Alternative Measures of Competitive Balance in Sports Leagues

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The most commonly used measures of competitive balance in sports leagues do not capture season-to-season changes in relative standings. This article describes an alternative measure of competitive balance, the Competitive Balance Ratio (CBR), that reflects team-specific variation in winning percentage over time and league-specific variation. Based on estimation of a model of the determination of annual attendance in professional baseball during the past 100 years, variation in the CBR explains more of the observed variation in attendance than other alternatives measures of competitive balance, suggesting that CBR is a useful metric.

Competitive balance is thought to be an important determinant of demand for sporting events. Competitive balance reflects uncertainty about the outcomes of professional sporting events. The conventional wisdom holds that to induce fans to purchase tickets to a game or tune in to a broadcast, there must be some uncertainty regarding the outcome. Neale (1964) called this the League Standing Effect. If a league lacks competitive balance, fan interest in the weaker teams will fall and, eventually, fan interest in the stronger teams will also decline. Thus, greater competitive balance should lead to greater demand, other things held equal. Quirk and Fort (1997) attribute the demise of the All American Football Conference, which started play in 1946 and merged with the National Football Conference in late 1949, to a lack of competitive balance.

One commonly used measure of competitive balance is the dispersion of winning percentage within sports leagues. This measure of competitive balance has been used extensively by Scully (1989), Quirk and Fort (1997), and others to assess the performance of teams in sports leagues. Formally, this measure of competitive balance uses the standard deviation of winning percentage (*WPCT*), defined as the ratio of wins to total games played, as a measure of competitive balance. Consider a

AUTHOR'S NOTE: *Mike Bradley, Kathleen Carroll, Dennis Coates, Alan Sorkin, Stefan Szymanski, and especially Andy Zimbalist provided helpful comments on this article.*

JOURNAL OF SPORTS ECONOMICS, Vol. 3 No. 2, May 2002 133–148

league with N teams during a period of T seasons. If $WPCT_{i,t}$ is the winning percentage of team i in season t, and $i = 1, \ldots, N$ indexes teams and $t = 1, \ldots, T$ indexes seasons, then the standard deviation of winning percentages for this league is

$$\sigma_L = \sqrt{\frac{\sum_{i=1}^{N} \sum_{t=1}^{T} \left(WPCT_{i,t} - 0.500\right)^2}{NT}}\ .$$

σ_L has a convenient comparison value based on the dispersion of winning percentages in an idealized league where each team is of equal strength; thus, the probability of winning any particular game is 0.5. The standard deviation of winning percentages in an idealized league would be

$$\sigma_I = \frac{0.500}{\sqrt{G}}\ ,$$

where G is the number of games played by teams in the league. σ_I is decreasing in the number of games played.

Although σ_L is a reasonable measure of competitive balance in a single season, it has some shortcomings when applied during a large number of seasons. In particular, the standard deviation of winning percentage cannot capture changes in the relative standings of teams within a sports league over time. To illustrate this point, consider the records for teams in two hypothetical five-team leagues in Table 1, which shows the won-loss record for each team in each of five seasons.

Each league has the same σ_L during this five-season period, 0.35, indicating that these leagues have similar levels of competitive balance during this period, according to this metric. These leagues have the same σ_I as well, 0.25. However, the relative standings over time in these two leagues are quite different. In League 1, the relative standings in each year are identical and Team A dominated the league, winning the championship in each season; there is no variation in relative standings over these 5 seasons in this league. League 2 has much more variation in relative standings during the period. Each of the five championships were won by a different team, and each team also finished last once during these 5 seasons. League 2 has more competitive balance over time than League 1 because of the turnover in relative standings. Clearly, an alternative measure of competitive balance that could distinguish between these two cases would be a useful complement to the standard deviation of winning percentage.

