975	1989		
	[74, 76]	[86, 90]		
Toronto Maple Leafs	1966	1984	1990	1998
	[65, 67]	[83, 85]	[89, 90]	[97, 99]
Vancouver Canucks	1976	1980	1996	
	[74, 77]	[79, 81]	[94, 11]	

Note. Brackets denote 90% confidence interval for break date. Year listed is year that season started or was originally scheduled to start. The Boston Bruins, Montreal Canadiens, New York Rangers, and Toronto Maple Leafs had missing/limited attendance data treated as stated in the text, 1977-1978. Nonstationary: Buffalo Sabres and Pittsburgh Penguins.

analysis for the AL found a (−, +) alteration. Our sample includes 19 of the 28 teams in MLB for this episode, but only 5 teams exhibited break points near this time, predominantly (−, +), two of which were actually in the NL (CIN and PHI).

Second, there was a lockout in the NBA for a portion of the 1998-1999 (the 2011-2012 lockout is precluded by the end point of the data). We include 10 of the 29 teams in existence at the time. The work on league-level aggregate attendance found a small (−, 0) shift shortly before that season, but at the team level, only three teams show a break point within 2 years before or after the lockout, and the direction of the impacts are across the spectrum; only Seattle matched the (−, +). Very few teams are affected and each in a different way, highlighting the possibility that our team-level series eligible for analysis based on our selection criteria may not be fully representative of the aggregate NBA attendance series.

Further, there was a lockout in the NHL for most of the 1994-1995 that, while not estimated as a structural change in the league aggregate series, showed some signs of behavior similar to the (−, +) changes seen in other leagues around labor disputes. Our team-level estimates are consistent with finding little structural change taking place near with the labor disputes in 1994-1995 and 2004-2005. Our team-level analysis, however, includes only 9 of the 26 teams existing at the time. Only three teams showed any impact, Montreal (+, +), Philadelphia (+, 0), and Vancouver

