WHO MADE WHO?

AN EMPIRICAL ANALYSIS OF COMPETITIVE BALANCE IN EUROPEAN SOCCER LEAGUES

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INTRODUCTION

Since the very beginning of the rapidly growing field of sport economics, the relationship between fan attendance and uncertainty of outcome has been playing a major role in empirical research. To our best knowledge it was Rottenberg [1956, 246] who first stated that "uncertainty of outcome is necessary if the consumer is to be willing to pay admission to the game". Following Fort and Maxcy [2003], this statement, also known as the uncertainty of outcome hypothesis, is at the core of one of two[1] distinct lines in the literature on competitive balance, which aims to derive fan demand and its (possible) dependence on uncertainty measures. In contrast to this, the second line of literature, the analysis of competitive balance, is primarily concerned with descriptive methods.

The success of Rottenberg's statement is beyond doubt as nowadays the idea of competitive balance is omnipresent when it comes to issues of institutional design in professional sports leagues. Concepts such as gate revenue sharing, centralized TV rights marketing (and subsequent sharing) or salary caps are only but a few battleships in the debate on league organization where the "uncertainty of outcome hypothesis" serves as a source of legitimacy.

The theory behind the "uncertainty of outcome hypothesis" is rather simple and can be stated as a set of three basic assumptions (see Szymanski [2003]): First that an unequal distribution of resources for teams leads to unequal competition, second that fan interest declines when outcomes become less uncertain and, third that specific redistribution mechanisms are suited to produce more outcome uncertainty. We shall refer to the first two assumptions as the core assumptions throughout this paper.

Although the core assumptions seem to make sense at an intuitive level, reality places some surprising observations right in front of us. For example fan attendance has been growing during the last two decades in most European football[2] leagues

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despite of the fact that competitive balance did not significantly increase.[3] Figure 1 shows the rising number of spectators in the 1. Bundesliga in Germany since the mid-eighties. At the same time the idealized standard deviation (*ISD*) reveals the league to deviate strongly from its ideal competitive balance level of 1.[4]

Moreover, important actors of the sports industry exhibit behaviour, which, at first glance, may seem to contradict the core assumptions of competitive balance theory. For example, recently in German football, officials from FC Bayern München have been showing a growing resistance against redistribution mechanisms introduced to enhance competitive balance in the 1. Bundesliga. Being perhaps the most influential club in professional German football, Bayern München is stuck in the middle of two competitions: On the one hand, the club is a member of the 1. Bundesliga in the German Championship and each season faces a schedule of 34 games against other league opponents. On the other hand, participation in the UEFA Champions league exhibits the club to additional competition on a European scale. In order to compete for the UEFA Champions League Championship against clubs as Real Madrid, Juventus Turin or FC Chelsea, club officials argue that they need two things (see the interview with Karl-Heinz Rummenigge, CEO of Bayern München, by Hoeltzenbein and Selldorf [2005]): Both a bigger "cake" of TV revenues in German football and second, a bigger share of this cake for Bayern München. Obviously, the management of Bayern München values the revenues from an improved playing strength in the Champions League higher than the potential costs from a loss in fan interest by becoming more affluent and dominant in German football, otherwise it would prefer to stick to the current level of team solidarity.

It is certainly not surprising that critics of Bayern München oppose the plan by predicting in line with Rottenberg that increased competitive imbalance in the 1. Bundesliga will reduce fan interest and ultimately harm Bayern München (see, for example, the interview with Harald Strutz, President of FSV Mainz 05, by Zitouni [2005]).

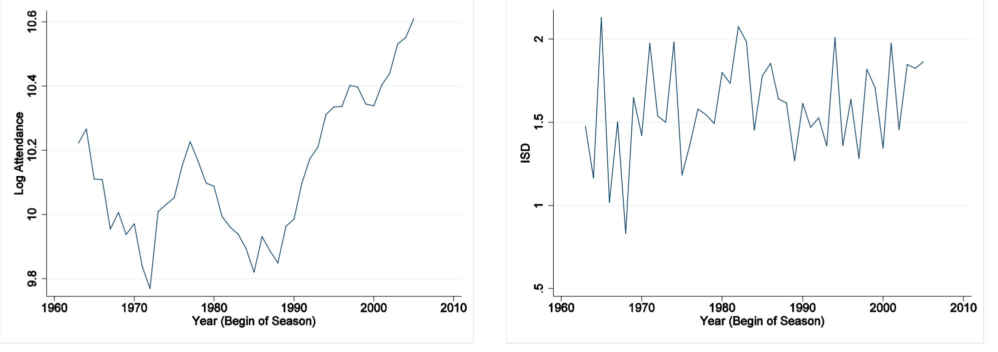
Although we have focused on the German Bundesliga so far, similar observations hold for other European Football Leagues. For example, in Italy, centralized TV rights selling has been abandoned. Thus, each team has the right to sell its TV rights separately, which obviously favors the strong teams, such as AC Milan, Inter and Juventus.

Both rising fan interest in European Soccer Leagues despite persisting competitive imbalance and the push towards lower levels of redistribution would be less puzzling if it would turn out that the proposed relationship between competitive balance and fan demand is only of minor importance to consumers.