Eckard (1998, 2001a, 2001b) proposed a variance decomposition to account for season-to-season turnover in relative standings. Eckard's variance decomposition is

$$\sigma^2{}_L = \sigma^2{}_{CUM} + \sigma^2{}_{time}. \tag{1}$$

TABLE 1: Won-Loss Records in Two Hypothetical Leagues

League 1						*League 2*					
Team	*1*	*2*	*3*	*4*	*5*	*Team*	*1*	*2*	*3*	*4*	*5*
A	4-0	4-0	4-0	4-0	4-0	F	4-0	3-1	2-2	1-3	0-4
B	3-1	3-1	3-1	3-1	3-1	G	3-1	2-2	1-3	0-4	4-0
C	2-2	2-2	2-2	2-2	2-2	H	2-2	1-3	0-4	4-0	3-1
D	1-3	1-3	1-3	1-3	1-3	I	1-3	0-4	4-0	3-1	2-2
E	0-4	0-4	0-4	0-4	0-4	J	0-4	4-0	3-1	2-2	1-3

The Eckard decomposition for the two leagues shown above is $\sigma^2_{time} = 0.0$, $\sigma^2_{CUM} = 0.35$ for League 1, and $\sigma^2_{time} = 0.35$, $\sigma^2_{CUM} = 0.00$ for League 2. The decomposition shows that only cross-sectional variation in won-loss percentages is important in League 1 and only team-specific variation is important in League 2.

There are some problems with Eckard's approach. The most important is that the two terms on the right-hand side of Equation 1 only sum to the left-hand side (the square of σ_L) under special conditions. A fundamental rule of variances is that

$$var(X + Y) = var(X) + var(Y) - 2cov(X, Y).$$

Eckard's variance decomposition sums to the square of σ^2_L only when the covariance between σ^2_{time} and σ^2_{CUM} is zero, a situation that rarely occurs in actual sports leagues. In many instances, the covariance accounts for 20% to 30% of the overall variance. Because the two components rarely sum to σ^2_L in practice, the two terms in the decomposition are difficult to compare to the other commonly used measure of competitive balance during any period of time.

Several other measures of competitive balance have been applied to sports leagues. Hirfindahl-Hirschman Indexes (HHIs) of the concentration of championships and other outcomes are one example. These indexes reflect the concentration of championships in a sports league over time in that they reflect the distribution of the shares of championships. For League 2 in Table 1, each team captured one fifth of the first-place finishes during the 5 seasons for an HHI of 0.2; the HHI for League 1 is 1.0, as one team captured all of the first-place finishes. The distributions of lifetime won-loss percentages, Lorenz Curves, and Gini Coefficients reflecting the distributions of championships and average spreads of won-loss percentages have also been used as measures of competitive balance in sports leagues. Each of these measures has its strengths and weaknesses, but none of them directly addresses the shortfall of σ_L discussed above.[1] Buzzacchi, Szymanski, and Valletti (2001) develop a dynamic measure of competitive balance based on the probability of equally matched teams finishing in the top *k* positions in a league. This measure avoids the problems associated with σ_L mentioned above and is designed for assessing competitive balance in open leagues with promotion and relegation systems commonly found in European sports leagues.

AN ALTERNATIVE MEASURE OF COMPETITIVE BALANCE

The example above describes a dimension of competitive balance, the variation in the relative standings of teams in a sports league over time, that σ_L does not reflect. Variation in won-loss percentages in a sports league during a number of seasons can be calculated in two different ways: within-team variation in won-loss percentages that capture team-specific variation during seasons, and within-league variation in won-loss percentages that capture league-specific variation. The standard deviation of each team's won-loss percentage across seasons is a measure of within-team variation

$$\sigma_{T,i} = \sqrt{\frac{\sum_t \left(WPCT_{i,t} - \overline{WPCT_i}\right)^2}{T}}, \tag{2}$$

where the second term in the numerator is each team's average won-loss percentage during the T seasons. In this case, there will be a vector of $\sigma_{T,i}$, one for each team in the league. The smaller the value of $\sigma_{T,i}$, the less the variation in team i's winning percentage during the seasons being analyzed. For the hypothetical leagues shown on Table 1, each team in League 1 has $\sigma_{T,i} = 0.0$ and each team in League 2 has $\sigma_{T,i} = 0.35$.