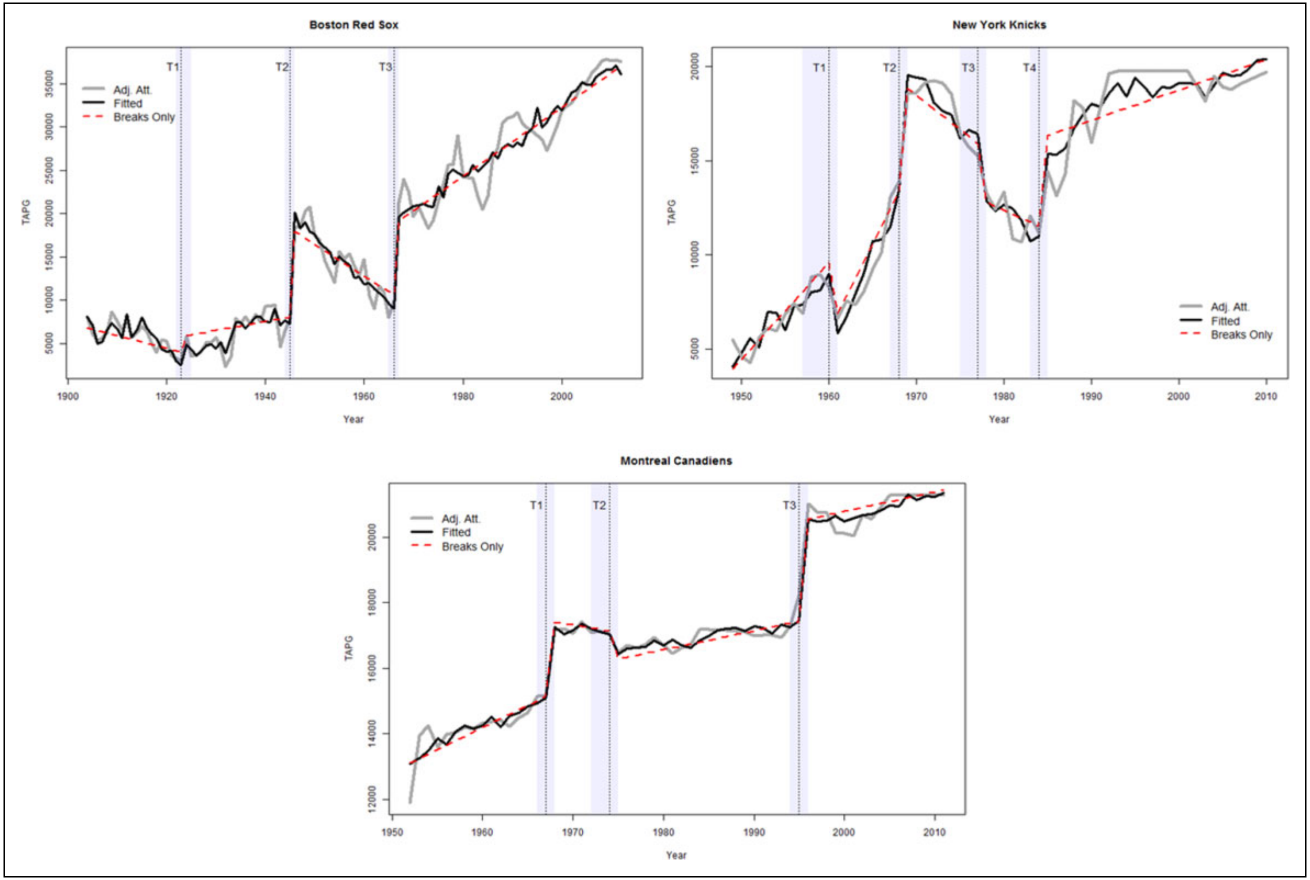

Figure 1. Selected fitted team average attendance per game for Boston (Major League Baseball), New York (National Basketball Association), and Montreal (National Hockey League).

Table 4. Structural Breaks in Attendance Literature Comparison.

World War I	World War II	Great Depression	Labor Unrest	Expansion/Merger	PEDs MLB 1987
LF08 (+, 0)	LF08 AL (+, −)	LF08 (0, 0)	MLB Strike	NHL Expansion	LF08 AL (+, +)
MF14 AL (+, 0)	MF14 AL (+, −)	MF14 (0, 0)	(1994 and 1995)	(1966-1967)	MF14 (0, 0)
			LF08: (0, 0)	MF14 (−, +)	
LF08 NL (+, −)	LF08 NL (+, +)	Team Level (MLB):	MF14: (−, +) AL		Team Level (MLB):
MF14 NL (+, 0)	MF14 NL (+, +)	BSN (−, 0)		Team Level (NHL):	DET (−, +)
		BRO (−, +)	Team Level (MLB):	MON (+, −)	MIL (−, +)
Team Level (MLB):	Team Level (MLB):	CHC (−, +)	BAL (0, −)	TOR (+, 0)	SDN (−, +)
BSN (+, +)	BOS (+, −)	PHA (+, +)	CIN (−, +)		TEX (+, +)
BRO (+, +)	BRO (+, −)	PHI (−, +)	HOU (+, −)	NBA Expansion	
PIT (−, +)	BSN (+, 0)	WAS (−, +)	KCR (−, +)	(1987-1988)	
WAS (+, +)	CHC (+, −)		OAK (−, +)	MF14 (+, +)	
	CHW (+, −)		PHI (−, +)	Team Level:	
	CIN (+, 0)			Atlanta (−, +)	
	CLE (+, −)		NBA Lockout	Detroit (−, −)	
	DET (+, −)		(1998-1999)	Portland (+, 0)	
	NYG (+, −)		MF14: (−, 0)	Seattle (+, +)	
	PHI (+, −)		Team Level (NBA):	NHL Merger	
	PIT (+, −)		PHI (+, +)	(1975-1976)	
	STL (+, −)		PHO (−, +)	MF (−, +)	
	WAS (+, −)		Seattle (−, +)	Team Level (NHL):	
			NHL Lockout	BOS (−, +)	
			(1994-1995)	DET (−, +)	
			MF14 (+, +)	MON (−, +)	
			Team Level:	NYR (0, −)	
			MON (+, +)	STL (−, +)	
			PHI (+, 0)		