The purpose of this paper is, therefore, to analyze in more detail the relationship between competitive balance and fan attendance in European Football. In particular, we want to know, how these variables interact with each other: Does competitive balance drive attendance or could it be the other way round?[5] Therefore, we estimate vector autoregressive (VAR) models to avoid an a-priori classification into endogenous and exogenous variables.

The empirical results are based on seasonal average match attendance data in professional German, English, Italian and French football during the seasons 1963/64 to 2005/06.

FIGURE 1
Seasonal Development: Average Match Attendance and Competitive Balance in the German 1. Bundesliga 1963/64 - 2005/06



Using Cain and Haddock [2006]'s version of the idealized standard deviation of winning percentages, the CR5 concentration ratio, and the Herfindahl-Index, we find significant differences in the relationship between competitive balance and match attendance across countries. Interestingly, the results also differ across different divisions within the same country. Our results are especially noteworthy, as they represent the first empirical evidence on the relationship between attendance and competitive balance for a variety of international leagues in European Soccer. More precisely, no previous study has simultaneously analyzed cross-country data within the same discipline. Since the first paper using time series analysis in sports,[6] the majority of studies[7] have focused on Major League Baseball. Hopefully, the analysis presented in this paper will serve as a starting point towards additional research in other sports disciplines.

The remainder of the paper is organized as follows: In section "Endogenous Competitive Balance" we argue why fan attendance and competitive balance may each be viewed as the endogenous or exogenous variable. This motivates our approach to estimate vector autoregressive models. A detailed discussion of our competitive balance measures and the corresponding results for Germany is given in section "Empirical Analysis". This section also contains test statistics from Granger causality tests. The results for France, England and Italy which can be found in section "Empirical Results on England, Italy and France" are derived analogously. For the latter two, we also analyze the underlying relationship for the Championship and Serie B divisions. Our results show a strong heterogeneity in the relationship between fan attendance and competitive balance across countries and across tiers within the same country. Possible implications of our findings for governing bodies in European football are discussed in the concluding section.

ENDOGENOUS COMPETITIVE BALANCE

Within the theory of competitive balance, it has always been attendance that served as the endogenous variable. In contrast to that, measures for competitive balance have always been used as exogenous variables in regression specifications. However, to a certain extent this distinction seems to be arbitrary, as we need to know where competitive balance comes from. In the following, we will show why it might indirectly be the distribution of fan attendance that decides about a league's degree of competitive balance.

Based on data from the English Premier League, Hall, Szymanski and Zimbalist [2002] found Granger causality from payrolls to performance. Thus, it seems reasonable to expect that differences in payrolls cause differences in performance. It is, therefore, important to understand where these differences in payrolls may come from. Certainly, a club's revenues will play a major role for its next season budget.[8] Thus, we have to be aware of the different sources of team revenues in European Soccer. Basically, we can distinguish between ticket sales, advertising, merchandise, transfers and TV revenues. In the Bundesliga, over the seasons 2001/2002 to 2003/2004 the combined share [Straub and Müller, 2005; own calculations] of ticket sales, advertising (and merchandise[9]) were 39.88% (43.22%), 45.71% (49.48%) and 49.53% (53.51%), respectively.

Here, the combination of advertising and ticket sales is based on evidence by Czarnitzki and Stadtmann [2002], who state that fan attendance does not only affect revenues related to admission tickets. Moreover, they find a positive correlation between the willingness of firms to choose a team as an advertising partner and its number of spectators in the previous season. Thus, we can state that ticket sales and advertising seem to play an important role for a club's revenues.

Furthermore, it seems straightforward to suspect that a more [less] equal distribution of clubs' fan attendances leads to a better [worse] competitive balance. Changes in fan attendance are viewed as exogenous shocks in our analysis. These shocks should influence competitive balance, because they may lead to the assimilation [dissimilation] of financial resources (budgets) and convergence of marginal productivity of player talent. If additional demand for tickets mainly referred to small clubs, the homogeneity in the distribution of financial endowments in the league would be higher. An improved (i.e., more equal) distribution of player talent per team[10] (as clubs can afford to invest similar amounts of money) should be expected in this case.

The marginal productivity argument goes as follows: Competition in professional team sports leagues is generally described using a so-called contest success function for the clubs (see, for example, El-Hodiri and Quirk [1971]; Dietl, Franck and Roy [2003] or the detailed review by Szymanski [2003]).[11] In its simplest form, we can write the logit specification of a contest success function as

$$p_A = \frac{t_A}{t_A + t_B} \tag{1}$$

where p_A[12] denotes the expected percentage of matches won by team A and t_A, t_B are talent investments for each club. In this context, it is usually assumed that clubs face identical positive, but decreasing marginal productivity of player talent (see, for example, Dietl et al. [2003]), in other words:

(2) $$\frac{\partial p_A}{\partial t_A} > 0; \qquad \frac{\partial p_A^2}{\partial t_A^2} < 0$$

Assume now, that there is a strong club, called *B*, and a weak club, denoted by *A,* competing with each other. The strong club may be expected to have higher investment costs in player talent. As a result, it faces a smaller marginal impact of investing another Euro into player talent than the weak club.