The within-season variation in won-loss percentages can be measured by the standard deviation of the won-loss percentage in each season across all teams in the league:

$$\sigma_{N,t} = \sqrt{\frac{\sum_t \left(WPCT_{i,t} - 0.500\right)^2}{N}}. \tag{3}$$

In this case, $\sigma_{N,t}$ is a vector with one value for each season being examined. For each year, $\sigma_{N,t}$ is identical to σ_L.

These two types of variation in won-loss percentages can be averaged to arrive at league-wide measures of each type of variation for the period. A measure of the average variation in teams' won-loss percentages can be found by averaging the $\sigma_{T,i}$s across teams in the league:

$$\overline{\sigma}_T = \frac{\sum_i \sigma_{T,i}}{N}. \tag{4}$$

Similarly, the average variation in won-loss percentages in each season can be found by averaging the $\sigma_{N,t}$s across each season:

$$\bar{\sigma}_N = \frac{\sum_t \sigma_{N,t}}{T}. \tag{5}$$

Note that if the same N teams play an identical number of games in each season, then this ratio will be equal to σ_L. But league expansion, schedule adjustment, strikes, and postponed games that are not played reduce the periods during which this condition holds in professional and college sports leagues.

Consider the values of these two statistics for the two hypothetical sports leagues shown on Table 1. $\sigma_{T,i}$ is zero for each team in League 1; thus, the statistic is zero for that league. Each team in that league finished in the same position in each season, so there is no time variation in winning percentages during those five seasons. $\sigma_{T,i}$ is 0.35 for each team in League 2, so the statistic is 0.35 for that league. Notice that in this case the average variation in won-loss percentage over time for each team is the same as the average variation in won-loss percentage in each season.

Using these two measures of average variation, define the Competitive Balance Ratio (CBR) as

$$CBR = \frac{\bar{\sigma}_T}{\bar{\sigma}_N}. \tag{6}$$

The CBR scales the average time variation in won-loss percentage for teams in the league by the average variation in won-loss percentages across seasons; it indicates the relative magnitude of each type of variation across a number of seasons. Expressing these two types of variation as a ratio has a number of appealing intuitive properties. First, unlike the standard deviation of winning percentage, this ratio is easier to compare during different time periods because it does not have to be compared to an idealized value that depends on the number of games played in each season. In Major League Baseball (MLB), σ_I changes as the schedule expanded from 154 games to 162 games. This makes it difficult to compare the σ_L from the 1980s to that from the 1930s. Because it is a ratio, the CBR also has intuitively appealing upper and lower bounds of zero and one. This can be seen from the CBR for the two leagues shown on Table 1, which also illustrates the two bounding cases of the CBR. League 1 has no team-specific variation in won-loss percentage during these 5 seasons; each team in the league finishes in the same place in each season. The CBR for League 1 is zero. In League 2, the team-specific variation in won-loss percentage is equal to the within-season variation during these 5 seasons; the CBR for League 2 is one. In a league with a CBR of 0.5, the team-specific variation is half the size of the within-season variation during the period.

Because the denominator of the CBR is related to σ_L, these two metrics are inversely related; the CBR reflects some of the same information as the standard deviation of winning percentage. However, the CBR is a useful complement to σ_L because it also reflects the average amount of team-specific variation in won-loss percentage that will not be reflected in σ_L.

APPLICATION: PROFESSIONAL BASEBALL

To illustrate the usefulness of the CBR relative to other measures of competitive balance, I calculated several alternative measures of competitive balance for MLB during the past 100 seasons. This particular setting is an interesting case because competitive balance in MLB has been examined in a number of recent studies. The first application of the standard deviation of winning percentage as a measure of competitive balance was MLB, in Scully's book *The Business of Major League Baseball* (1989). Competitive balance in MLB has also been examined by Fort and Quirk (1995), Quirk and Fort(1997), Butler (1995), Zimbalist (1992), and others.

Table 2 shows standard deviations, CBR, and HHI of first-place finishes for MLB by decade for the American League (AL) and National League (NL). The σ_Ls differ somewhat from those reported by Quirk and Fort (1997) because the data on Table 2 reflect only the won-loss records of teams that played in each year of each decade; the sample is restricted to teams with the same denominator for $\sigma_{T,i}$. Thus, Seattle and Toronto are not included in the AL in the 1970s because they did not join until 1976, and Milwaukee is excluded from the 1990s because the Brewers played 8 seasons in the AL and 2 seasons in the NL during this decade. For this reason, I also calculated standard deviations using the sampling correction (N – 1 in the denominator) rather than the population statistic (N in the denominator) used by Quirk and Fort. σ_I, the idealized variation in won-loss percentage, is 40 for the first five decades and 39 for the second five decades.