Note. MLB = Major League Baseball; NBA = National Basketball Association; NHL = National Hockey League; LF08 = Lee and Fort (2008); MF14 = Mills and Fort (2014). See Table A1 in the supplementary online appendix for team abbreviation key.

(−, +). However, Montreal and Philadelphia are both concurrent with the opening of a new arena with expanded capacity.

Expansion in the NHL (1966-1967) and NBA (1987-1988) and merger in the NHL (1975-1976) also have a place in the previous literature on the league-level aggregate attendance. For the NHL expansion (we include five of the six teams in existence), MF14 find (−, +), but here we only find break points for two teams, (+, −) and (+, 0).[23] As for the NBA expansion (we include 10 of the 23 teams in existence), MF14 find (+, +). Here, at the team level, we find four teams with break points: two negative shifts with opposite following trends and two positive shifts with nonnegative following trends. There are additional structural changes taking place in the mid-1980s as well as various strongly positive trends that begin before expansion. The aggregate of these trends and shifts is likely to have resulted in the estimation of a single structural shift upward in the aggregate data. This highlights the importance of understanding the time series behavior of league-aggregate attendance more granularly, as we exhibit here. Specifically, large structural shifts in aggregate data may, in fact, be the result of various shifts at nearby time points or changes in trends across teams. Further care should be taken with respect to implications related to aggregate-level shifts when relating them to policy changes in leagues.

Finally, for the NHL merger (we include 10 of the 18 teams in existence around this time), MF14 find (−, +), indicating a short-term negative effect of the World Hockey Association (WHA), followed by positive trends shortly after the merger were at play for the league. Five of the six team-level breaks match this pattern here,[24] and the Rangers were the only anomaly (0, −). Not a single shift was positive in any of the cities more directly affected by WHA competition—Detroit, Montreal, Boston, New York, St. Louis, or Vancouver. Subsequently, there were six teams with either upward shifts or subsequent upward trends detected in our analysis from 1984 through 1991, consistent with (1) the significant expansion of the NHL after the merger with the WHA after the 1979 season and (2) the elimination of competition (in addition to Detroit and New York, the NHL Maple Leafs no longer faced the WHA rival Toros).

There is one final episode in the literature on league-level aggregates, namely, 1987 (+, +) in the American League only. Our included teams represent 24 of the 26 teams in existence. LF08 find (+, +) for only the AL, but MF14 find no breaks at all at this time in the league-level aggregate time series of either MLB league. There are three team-level break points in our results between 1985 and 1989, two of which were in the AL (DET and TEX). Two of those three exhibit (−, +), while only Texas shows the same (+, +) found by LF08. The explanation in the previous literature concerned an increase in power hitting, possibly tied to the use of performance enhancing drugs. But the results at the team level seem not to support this, except at Texas.[25]

In closing on comparisons with past results, league-level annual aggregate attendance analysis showed breaks that do not have any counterpart in our team-level

Table 5. Outcome Uncertainty Regression Results for TAPG.