Formally, it can easily be seen that

(3) $$\frac{t_B}{(t_A + t_B)^2} = \frac{\partial p_A}{\partial t_A} > \frac{\partial p_B}{\partial t_B} = \frac{t_A}{(t_A + t_B)^2}, \text{ iff } t_B > t_A; \qquad t_B, t_A > 0$$

As a consequence, the weak team will always improve more on its contest-success function, as long as $t_A < t_B$, thereby increasing its expected share of games won.[13] In other words, regarding its effect on a team's playing strength, a ten percent increase in fan demand is worth more to weak teams than to strong teams. Notice that this argument is independent of the distribution of the increase in fan attendance.[14]

However, one may also imagine a negative influence of changes in fan attendance from season $t - 2$ to season $t - 1$ on competitive balance changes from season $t - 1$ to season t: Given that our idea stated above is correct, better teams should face a more constant demand for tickets. This may enable them to invest into players earlier as a potential "critical revenue level" for investments can be reached faster. If these players picked earlier were players of a higher quality than those who are available at the end of the transfer window, competitive balance in the next season might actually be worse than in the subsequent season (where the budget will then be assimilated).

Thus, whereas it is plausible that an increase in fan attendance affects competitive balance in a league, its a-priori effect is unclear.

EMPIRICAL ANALYSIS

MEASURES OF COMPETITIVE BALANCE

Which standards must a league meet in order to be judged as competitively balanced? This is a key question for empirical investigations of competitive balance in sports leagues. It requires that measuring uncertainty of outcome[15] cannot be done without further ado: To derive sensible measures for competitive balance it is crucial to first specify the time horizon on which the degree of competitive balance is to be analyzed. Over the years, three different time horizons emerged (see, for example, Quirk and Fort [1997]; Czarnitzki and Stadtmann [2002] and Borland and Macdonald [2003]): match, season and long-run, where it has to be mentioned that different time-horizons may necessitate different measures. Throughout this paper we will exclusively focus on the seasonal horizon.[16] Within the significant number of measures, two main types can be distinguished, static and dynamic ones. Given that most previous studies have been performed with static measures (see, for example, Quirk and Fort [1997]; Horowitz [1997], and Michie and Oughton [2004]), we adopt this approach in our study.

As we want to make sure that our results are robust and are not due to the choice of a specific measure, we work with several measures of competitive balance in the empirical analysis.

THE IDEALIZED STANDARD DEVIATION

Measuring seasonal competitive balance by the idealized standard deviation of winning percentages has by far been the dominating approach by researchers. Surely, one reason for this lies in the measure's simplicity.

However, Michie and Oughton [2004] point to the drawbacks of measuring competitive balance by the standard deviation of winning percentages in a European sports environment. The main problem of applying this measure to European soccer lies in the existence of possible draws between contenders. Whereas in American sports draws only happen very rarely, it is common for European soccer teams to end a season with a significant number of draws. To circumvent this problem, in a recent paper, Cain and Haddock [2006] propose the following procedure:

Rather than viewing each team as having an ex-ante winning probability of 0.5 as the ideal situation (as would be the case in a perfectly balanced US sports league), they state that soccer matches often end before the better team has the chance to reveal itself. In their words [Cain and Haddock, 2006, 331], "0.5 is a conditional probability: it is the probability that, were the contest to continue to resolution, the probability of each team winning in overtime is 0.5. The Fort-Quirk ISD does not take into account the probability that, before the fact, one of the outcomes of the competition is a tie."

We follow Cain and Haddock [2006] and derive the empirical distribution of wins, ties and losses for the German 1. Bundesliga in the period 1963 - 2005. Their relative frequencies are given by 37%, 26% and 37%, respectively.

Based on these figures, the expected number of points per match and, subsequently, its standard deviation is derived. In a season with N games per team under a 2-point regime,[17] the standard deviation is given by

$$\sqrt{0.74N} \tag{4}$$

The values for the ISD for season t is given by

$$ISD_t = \frac{\sigma_t(PW)}{\sqrt{0.74N}} \tag{5}$$

where $\sigma_t(PW)$ denotes the standard deviation of points won by each team at the end of season t.

THE CR^5 CONCENTRATION RATIO

The CR^5 concentration measure of competitive balance allows for a comparison between the top 5 clubs in a league and the remaining teams. This index may be interpreted as a measure for the degree of dominance by the top 5 teams within season t.

We follow Koning [2000] and Haan, Koning and van Witteloostuijn [2002], who calculate the index as follows:

(6)
$$CR_t^5 = \frac{\sum_{i=1}^{5} P_{it}}{5W(2N-5-1)}$$

where N and W refer to the number of teams within the league in season t and the number of points awarded for a win, respectively. Finally, P_{it} denotes the number of points at the end of season t for the team ranked ith.

However, it should be noted that [Koning, 2000, 426] "the concentration ratio is not a measure of competitive balance in the whole competition; it applies to the quality of the top teams".

THE HERFINDAHL INDEX

For reasons of comparability with previous studies only,[18] we also calculate the Herfindahl-Index at the end of each season. Originally, this index was developed to analyze inequalities between all firms in an industry. Using the market share of each firm, the index is calculated as follows:

(7)
$$H_t = \sum_{i=1}^{N} s_{it}^2$$

where N denotes the number of firms and s_{it} is the market share of firm i in year t. In the context of sports leagues these variables become the number of teams and team i's share of points during season t in the league, respectively.