Table 2 also shows HHIs by decade for first-place finishes in each league for the period 1901-1968 and in each division from 1969-1999. These indexes are calculated by squaring the share of the first-place finishes for each team in each decade. If a team finished first in the AL in 1 year in the 1920s, then that team's share of that decade's first-place finishes was one tenth. If another team finished first in the AL twice, then that team's share was one fifth.

Notice that σ_L and the CBRs convey some of the same information during this period. The σ_Ls have generally fallen and the CBRs generally risen over time, suggesting that competitive balance has increased in professional baseball during the past century. The coefficient of correlation between these two measures of competitive balance is –0.56, confirming the inverse relationship discussed above. The HHIs are largest in the 1950s and smallest in the past 20 years for both leagues, suggesting the same conclusion. However, the CBR uncovers important distinctions between several periods that have similar σ_Ls and HHIs. One of the most striking of these periods is the NL between 1910 and 1929. The standard deviations and HHIs

TABLE 2: Measures of Competitive Balance Ratio (CBR): Major League Baseball

League	*1900s*	*1910s*	*1920s*	*1930s*	*1940s*	*1950s*	*1960s*	*1970s*	*1980s*	*1990s*	*1990-1994*	*1995-1999*
AL												
σ_L	98	104	92	107	89	98	75	71	67	66	63	72
CBR	0.76	0.82	0.76	0.68	0.71	0.58	0.8	0.8	0.86	0.87	0.97	0.63
HHI	0.26	0.36	0.32	0.34	0.32	0.66	0.29	0.18	0.11	0.12	0.14	0.25
NL												
σ_L	125	91	89	91	97	81	64	70	65	67	70	68
CBR	0.66	0.83	0.57	0.63	0.69	0.69	0.83	0.69	0.92	0.89	0.86	0.74
HHI	0.34	0.24	0.26	0.28	0.28	0.44	0.19	0.23	0.12	0.17	0.21	0.26

NOTE: AL = American League, HHI = Hirfindahl-Hirschman Indexes, and NL = National League.

for these two decades are very similar, suggesting that competitive balance was comparable across these two decades. However, the CBR for the 1910s is much larger than for the 1920s.[2]

Table 3 shows the final standings in the NL for each of these seasons, and $\sigma_{N,t}$ and $\sigma_{T,i}$ for each team and each season during the period. An examination of the $\sigma_{T,i}$s for each decade underscores the difference between these two periods that the CBR captures. Bear in mind that the CBR is based on variation in won-loss percentages, not standings, but I have reported final standings on Table 3 to highlight the relative position of each team.

There was an average amount of team-specific variation in won-loss percentage, and thus standings, in the period 1910-1919. The annual average standard deviation of *WPCT* was 79 during this period, which is only slightly below 84, the average in the NL during the entire 100 seasons in the sample. The final standings also bear this out. Although New York won four pennants during the period, they also finished last in 1915 and fourth in 1916. Even though Boston was terrible early and late in the period, the Braves managed to finish first, second, and third from 1914-1916.

The 1920s, however, were a different story. The smallest average team-specific variation in won-loss percentage in the 1910s, 65 for Brooklyn, is about the same as the largest average team-specific variation in won-loss percentage in the 1920s, 66 for Chicago. The annual average standard deviation of *WPCT* is 53 for the 1920s, and statistically different from that in the 1910s at the 1% level. Team-specific variation in won-loss percentage was significantly lower in the 1920s than in the 1910s. This means that the CBR for the 1910s is statistically different from the CBR for the 1920s in the NL, as the denominators for these two decades are not statistically different from one another.[3] The p value for a one-tailed test of the hypothesis that the CBR in the 1910s differs from the CBR in the 1920s in the NL is less than .01.