Team	GU (*TL*)	PU (*PLU*)	CSU (*Corr3*)
MLB			
Chicago White Sox		−119,738 (*2.15*)**	
Cleveland Indians		108,929 (*−2.13*)**	
Detroit Tigers	4,967 (*2.32*)**		
Kansas City Royals		165,174 (*2.09*)**	
Oakland Athletics		−264,293 (*−2.91*)***	−4,974 (*−2.22*)**
Philadelphia Athletics	−8,564 (*−4.50*)***	−2,378 (*−3.67*)***	−2,378 (*−3.67*)***
Philadelphia Phillies	−3,800 (*−2.36*)**	115,602 (*2.54*)**	
St. Louis Cardinals	4,425 (*3.24*)***		
NBA			
Atlanta Hawks	−5,977 (*−2.20*)**		
Cleveland Cavaliers	−7,641 (*2.16*)**		−11,986 (*−6.89*)***
Houston Rockets			−4,259 (*−2.86*)***
Philadelphia 76ers			−5,094 (*−3.89*)***
Phoenix Suns		−93,055 (*−2.63*)**	−2,616 (*−2.52*)**
Portland Trailblazers	−3,410 (*−2.19*)**		
NHL			
Los Angeles Kings		−165,525 (*−3.71*)***	
St. Louis Blues	2,434 (*2.71*)***	−230,950 (*−3.26*)***	2,586 (*2.44*)**

Note. Associated *t*-values are italicized in parentheses. TAPG = team average attendance per game; MLB = Major League Baseball; NBA = National Basketball Association; NHL = National Hockey League; *GU* = game uncertainty; *PU* = playoff uncertainty; *CSU* = consecutive season uncertainty.
**p* < .10. ***p* < .05. ****p* < .01.

analysis here. For example, the league-level aggregate attendance showed breaks in the American League for 1962 or 1963 (LF08 and MF14), but we find breaks near this time only for the National League's Pittsburg Pirates and St. Louis Cardinals and none in the American League. In the National League, LF08 find a break in 1967, while here we find only two National League teams have breaks with confidence intervals covering this year. Based on this, it is clear that much of the structural change stemmed from the expansion in the 1960s to new markets excited to receive baseball teams, rather than some sudden demand change among individual franchises existing prior to this time. The upward trajectory taking place starting in the 1960s seems to have been prime for expansion of the league. For both American League and National League, MF14 find breaks around 1975-1978, and here the Baltimore Orioles, Cincinatti Reds, Kansas City Royals, San Francisco Giants, and Texas Rangers are estimated to have breaks at this time, with the Chicago White Sox falling just outside this range. Lastly, individual teams have a number of breaks that were not captured in the league-level analysis, highlighting important caveats when attempting to estimate panel demand models, where the various structural changes would be difficult to estimate alongside other coefficients of interest.

Outcome Uncertainty

Table 5 presents a summary of the statistically significant coefficient estimates for each of the three variables used to measure outcome uncertainty.[26] Statistically, *W%* was an important predictor for most teams under analysis here. We leave discussion of win percentage aside due to possible complications of the direction of causality of the measure and use it simply as a control variable for the break point estimation. We do, however, note that the win percentage effects are in the expected direction across all leagues, as found in Davis (2008) for MLB.

We also note that playoff appearances and championships are exogenous to our models—for reasons originally described by Lee and Fort (2008)—which are sometimes associated with upward-level shift changes after championship success. This result provides important lessons for future empirical evaluation of demand in professional sports leagues. Because the BP method is intended to detect sustained structural change, rather than short-term blips, our estimates may indicate that including a single-year lagged dummy variable for a championship appearance will not be sufficient in some demand estimations. Given that many demand analyses include these types of lagged dummy variables, further investigation into these more permanent structural shifts is necessary.

The glaring outcome in Table 5 is that relatively few statistically significant coefficient estimates for outcome uncertainty measures were found in any league. The totality of the significance across leagues is rather small. Outcome uncertainty in any form statistically significantly impacts team-level annual attendance for eight teams in MLBs, six teams in the NBA, and two teams in the NHL. However, there is little consistency with respect to the direction of effects across teams and leagues. In MLB, of the 12 statistically significant coefficients, only 7 support the classical predictions of UOH and its consecutive season extension (*GU* for the Detroit Tigers and St. Louis Cardinals; *PU* for the Chicago White Sox, Oakland Athletics, and Philadelphia Athletics; *CSU* for the Oakland Athletics and Philadelphia Athletics). For NBA, the number is five of the eight (*PU* for the Phoenix Suns; *CSU* for the Cleveland Cavaliers, Houston Rockets, Philadelphia 76ers, and Phoenix Suns). For the NHL, three of the four coefficients in Table 5 are directionally in support of UOH predictions (*GU* for the St. Louis Blues; *PU* for the Los Angeles Kings and St. Louis Blues).[27]