As can be seen from equation (7), H_t depends on the absolute number of teams. To circumvent this problem, we will work with a standardized version of the index, that has been proposed by Michie and Oughton [2004], where H_t is multiplied by $100/(1/N)$; a perfectly balanced league would then exhibit a value of 100.

It is important to understand that for all measures of competitive balance, CB, an increase in the value for CB_t, refers to a greater imbalance in season t.

THE VECTOR AUTOREGRESSIVE MODEL

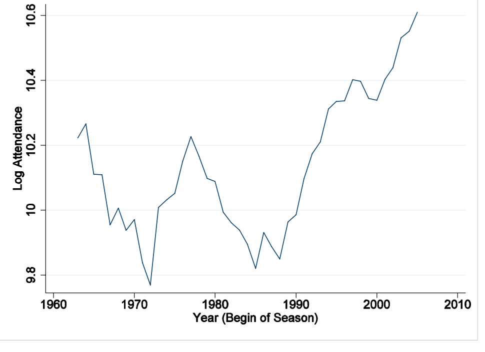
Competitive balance theory assumes that competitive balance influences fan attendance. In section "Endogenous Competitive Balance", we discussed why it might be justified to analyze the relationship of interest without a decision on exogeneity and endogeneity. Vector autoregressive (VAR) models provide an empirical framework for this type of analysis.[19]

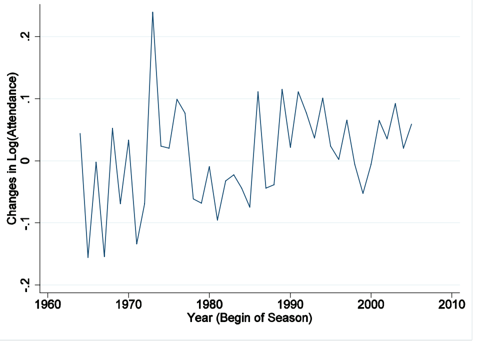
In order to estimate vector autoregressive models, we have to be assured of the series' stationarity and the non-existence of co-integration.

STATIONARITY AND COINTEGRATION

Figure 2 exposes the logarithmic seasonal development of average match attendance in the 1. Bundesliga since its beginning in the season 1963/64 until 2005/06. We also show the seasonal percentage changes.

FIGURE 2
Logarithmic Seasonal Development of Fan Attendance in 1. Bundesliga 1963/64 - 2005/06





The logarithmic transformation is used to decrease the scale in the graph. In Table 1 the corresponding descriptive statistics are displayed. To provide the reader with a more detailed view on the variables used in this study, descriptive statistics for all competitive balance measures are included as well.

TABLE 1
Descriptive Statistics: 1. Bundesliga

	Log (Attendance)	ISD	CR^5	Herfindahl
Mean	10.133	1.596	0.718	105.756
Median	10.098	1.578	0.723	105.318
Max	10.611	2.128	0.797	109.614
Min	9.769	0.832	0.642	101.423
Std. Deviation	0.216	0.290	0.037	2.069

From Figure 2 the strong increase in fan attendance since the end of the eighties is immediately revealed. Seasonal changes, however, seem to be generated by a stationary process. In order to verify our impressions, we perform the Augmented-Dickey Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests for unit-roots on the series. As we use two tests, which differ in the formulation of the null hypothesis (ADF: nonstationary; KPSS: stationary), this is also called confirmatory data analysis (see, for example, Maddala [2001, 553]). It should be mentioned however, that this procedure may sometimes result in controversial findings. This can be explained by the low power of unit root tests. For this reason, we also give the results from the Dickey-Fuller GLS test as the latter possesses a higher power. As shown in Table 2, for the original series,[20] we can not reject the null hypothesis that there is a unit root for Log(*Attendance*) and the CR^5.

TABLE 2
Test-Statistics from Unit-Root Tests for the German 1. Bundesliga

	Log (Attendance)	CR^5	ISD
Augmented Dickey Fuller			
Level (None)	0.745506	-0.084883	-0.037366
Level (Constant)	-0.174467	-2.524339	-7.675364***
Level (Const. + Trend)	-1.724331	-2.659850	-8.141650***
1st Differences (None)	-2.448335**	-15.96841***	-7.680026***
1st Differences (Const.)	-6.108195***	-15.76622***	-7.576232***
1st Differences (Const. + Trend)	-6.792918***	-15.56543***	-7.507523***
KPSS			
Level (Constant)	0.456196*	0.262662	0.346222
Level (Const. + Trend)	0.167171**	0.151672**	0.096460
1st Differences (Const.)	0.307336	0.184789	0.191217
1st Differences (Const. + Trend)	0.052731	0.177093**	0.181566**
Dickey Fuller GLS			
Level (Constant)	-0.430460	-2.526918**	-7.659058***
Level (Const. + Trend)	-1.339292	-2.705627	-8.321174***
1st Differences (Const.)	-5.907532***	-14.86588***	-12.58642***
1st Differences (Const. + Trend)	-6.612012***	-15.23881***	-7.127443***

*, ** and *** denote rejection on $\alpha = 10\%$, $\alpha = 5\%$ and $\alpha = 1\%$ significance levels, respectively.

The results from Table 2 support our impression from Figure 2: For the seasonal changes, i.e., the first differences in fan attendance, the existence of a unit-root is clearly rejected.[21] Regarding the competitive balance measures, we state that *ISD* and *Herfindahl* do not show a non-stationary behavior.[22] For the CR^5, taking first differences is required to obtain a stationary series.