The standings bear this difference in CBRs out. In the 1920s, the top of the standings were dominated by New York, who won four pennants and only finished in the lower half of the league once, and by Pittsburgh, who won two pennants and never finished in the lower division. The cellar was occupied by Boston and Philadelphia, who accounted for 15 of the 16 eighth-and seventh-place seasons and never finished higher than fourth- and fifth place, respectively, and by Brooklyn, who won the pennant in 1920 but managed just one other upper division finish in the decade.

Notice that the HHI changes relatively little in the NL across these two decades. The distribution of league championships in the 1910s by team was 4,2,1,1,1,1 across six teams for an HHI of .24, and in the 1920s the distribution by team was 4,2,2,1,1 across five teams for an HHI of .26. The 10 league championships were distributed among one fewer team in the 1920s. This further underscores the difference between the CBR and other measures of competitive balance. There was very little turnover in relative standings in the 1920s, whereas the league championships were distributed among roughly the same number of teams. The same set of teams (Pittsburgh, St. Louis, and New York) were consistently in the upper division and

TABLE 3: National League Standings: 1910-1929

Team	*1910*	*1911*	*1912*	*1913*	*1914*	*1915*	*1916*	*1917*	*1918*	*1919*	$\sigma_{T,i}$	*1920*	*1921*	*1922*	*1923*	*1924*	*1925*	*1926*	*1927*	*1928*	*1929*	$\sigma_{T,i}$
Boston	8	8	8	5	1	2	3	6	7	6	108	7	4	8	7	8	5	7	7	7	8	60
Brooklyn	6	7	7	6	5	3	1	7	5	5	65	1	5	6	6	2	7	6	6	6	6	60
Chicago	1	2	3	3	4	4	5	5	1	3	79	6	7	5	4	5	8	4	4	3	1	66
Cincinnati	5	6	4	7	8	7	8	4	3	1	86	3	6	2	2	4	3	2	5	5	7	50
New York	2	1	1	1	2	8	4	1	2	2	68	2	1	1	1	1	2	5	3	2	3	40
Philadelphia	4	4	5	2	6	1	2	2	6	8	79	8	8	7	8	7	6	8	8	8	5	56
Pittsburgh	3	3	2	4	7	5	6	8	4	4	81	4	2	4	3	3	1	3	1	4	2	31
St. Louis	7	5	6	8	3	6	7	2	6	7	67	5	3	3	5	6	4	1	2	1	4	59
$\sigma_{N,t}$	108	110	123	106	67	49	97	90	85	116		69	95	92	108	106	66	68	108	127	90	

the same set of teams (Boston, Brooklyn, and Philadelphia) were consistently in the lower division during the 1920s. The CBR captures this relative stratification in standings but the other two measures do not.

The CBR also reveals a change in the level of competitive balance in the second half of the 1990s relative to the first half of that decade that is not reflected by the standard deviation of winning percentage. This can be seen in the right panel of Table 2, which divides the 1990s into two 5-year periods. Note that the values for the entire decade will not, in general, be the average of the two subperiods for any of these measures of competitive balance. The CBR and σ_L are variances, and recall that $var(A + B) \neq var(A) + var(B)$. The HHI is the sum of fractions that do not have the same denominator, so they should not sum either.

From Table 2, σ_L rose in the last half of the 1990s in the AL and fell in the NL. However, there is no statistical difference between these figures, so based on this measure of competitive balance there does not appear to have been any change in competitive balance during this period. The CBR fell in both leagues, although only the drop in the AL is statistically significant; the *p* value on a one-tailed test of the hypothesis that the CBR differs across these two 5-year periods is .03 for the AL and .12 for the NL. The CBR indicates that the level of competitive balance in the AL was significantly lower after 1994. Whereas the CBR falls from .86 during 1990-1994 to .74 during 1995-1999, this drop just misses statistical significance at the 10% level. The HHIs rose in the latter half of the decade but the change is not statistically significant. Like in the earlier period, the CBR contains information about the level of competitive balance not reflected in the other two alternative measures.