Economic Significance

In order to assess the economic significance of changes in the competitive balance variables, we take an approach similar to LF08 and MF14: evaluating the attendance change associated with changing each UOH measure by the respective average year-to-year within the data set.[28] We then apply the dollar values from the Fan Cost Index data for the associated attendance changes from Team Marketing Report (accessed through Rod's Sports Business Data, 2013). As a whole, even when the impacts of balance measures are *statistically* significant, the economic impact of changes in these variables is minimal for the majority of teams (usually less than 3% in expected attendance changes). The largest relative to revenue are as follows: for GU, St. Louis in the NHL at 5.62%; for PU, St. Louis in the NHL at 6.14%; and for CSU Cleveland in the NBA at 8.58%.[29] These results paired with the varying directional relationships across teams largely reinforce those found at the league level—improved outcome uncertainty has only small impacts on revenues.

Observations and Discussion

We discuss the implications for these findings with respect to league policy and future research. First, as with aggregate league-level attendance work, the break points found for a variety of teams in the three leagues stand as a caution to level data analysis at the team level. Without accounting for breaks, coefficient standard errors could be biased in cross-sectional panel considerations. There are stationary subperiods inside the longer series evaluated here, and researchers should be sure to take that into account to avoid spurious correlation findings. The various breaks found at the team level, but not at the league level, could result in estimation problems in panel data if individual team series are not stationary between aggregate-level shifts or trend changes.

Turning to the structural breaks, themselves, our results suggest the following. For WWI and WWII, this seems pretty clearly to be pent-up postwar attendance. To highlight the variation revealed by our team-level analysis, there is a difference in the number of cities in each case, a few for WWI and nearly all for WWII. Second, there is a difference in the trend following WWI, decidedly positive, while after WWII, there appears to be a decided return to prewar levels of attendance. But the variation across teams in each league and the happening for some teams but not others in the same city beg further investigation. And this last point also holds for the Great Depression. There also appears to be variation in the impact of strikes and lockouts, across leagues and across teams in the same league, worth further investigation.

Perhaps the most interesting indications for further analysis are in what is not found. On the one hand, LF08 and MF14 find break points in league-level annual aggregate MLB attendance not found in the team-level analysis. To begin, there is nearly no support at the team level for the earlier suggestion in the literature that 1987 might mark the beginning of fans being attracted to the game due to offensive increases at the start of a performance enhancing drugs era. And while LF08 found break points in MLB in the early 1960s, much of this change seems to be driven by earlier increases in attendance trends and the expansion of the league during that time.

A host of break points are found in the team-level analysis that has no correspondence with league-level results. We think it is safe to say that since the likely causes of structural change for individual teams are more varied than for league-level aggregate attendance, these require further microlevel analysis to determine local economy impacts or the impact of national economic occurrences locally. The NBA is prime territory here, with potential team-level "episodes" in the mid-1970s (Portland, Cleveland, New York, and Seattle) and mid-1990s (Boston, Portland, Cleveland, and Philadelphia). The expansion and competition in hockey as well as the expanded size of arenas comes to mind.

Most interesting on this point might be a direct analysis of city episodes. For example, what happened in Boston in the mid-1970s (NBA-NHL)? What happened in Detroit in the late 1980s (all three leagues)? City-specific patterns were also apparent in New York in the mid-1970s (NBA-NHL), mid 1980s (MLB-NBA), and early 1990s (MLB-NHL) as well as in Philadelphia in the mid-1990s (all three leagues).