Let us introduce the Δ-Operator to denote First Differences of a series, i.e.

$$\Delta(\text{Fans})_t := Fans_t - Fans_{t-1} \tag{8}$$

This has important consequences for our interpretation of the estimation results. The corresponding VAR specifications can be expressed as

$$CB_t = \alpha_{10} + \sum_{i=1}^{j} \beta_{1i} CB_{t-i} + \sum_{i=1}^{j} \gamma_{1i} Fans_{t-i} \tag{9}$$

$$Fans_t = \alpha_{20} + \sum_{i=1}^{j} \beta_{2i} CB_{t-i} + \sum_{i=1}^{j} \gamma_{2i} Fans_{t-i} \tag{10}$$

where CB_{t-i}, i=1, …, j denotes the value of the competitive balance measures (in each estimation, there is only one measure) for the season [t-i, t-(i-1)]. Both equations are estimated simultaneously. The important task is to determine the maximum lag order j. This decision can be based on different so-called information criteria. Simply spoken, information criteria are based on the error terms' variance, i.e. the unexplained part of the model. Thus, the lag structure yielding the lowest information criterion is the best. Perhaps the best known information criteria are the Akaike information criterion (AIC), Hannan-Quinn criterion (HQC) and the Schwarz criterion (SC). In this paper, we choose the SC. The reason for this choice is motivated by the fact that [Lütkepohl, 2006, 490] "generally, in small samples of fixed size $T \geq 16$,

$$\hat{\rho}(SC) \leq \hat{\rho}(HQC) \leq \hat{\rho}(AIC) \tag{11}$$

where $\hat{\rho}(AIC)$, $\hat{\rho}(HQC)$ and $\hat{\rho}(SC)$, denote the orders selected by AIC, HQC and SC, respectively". Thus, we want to avoid the situation, in which we include irrelevant lags. This is the more likely using the AIC, as the "AIC criterion tends to overestimate the order asymptotically and the HQC and SC criteria are both consistent [Lütkepohl, 2006, 489-90]".

Although it seems as if we could now proceed with the stationary series and apply the usual Box-Jenkins analysis, there may be another important effect, which we have to account for: co-integration of the series.[23]

Simply spoken, co-integration describes the fact that for two series that are non-stationary, there is a linear combination, given by the co-integrating vector, of the series which is stationary. The important consequence from co-integration is that there exists a long-run relationship between both variables.

Following the two step procedure proposed by Engle and Granger [1987], we estimate simple regression models of the form

$$\text{Log}(Attendance)_t = \beta_0 + \beta_1 CB_t + \varepsilon_t. \tag{12}$$

CB = ISD, CR^5*, Herfindahl.* We then perform unit root tests on the estimated residuals in order to check for the co-integration of Log($Attendance$)$_t$ and CB_t. For all measures,[24] we are not able to reject the existence of a unit root, i.e. of no co-integration. Thus, there is no need to rely on error correction models.

ESTIMATION RESULTS FOR THE VAR MODELS

Table 3 contains our estimation results for the German 1. Bundesliga. Based on the SC, all measures of competitive balance reveal a VAR(1).[25]

As can be seen from Table 3, there is a significant influence from attendance to competitive balance for the *ISD* and *Herfindahl*. Interestingly, the coefficients for attendance reveal a positive sign. To derive a better understanding of these results, we perform Granger Causality Tests on these relationships.

TABLE 3
VAR results for the German 1. Bundesliga

	Dependent Variable: Δ(Fans)			Dependent Variable: CB		
	Lag (-1) indep. var.	Lag (-1) dep.var.		Lag (-1) indep. var.	Lag (-1) dep. Var.	
Measure	CB	Attendance	Constant	Attendance	CB	Constant
ISD	0.023896	0.042226	-0.029993	0.945425	-0.147601	1.837121
	(0.04608)	(0.16776)	(0.07487)	(0.56565)	(0.15537)	(0.25245)
	[0.51860]	[0.25171]	[-0.40060]	[1.67139]	[-0.95000]	[7.27730]
$\Delta(CR^5)$	0.110483	0.028839	0.008245	0.062005	-0.716876	-0.000467
	(0.25179)	(0.16352)	(0.01299)	(0.07205)	(0.11095)	(0.00572)
	[0.43880]	[0.17636]	[0.63473]	[0.86052]	[-6.46145]	[-0.08150]
Herfindahl	0.001974	0.030577	-0.200499	7.481972	-0.001387	105.9237
	(0.00656)	(0.16639)	(0.69355)	(4.08833)	(0.16114)	(17.0407)
	[0.30103]	[0.18376]	[-0.28909]	[1.83008]	[-0.00861]	[6.21594]

Standard-errors in () and t-values in []

TESTING FOR GRANGER CAUSALITY

Simply spoken, the concept of Granger Causality says that if *x* Granger causes *y* it is possible to make better forecasts on *y* if one takes current and historical values of *x* into account instead of relying purely on values of *y*. The big advantage of Granger Causality tests is the possibility to explicitly address the direction of interaction. In Table 4, we give our estimation results on Granger Causality tests based on fan attendance and measures of competitive balance.