AN EMPIRICAL TEST OF ALTERNATIVE MEASURES OF COMPETITIVE BALANCE

The discussion in the previous section shows that, in the case of professional baseball during the past century, widely used measures of competitive balance exhibit strikingly different patterns over time. These differences may be due to the different facets of competitive balance captured by each metric. It also makes it difficult to reach a definitive conclusion about the extent to which competitive balance in professional baseball has changed over time.

The lack of consensus among competing measures of competitive balance highlights a more important point: The focus of economic analysis of competitive balance in sports leagues should be the effect that changes in competitive balance have on the behavior of consumers, not on comparisons of the degree of competitive balance over time. Thus, analyzing the relationship between variation in competitive balance and the behavior of baseball fans, the consumers of professional baseball, is important to our understanding of competitive balance. In a sense, this can be viewed as an empirical test of Neale's (1964) League Balance Effect of competitive balance on attendance.

The behavior of fans could be measured in a number of ways. In this case, I use attendance at baseball games as a measure of fan behavior. Data on attendance at MLB games are readily available for the past 100 seasons and econometric modeling of attendance at professional baseball games has a long history, beginning with the work of Noll (1974). To analyze the effect of competitive balance on attendance, I use a linear reduced form model of the determination of attendance:

$$ATT_{it} = \alpha_i + \delta D_{it} + \beta S_{it} + e_{it}, \tag{7}$$

where ATT_{it} is total attendance in the major league i (i = AL, NL) in season t (t = 1901, 1902, . . ., 1999), D_{it} is a vector of variables that affect demand for attendance at MLB contests, S_{it} is a vector of variables that affect the supply of MLB contests, e_{it} is a random error term, and α_i, δ, and β are vectors of unknown parameters to be estimated. Table 4 describes the variables in Equation 7 and their sources.

The attendance variable is home attendance for the entire league in hundreds of thousands. There are 198 league years in the sample. Population clearly affects the demand for attendance at MLB games. The larger the population, the greater the demand, all other things being equal. However, there may be other factors that affect demand for attendance at baseball games that change systematically over time, like changes in consumer preference for leisure and entertainment goods, competition from other sports and leisure activities, travel costs, and so forth. I include a separate time trend for each league to capture these factors. Televised games may also be a substitute for attendance. Equation 7 includes a dummy variable for the period after 1951 when, according to Horowitz (1974), broadcasting of baseball games became widespread.

I also allow for the effect of television on attendance to change over time by including linear and quadratic time trends beginning in 1952. During the two world wars in the previous century, a large portion of the population was overseas or otherwise engaged in the war effort. I include a dummy variable for war years in Equation 7 to control for the effect of these events on attendance.

The baseball schedule has changed several times during the past century. To control for variation in the length of the season, as well as the effect of rain-outs that are not made up and other factors that affect the schedule, I include the number of games played in Equation 7 as a control variable. The number of teams in each league also affects total league attendance, and I include the number of teams in each league in each season as a regressor to control for this. I also include a dummy variable that is equal to one in each of the years when there was a work stoppage in MLB. This variable captures supply and demand effects associated with strikes.

Finally, I include the three measures of competitive balance discussed above as regressors in Equation 7 separately. Including these measures of competitive balance in the attendance model assumes that the level of competitive balance matters to fans, and that changes in the level of competitive balance shift the demand curve

TABLE 4: Variables in Equation 7

Variable	*Source*
Total U.S. population	NBER Macrohistory Database (http://www.nber.org)
War dummy	Equals 1 in 1917, 1918, 1919, 1941, 1942, 1943, 1944, and 1945
Strike dummy	Equals 1 in 1972, 1981, 1994, and 1995
Attendance	The Baseball Archive (http://www.baseball1.com/)
Number of games played	The Baseball Archive (http://www.baseball1.com/)
Number of teams in league	The Baseball Archive (http://www.baseball1.com/)
Television dummy	Equals 1 after 1951
Television time trend	Begins in 1952
AL and NL time trends	Begin in 1901

NOTE: NBER = National Bureau of Economic Research, AL = American League, and NL = National League.

for baseball. To sign these variables, I assume that more competitive balance will increase demand for attendance, other things being equal. Under this assumption, the sign on the CBR should be positive, the sign on the standard deviation of winning percentage should be negative, and the sign on the HHI should be negative. CBR can only be calculated during a period of seasons, not for an individual season. I calculate the CBR for 5-year periods for each league in the sample. To make a proper comparison, I also average σ_L and the HHI during the same 5-year periods for each league.