Three of these episodes—Boston, New York, and Philadelphia—had directly opposite team effects within the given city. While the direct causal effects are not identifiable here, large shifts in opposite directions may provide preliminary evidence of substitution between sports teams within the same market.

The most obvious shifts in opposite directions in Boston occurred for the Bruins and Celtics in the 1974-1978 period. The Bruins experienced a downward shift, while the Celtics enjoyed an upward shift in attendance. It is notable that the size of these shifts was nearly identical, at about 5,000 fans per game. It is unclear, however, whether the Bruins downward shift would indicate fans moving to see Celtics games, the impact of WHA operations, or both. The Celtics also experienced an upward shift in attendance concurrent with the MLB and NHL labor disputes in 1994-1995. In 1994, the Celtics experienced a small upward shift of about 2,000 fans per game. However, disentangling the causes of these breaks—such as the opening of a new arena—requires more microlevel panel analysis.

Turning finally to outcome uncertainty and potential policy suggestions, it is important to note the limitations of the methods here. Because of a lack of microlevel analysis, fan interests cannot be discerned as they may be in a fully specified demand model. This makes the conclusions with respect to balance limited in their reach with respect to managerial implications. Our results do not necessarily mean fans are uninterested in competitive balance. It may be that market sizes of teams in each of these leagues are relatively close as to not affect fan behavior in any significant economic way. If this is so, it may have important implications with respect to analysis of optimal league size, given the viable markets for professional teams. It may also simply mean that in their striving for more balance, leagues have closely managed uncertainty of games and playoff races through their organizational policies, such that imbalance does not reach extremes that would motivate fans to avoid games.

Conclusions and Suggestions for Future Research

We extend the attendance break point literature to the team level, addressing structural change and season aggregated outcome uncertainty for franchises in three of the four North American major leagues, namely, MLB, the NBA, and the NHL. The NFL is omitted because our technique is not well suited for the substantial censoring due to sellouts. The work here lays a foundation for informed time series analysis on professional sports attendance data. It is both complementary to and informative for work done at other levels of aggregation.

We compare the larger variation at the team level with past time series analysis of league-level annual aggregate attendance. The main result for WWI and WWII, the Great Depression, episodes of labor unrest, expansion and league merger, and a possible starting date for fan recognition of performance enhancing drug use find some similarities but mainly variation at the team level that begs further work relative to previous findings that used league-level annual aggregate attendance. We also find little evidence of outcome uncertainty impacts on team-level attendance as predicted by UOH. What is there differs both across leagues and across teams within leagues.

It may be that preferences for or against uncertainty may have changed over time. After all, our attendance series include over 100 years of data. Ahn and Lee (2014) take the literature in this direction, and we find this to be a fruitful line of research. The BP approach may be helpful in detecting changes in attendance response to outcome uncertainty in this context by allowing covariate coefficients to vary across regimes. However, more granular data are likely needed to estimate these changes, as degrees of freedom are limited at the annual aggregated level (both the league level and team level).

Perhaps more important are the implications for past league policy implied by our findings. First, as in LF08 and MF14, there tends to be little consistent pattern of sudden and lasting impact (structural change) of league policy decisions. Owners often espouse the idea that implementing rules such as free agency and the draft are used in order to preserve competitive balance and ultimately help the league to thrive through more fan interest. However, there is little evidence of significant structural change in attendance near these policy changes that would be expected to occur due to induced changes in outcome uncertainty.

Rottenberg (1956) and Fort and Quirk (1995) inform us that this is to be expected, as moves such as the amateur draft and free agency tend to redistribute profits to owners from players, rather than change balance in any way. Ceteris paribus, if balance is not changed, then the UOH would predict that fan interest in the league would also remain unchanged. Fort and Lee (2006, 2007) exhibit that there are also no competitive balance structural breaks near these policy changes, lending further evidence to Rottenberg's claims regarding the *invariance principle* in North American sports leagues.