TABLE 4
Output from VAR Granger Causality/Block Exogeneity Wald Tests on Fan Attendance and Competitive Balance Measures (1. Bundesliga)

Null Hypothesis	DF	Chi-Sq	Prob.
Δ(*Fans*) does not Granger Cause *ISD*	1	2.793538	0.0946*
ISD does not Granger Cause Δ(*Fans*)	1	2.052272	0.1520
Δ(*Fans*) does not Granger Cause $\Delta(CR^5)$	1	0.740499	0.3895
$\Delta(CR^5)$ does not Granger Cause Δ(*Fans*)	1	0.192542	0.6608
Δ(*Fans*) does not Granger Cause *Herfindahl*	1	3.349201	0.0672*
Herfindahl does not Granger Cause Δ(*Fans*)	1	0.090622	0.7634

*, ** and *** denote significance on $\alpha = 10\%$, $\alpha = 5\%$ and $\alpha = 1\%$ significance levels, respectively

Summarizing, we can say that competitive balance does not seem to play an important role for fan attendance on a seasonal level. In other words, connecting our findings to the results by Borland and Macdonald [2003], it seems that the requested long-term effect of competitive balance on fan demand can not be verified on an average seasonal level. Thus, the data from the 1. Bundesliga do not provide a basis for organizational regulations or restrictions aimed at maintaining competitive balance in order to secure fan attendance. Interestingly, for the *ISD* and *Herfindahl* we find evidence for the endogeneity of competitive balance. However, in connection with the estimation results from our VAR specifications, we find surprising evidence that an increase in fan demand from season [t–2, t–1) to season [t–1, t) leads to a decrease in competitive balance in season t. Although this effect is only weakly significant (α = 10%), it seems as if, for some reason, our marginal productivity argument from section "Endogeneous Competitive Balance" does not apply in this situation.

EMPIRICAL RESULTS FOR ENGLAND, ITALY AND FRANCE

In order to obtain a fuller picture of competitive balance and match attendance in European Football, we now broaden our analysis to the English Premier League, Italian Serie A, and French Ligue 1.[26] Besides this cross-country approach, we will also analyze the English Championship Division and Italian Serie B to understand whether there are significant differences within a country.

ENGLAND

For the English Football League, we decided to include the two top tiers, the Premier League and the Championship Division. We begin with our results from the English Premier League.

PREMIER LEAGUE

In Figure 3 we display the development of logarithmic average match attendance per season together with the development of the idealized standard deviation.

FIGURE 3
Seasonal Development: Average Match Attendance and Competitive Balance in the English Premier League 1963/64 - 2005/06

Figure 3 shows the low level in average match attendance during the 1980s. This period was strongly affected by hooliganism in British Football. In comparison to that, the *ISD* measure seems to be stationary. Based on the ADF and KPSS tests,[27] we find, similarly to the results for Germany, average match attendance to be difference stationary. For the *ISD* and CR^5, the existence of a unit root can be rejected. Finally, the Herfindahl Index exhibits a trend stationary behaviour.

Based on these results, co-integration may only be present for *Herfindahl*. However, applying the 2-step procedure by Engle and Granger [1987], the existence of co-integration could be rejected on a 5% level of significance.

The VAR results for the English Premier League [see Table 15 in the Appendix] reveal a different picture than for Germany. Independent of the underlying competitive balance measure, we do not find any significant influence between fan attendance and competitive balance.

TABLE 5
Output from VAR Granger Causality/Block Exogeneity Wald Tests on Fan Attendance and Competitive Balance Measures for the English Premier League

Null Hypothesis	DF	Chi-Sq	Prob.
Δ(*Fans*) does not Granger Cause *ISD*	1	1.150127	0.2835
ISD does not Granger Cause Δ(*Fans*)	1	0.002720	0.9584
Δ(*Fans*) does not Granger Cause CR^5	1	1.196110	0.2741
CR^5 does not Granger Cause Δ(*Fans*)	1	0.319263	0.5721
Δ(*Fans*) does not Granger Cause *Herfindahl*	1	0.915449	0.3387
Herfindahl does not Granger Cause Δ(*Fans*)	1	0.000811	0.9773

*, ** and *** denote significance on α = 10%, α = 5% and α = 1% significance levels, respectively

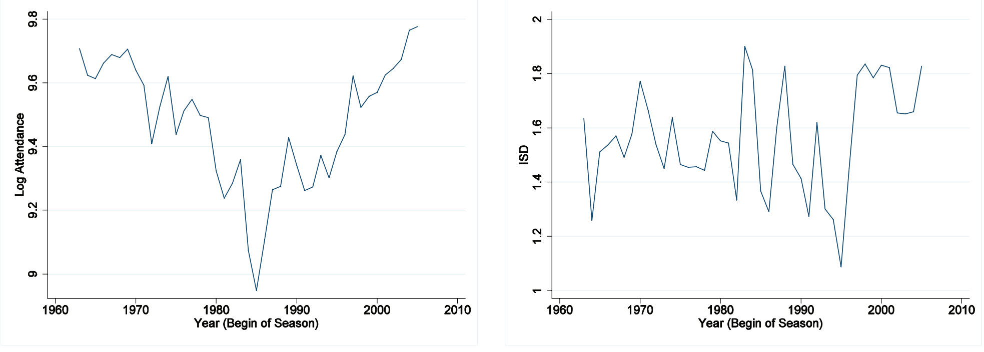
This effect is also shown in Table 5. To analyze this surprising finding further, we now turn to the second highest tier in professional English Football, the Championship Division. Similar results for this division might hint at a "country-specific" consumer attitude towards competitive balance.