Assuming that the error term has the usual properties, the parameters of Equation 7 can be estimated using Ordinary Least Squares. Table 5 shows the results of this estimation using the three measures of competitive balance—CBR, σ_L, and HHI—as regressors.[4]

This model explains more than 97% of the observed variation in attendance during the sample period. The parameters in the models are, in general, correctly signed, and most are significant at conventional levels. The intercept shift for the AL is not statistically significant, suggesting that separate intercepts are not needed. Notice that the population variable and the two league-specific trends are not individually significant. This is probably due to multicollinearity, as the population variable grows slowly and steadily throughout the period. A joint significance test on these three variables shows that they are highly significant when taken together (the p value on this F test is smaller than .01), so I have kept these three variables in the empirical model. The number of games played per season and the number of teams variables are correctly signed and significant, as are the war and strike dummy variables. Attendance may vary with the business cycle, falling during contractions and rising during expansions. However, the Federal Reserve Board's Index of Industrial Production, one measure of the business cycle, was not significant when added to Equation 7. Adding this variable had no effect on the other parameters.

TABLE 5: Ordinary Least Squares (OLS) Regression Results

Variable	*CBR Model*	σ_L *Model*	*HHI Model*
Intercept	–0.763	–0.438	–0.632
	(0.592)	(0.638)	(0.594)
AL dummy	0.053	0.055	0.052
	(0.454)	(0.458)	(0.458)
Population	–0.052	–0.057	–0.034
	(0.073)	(0.075)	(0.074)
AL trend	0.019	0.018	0.015
	(0.011)	(0.011)	(0.011)
NL trend	0.020*	0.02	0.017
	(0.011)	(0.011)	(0.011)
War dummy	–0.186*	–0.177*	–0.181*
	(0.047)	(0.048)	(0.048)
Strike dummy	–0.398*	–0.402*	–0.402*
	(0.097)	(0.099)	(0.098)
Number of games played	0.0009*	0.0008*	0.0009*
	(0.0004)	(0.0004)	(0.0004)
Number of teams in league	0.079*	0.083*	0.077*
	(0.037)	(0.037)	(0.038)
Television dummy	0.135	0.131	0.158
	(0.083)	(0.084)	(0.086)
Television time trend	–0.026*	–0.022*	–0.027*
	(0.011)	(0.011)	(0.012)
Television time trend squared	0.001*	0.001*	0.001*
	(0.00001)	(0.00001)	(0.00010)
CBR	0.210*	—	—
	(0.098)	—	—
σ_L	—	–1.153	—
	—	(1.161)	—
HHI	—	—	–0.179
	—	—	(0.114)
R^2	0.973	0.972	0.972

NOTE: CBR = Competitive Balance Ratio, HHI = Hirfindahl-Hirschman Index, AL = American League, and NL = National League. N = 198. Standard errors are shown in parentheses.
*Significant at 5% level.

The dummy variable for the television broadcast era is not significant, suggesting that the advent of televised baseball did not affect the level of attendance. However, the trend and trend squared terms are highly significant. Television appears to have continually eroded attendance at baseball games at an increasing rate during the past half century. But these trend terms could also reflect other changes in society during this period, so this entire effect cannot be attributed solely to television broadcasts.

The parameters on the measures of competitive balance are of most interest in this article. All three of the parameters on the competitive balance metrics are correctly signed, but only the parameter on the CBR is statistically significant; variation in the CBR is significantly related to variation in attendance in MLB. The HHI variable is nearly significant—the *p* value on a two-tailed *t* test of significance is .11 for this variable. The evidence here indicates that fans' decisions to attend baseball games may be influenced by the amount of turnover in relative standings in the league. This result confirms Neale's (1964) conjecture about the League Standing Effect. Total attendance rises (falls) when there is more (less) competitive balance, including relative turnover in final league standings over time. This can be due to reduced demand for tickets to perennial losers and winners.