As mentioned throughout this work, there are limitations with understanding the full effects of coefficients on balance measures in break point regressions. Because there is not currently an implementation of tobit analysis in the break point context, some coefficients—especially for those teams with consistent sellouts—will be biased toward zero. This issue may be resolved in a shorter term study with heterogeneous effects of balance measures in a censored panel model context. This is the next step in the progression of the break point literature.

Lastly, much of the literature regarding attendance and Rottenberg's (1956) UOH discusses uncertainty in a one-dimensional light as directly causing attendance changes. However—as Rottenberg originally states in his seminal work and as El-Hodiri and Quirk (1971) model—while uncertainty offers excitement, it is reasonable to expect that a preference for the home team reaching the playoffs would dominate preferences for suspense and balance for many fans (Coates, Humphreys, & Zhou, 2014). This interactive effect seems to be underemphasized in the literature and explicitly separating the two will be important if we want to understand the influence of uncertainty itself and the excitement it creates. We recommend future evaluation of direct and indirect effects of balance and team quality in order to more fully understand the interaction of these factors and extending this inquiry to other forms of fan support, such as television viewership.

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Notes

1. Reviews are in Szymanski (2003) and Fort (2006). For evidence on the uncertainty of outcome hypothesis (UOH) since then, see Lee and Fort (2008); Meehan, Nelson, and Richardson (2007); Rascher and Solmes (2007); Soebbing (2008); and Tainsky and Winfree (2010).
2. Work on various aspects of attendance, other than the UOH, in leagues besides Major League Baseball (MLB) is in Jones and Ferguson (1988); Paul (2003); Schmidt and Berri (2004); Leadley and Zygmont (2005, 2006); Coates and Humphreys (2007); and Winfree and Fort (2008).
3. Nearly, the entire focus of the time series work is upon *league-level* aggregates of attendance (see Coates & Harrison, 2005; Fort & Lee, 2006; Lee & Fort, 2008; Mills & Fort, 2014; Schmidt & Berri, 2001, 2002, 2004). The exception is Coates and

Harrison's (2005) study that analyze attendance per game using a panel of all U.S.-based teams, 1969-1996.

4. If attendance is nonstationary, then the use of level data (e.g., demand estimation using panel data) leads to biased estimates, and the direction of the bias is unknown (in sports, see Davies, Downward, & Jackson, 1995; Jones, Schofield, & Giles, 2000). In addition, if the data are stationary with break points, then coefficients estimated using variation between breaks—rather than across breaks—is appropriate.
5. This approach (Fort & Lee, 2006), based on the work of Perron (1989), Bai and Perron (1998, 2003), and Lee and Strazicich (2003, 2004), analyzes time series stationarity and the timing and size of unknown shocks. Lee and Fort (2008) apply the approach to *league-level* MLB attendance and Mills and Fort (2014) extends to the NBA, NFL, and NHL.
6. Presentation of the entire results would result in a paper unsuited to the usual journal length. The full test and regression results are in the *Data and Statistical Tests Appendix* available online at https://www.dropbox.com/s/4doqcfjhfrwjryp/MIllsFortAppendix.docx?dl=0
7. Included and omitted teams are in Tables A1 and A2, respectively, in the Online Appendix; there were 10 other MLB teams, 39 other NBA teams, and 27 other NHL teams. Start dates are generally recognized and include only the specific league, not any earlier league where the team may have played, for example, American Basketball Association or World Hockey Association (WHA). Changes in primary market signal a new team, and time-contiguous franchises in the same location are treated as one franchise (e.g., Washington Senators I and II).
8. Baseball-Reference (2015), Basketball-Reference (2015), Hockey-Reference (2015), and Rod's Sports Business Data (2015). The NHL was the most troublesome in terms of data collection and we used ancillary sources such as Hockey Zone Plus (2010), Andrew's Dallas Stars Page (2010), and the Hockey Summary Project (2011). The majority of the data at the team level was gleaned from this latter source, with the rest filling in missing data points in specific years (1961-1962, 1986-1987 to 1989-1990, and 1991-1992 to 1992-1993).
9. These are all listed in Table A2 in the Online Appendix.
10. We also used Stineman's (1980) method for interpolation of these dates and found nearly identical results.
11. The authors thank Professor Junsoo Lee for making the GAUSS code available for use.
12. For the NHL, which uses a point system to determine standings, we calculated win percentage by treating ties as one half of a win. The literature on the use of points versus win percent, and that little harm is done empirically using the former for work like ours, is covered in Fort (2007).
13. Among the alternatives in the literature, Mills and Fort (2014, henceforth MF14) show that these variables are best suited to ensure that breaks are not estimated in places where extreme balance changes occurred.
14. We note that these covariates were found to be stationary without breaks, precluding the need for a cointegration method to estimate our parameters.