CHAMPIONSHIP

As can be seen from Figure 4, the development within the English Championship Division resembles the development for the Premier League.

For the Championship Division, ADF and KPSS reveal average attendance, CR^5 and *Herfindahl* to be difference stationary, too. Again, *ISD* is found to be stationary.

FIGURE 4
Seasonal Development: Average Match Attendance and Competitive Balance in the English Championship Division 1963/64 - 2005/06



Interestingly, we are not able to reject the existence of co-integration between attendance and the CR^5 on the 5% level of significance. Thus, we specified an error correction model for the CR^5.[28] For the *Herfindahl* and *ISD*, no co-integration was detected.

Our estimation results for the Championship Division show a picture more similar to the German Bundesliga than to the Premier League. For the *Herfindahl* and *ISD*, we find a significant positive[29] influence from changes in fan attendance to competitive balance. For the CR^5, no significant relationship was found.

The reader should also note from Table 6 that Granger causality runs in both directions for the *ISD*. In line with the theory of competitive balance, we find a negative influence from a seasonal increase in competitive imbalance to subsequent average match attendance.

TABLE 6
Output from VAR/VEC Granger Causality/Block Exogeneity Wald Tests on Fan Attendance and Competitive Balance Measures for the English Championship Division

Null Hypothesis	DF	Chi-Sq	Prob.
Δ(*Fans*) does not Granger Cause *ISD*	1	8.708307	0.0032***
ISD does not Granger Cause Δ(*Fans*)	1	4.372717	0.0365**
Δ(*Fans*) does not Granger Cause Δ(CR^5)	1	1.932003	0.1645
Δ(CR^5) does not Granger Cause Δ(*Fans*)	1	0.124305	0.7244
Δ(*Fans*) does not Granger Cause Δ(*Herfindahl*)	1	8.071571	0.0045***
Δ(*Herfindahl*) does not Granger Cause Δ(*Fans*)	1	1.723985	0.1892

*, ** and *** denote significance on α = 10%, α = 5% and α = 1% significance levels, respectively

Based on our results for the English Premier League and Championship Division, we state that the relationship between competitive balance and fan demand may differ across tiers within the same country.

ITALY

We now turn to an investigation of the two top tiers in Italian Soccer, the Serie A and Serie B.

SERIE A

In Figure 5 we show the development of logarithmic average match attendance and the idealized standard deviation for the Italian Serie A. During the sample period, attendance figures generate an inverse U-shape. Based on a graphical inspection, there is no obvious relationship between fan demand and competitive balance.

Regarding the stationarity of our variables in the Serie A setting, we obtain *ISD* to be stationary, whereas fan attendance, CR^5 and Herfindahl-Index are difference stationary.

The VAR estimation results[30] for the Serie A show no significant relationship between the *ISD* and attendance. For the *Herfindahl*, we see that an increase in the measure will result in an increase in fan attendance.

FIGURE 5
Seasonal Development: Average Match Attendance and Competitive Balance in the Italian Serie A 1963/64 - 2005/06

TABLE 7
Output from VAR/VEC Granger Causality/Block Exogeneity Wald Tests on Fan Attendance and Competitive Balance Measures for the Italian Serie A

Null Hypothesis	DF	Chi-Sq	Prob.
$\Delta(Fans)$ does not Granger Cause *ISD*	1	0.003295	0.9542
ISD does not Granger Cause $\Delta(Fans)$	1	1.746748	0.1863
$\Delta(Fans)$ does not Granger Cause $\Delta(CR^5)$	1	0.609890	0.4348
$\Delta(CR^5)$ does not Granger Cause $\Delta(Fans)$	1	1.110658	0.2919
$\Delta(Fans)$ does not Granger Cause $\Delta(Herfindahl)$	1	1.359483	0.2436
$\Delta(Herfindahl)$ does not Granger Cause $\Delta(Fans)$	1	3.774522	0.0520*

*, ** and *** denote significance on $\alpha = 10\%$, $\alpha = 5\%$ and $\alpha = 1\%$ significance levels, respectively

For the Italian Serie A our results on Granger Causality, displayed in Table 7, support our findings from Table 17. Only for the Herfindahl-Index, we find a significant influence from competitive balance to attendance.

SERIE B

Figure 6 gives the graphical illustration of the development for attendance and competitive balance in the Italian Serie B.

Again, the ADF and KPSS test statistics indicate fan attendance to be difference stationary. For CR^5 and *ISD*, stationarity can not be rejected. Last but not least, the Herfindahl-Index is derived to follow a trend stationary process. For the latter, the existence of co-integration can not be rejected on the 5% level of significance.

The results (see Table 18 in the Appendix) do not show any significant relationship between attendance and competitive balance.

This finding is also reflected in the test statistics for Granger causality, displayed in Table 8: Independent of the underlying competitive balance measure, we do not find Granger causality in any direction.