These results need two important qualifications. First, they may reflect omitted variable bias. Equation 7 is basically a demand function that also contains variables that shift the supply of baseball games. This equation does not contain a variable capturing the price of attending baseball games, although the league-specific trends and intercepts may capture some of this effect. Consumer theory clearly defines a relationship between the price of a good or service and demand. Unfortunately, data on the price of baseball tickets are relatively scarce, especially during a 100-season period. Noll (1974) developed average price measures for a number of MLB teams in the 1970s and early 1980s and used these price data to analyze team-specific home attendance. However, these price variables were not statistically significant in a similar attendance model. The primary concern for these results would be the case where the omitted price variable is systematically positively correlated with the CBR, which would lead to an upward bias in the estimated parameter on that variable. There seems to be little reason to expect such a systematic positive correlation with the CBR.

Measurement error problems are the second qualification. The past 30 years of the sample period contain attendance for two franchises located in Canada, Montreal and Toronto, but the model contains no Canadian control variables and aggregating attendance to the league level makes controlling for these effects difficult. The empirical results were not affected by simply dropping data from the Canadian franchises from the sample, although this still leaves games played by these teams in U.S. cities in the data.

A second potential source of measurement error comes from averaging the competitive balance measures during 5-year periods. This averaging means that in some cases variation in competitive balance in future seasons is being used to explain variation in current attendance. Unfortunately, the CBR can only be calculated during a period of seasons. To assess the potential effect on the empirical results, I estimated a set of models where the three competitive balance measures were expressed as 3-season moving averages of past seasons, removing some (but not all) of this effect. I also estimated a set of models where the attendance variable was aggregated across 5-year periods and the population, number of games, and number of teams variables were averaged across the same 5-year periods. This reduced the sample size to 40. The results from these alternative models, which are available by request from the author, did not quantitatively change the results. Measurement error induced by averaging the competitive balance measures across 5-season periods does not appear to drive the results presented on Table 5, either because the underlying competitive balance in MLB changes relatively slowly or because consumers alter their perceptions of the state of competitive balance more slowly than the averaging done here.

CONCLUSIONS

The standard deviation of annual won-loss records has frequently been used as a measure of competitive balance in sports leagues. Although this measure of competitive balance is useful in many situations, it does not reflect variation in relative standings within a sports league over time. To address this problem, I have proposed a complementary measure of competitive balance, the CBR. This computationally simple statistic scales average team-specific variation in won-loss ratio during a number of seasons by the average within-season variation in won-loss percentage during the same period.

The NL in the 1910s and 1920s represents one case where the standard deviation of winning percentage measure of competitive balance and indexes of championship concentrations fail to distinguish between a period with high turnover in relative standings and one with low turnover. The AL in the 1990s represents another such case. Furthermore, variation in the CBR over time does a better job explaining observed variation in attendance in MLB than the other two alternative measures. These results suggest that CBR is a useful measure of competitive balance in sports leagues.

The CBR could be applied to a number of other interesting cases in the economics of sports. Expansion and free agency have been hypothesized to affect competitive balance in professional baseball to some extent. Comparing CBRs across different time periods may shed new light on these effects. As another example, in Bennett and Fizel (1995) and Eckard (1998), measures of competitive balance are used to assess the effect of the 1984 Supreme Court deregulation of college football telecasts. To the extent that the 1984 Supreme Court decision led to increased stratification in college football standings, the CBR may capture changes in competitive balance that other measures of competitive balance cannot.

NOTES

1. See Quirk and Fort (1997, chap. 7) for a comprehensive discussion of these techniques, and Schmidt (2001) for a discussion of Gini Coefficients.

2. Fort and Quirk (1995) used excess tail percentages from the distribution of won-loss percentages as a measure of competitive balance. The excess tail percentages for two standard deviations for this period, 39 and 37, are also similar.

3. The Competitive Balance Ratio (CBR) in the American League in the 1920s is not statistically different from the CBR in the 1910s.

4. The results on Table 5 were robust to White's (1980) correction for heteroskedasticity and the Newey and West (1987) correction for serial correlation and heteroskedasticity. These results are available by request.

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