15. We note that while the BP estimation reports various models depending on the significance level used for testing structural change location, we use the model reported at the 5% level from the “repartition method” as described by Bai and Perron (2003).
16. Generalized least squares Dickey–Fuller, augmented Dickey–Fuller (ADF), and Phillips–Perron (PP) test results are in Tables A3 through A5 in the Online Appendix. Note that we only considered a series stationary without breaks if both the ADF and PP tests were in agreement at the 95% level.
17. Two-break Lagrange Multiplier (LM) test results are in Tables A6 through A8 in the available Online Appendix; one-break LM test results are in Tables A9 through A11 and were applied to those not rejected in the two-break test at the 95% level.
18. Atlanta, Los Angeles Angels, Minnesota, New York Yankees, and St. Louis Browns in MLB; Chicago, Los Angeles Lakers, and Milwaukee in the NBA; and Buffalo and Pittsburgh in the NHL.
19. As a check on whether our break points might have been caused by our interpolation, rather than the data, we reestimated the BP models using the raw data provided in seasons where at least one game was reported. In the (very few) seasons where no data were provided for attendance, we simply average the attendance reports from the prior and following season for the given year, as in Lee and Fort (2008). There are two-break points that occur in interpolated series, the Boston Celtics in the NBA, 1977-1978, and New York Rangers in the NHL, 1986-1987 to 1988-1989. However, the results of BP analysis on the raw data are largely consistent with our BP findings from the data with interpolation.
20. The full complement of fitted team average attendance per game shift and trend visual aids, for all 44 teams, is in the Online Appendix, Figures A1 through A3 for MLB, the NBA, and the NHL, respectively.
21. Refer again to Table 1 in the text and Figure A3 for MLB in the Online Appendix.
22. We note that attendance was lower during the time of the Great Depression for the White Sox; however, like the American League series in MF14, the difference was apparently not large enough to warrant a structural change estimate.
23. Returning to the interpolation issue, only Chicago has interpolation overlapping with a break found in the league-level analysis for the NHL. None of the other teams have this for any other league.
24. Montreal Canadiens were only a 2.5-hr drive from Quebec City, where the WHA’s Nordiques were located, while the Whalers were placed in Hartford, CT, about 1.5 hr away from Boston. The Stags competed directly in Detroit and New York saw three different WHA teams—the Raiders, Golden Blades, and Jersey Knights.
25. Lee and Fort (2008) posited the Bash Brother episode in Oakland, but there is little evidence of that here.
26. These estimates come from Tables A12 through A14 in the Online Appendix, where readers can find the full regression output. For presentation purposes, we only include statistically significant estimates in our primary article.
27. We note that positive coefficients for *TL*, but negative coefficients for the *PLU* and *Corr3* measures, indicate preferences for more uncertainty (consistent with UOH predictions).

28. Ticket prices were not available for the Philadelphia Athletics and are therefore excluded from this portion of the analysis. Table A15, A16, and A17 in the Online Appendix contains all of our calculations.
29. The full results of these calculations are available in the Online Appendix, Tables A15, A16, and A17.

Supplemental Material

Supplemental material for this article is available online.

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