FIGURE 6
Seasonal Development: Average Match Attendance and Competitive Balance in the Italian Serie B 1963/64 - 2005/06

TABLE 8
Output from VAR/VEC Granger Causality/Block Exogeneity Wald Tests on Fan Attendance and Competitive Balance Measures for the Italian Serie B

Null Hypothesis	DF	Chi-Sq	Prob.
$\Delta(Fans)$ does not Granger Cause *ISD*	1	0.794202	0.3728
ISD does not Granger Cause $\Delta(Fans)$	1	0.588456	0.4430
$\Delta(Fans)$ does not Granger Cause CR^5	1	0.408417	0.5228
CR^5 does not Granger Cause $\Delta(Fans)$	1	0.310162	0.5776
$\Delta(Fans)$ does not Granger Cause *Herfindahl*	1	0.660139	0.4165
Herfindahl does not Granger Cause $\Delta(Fans)$	1	0.166806	0.6830

*, ** and *** denote significance on $\alpha = 10\%, \alpha = 5\%$ and $\alpha = 1\%$ significance levels, respectively

Summarizing our results from Italy, we state that the relationship between competitive balance and fan attendance remains unclear. A possible explanation could be the low degree of integrity in these leagues: During our sample period it almost regularly happened that points were deducted from teams or that teams were relegated due to some kind of misbehavior.[31] Thus, fans might be aware of a certain imbalance in the league, which can not be captured by our measures.

FRANCE

Figure 7 displays logarithmic average match attendance and the idealized standard deviation for the French Ligue 1.

As can be seen from Figure 7, average match attendance has significantly increased over the sample period. In contrast to that, the idealized standard deviation shows a stationary behavior.

Applying the ADF and KPSS tests, we find attendance to be difference stationary. All competitive balance measures, in turn, are found to be stationary. Therefore, the possible existence of co-integration is of no concern to us in the setting of the Ligue 1.

FIGURE 7
Seasonal Development: Average Match Attendance and Competitive Balance in the French Ligue 1 1963/64 - 2005/06

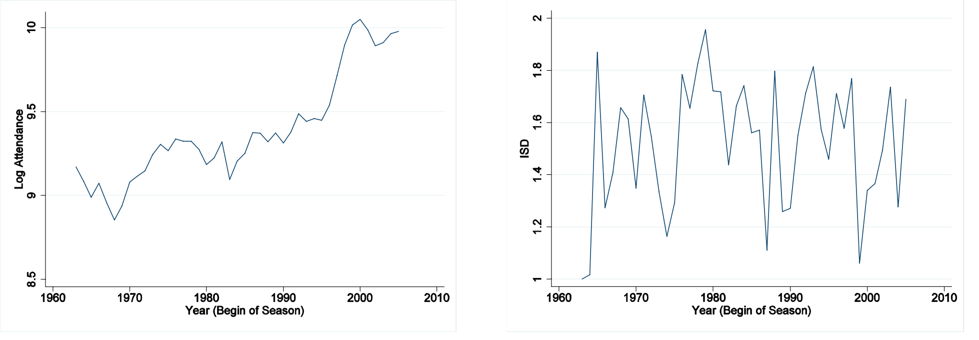


TABLE 9
Output from VAR Granger Causality/Block Exogeneity Wald Tests on Fan Attendance and Competitive Balance Measures for the French Ligue 1

Null Hypothesis	DF	Chi-Sq	Prob.
$\Delta(Fans)$ does not Granger Cause *ISD*	1	4.562709	0.0327**
ISD does not Granger Cause $\Delta(Fans)$	1	4.474809	0.0344**
$\Delta(Fans)$ does not Granger Cause CR^5	1	3.618358	0.0571*
CR^5 does not Granger Cause $\Delta(Fans)$	1	0.874708	0.3497
$\Delta(Fans)$ does not Granger Cause *Herfindahl*	1	1.788538	0.1811
Herfindahl does not Granger Cause $\Delta(Fans)$	1	6.760333	0.0093***

*, ** and *** denote significance on $\alpha = 10\%$, $\alpha = 5\%$ and $\alpha = 1\%$ significance levels, respectively

Testing for Granger Causality, we come up with ambiguous findings. As Table 9 displays, we find Granger causality from fan attendance to competitive balance for the *ISD* and CR^5. For both measures, we find evidence (see Table 19 in the Appendix) for the marginal productivity effect (see section "Endogeneous Competitive Balance") from an increase in fan demand to competitive balance. In contrast to that, we also obtain Granger causality from competitive balance to attendance for the *ISD* and Herfindahl-Index. Surprisingly, both measures show an increase in fan demand if competitive balance previously decreased.

Concluding our empirical analysis, we state that the relationship between fan attendance and competitive balance strongly differs across different leagues. As we will discuss in the next section, this has implications for the policies of the national and international governing bodies of football.

CONCLUSION

The purpose of this paper was to analyze the relationship between competitive balance and fan attendance in professional European Soccer. In particular, we discussed why an ex-ante decision on the exogeneity and endogeneity of the variables might not be as obvious as the theory of competitive balance assumes. This motivated us to apply a VAR estimation methodology, where this ex-ante decision can be omitted. Based on the resulting estimation coefficients, we then performed tests for Granger causality. Our results clearly show a heterogeneous pattern in the relationship between fan attendance and competitive balance, first, across countries and, second, across tiers within the same country: For the German Bundesliga, our results indicate a significant influence from fan attendance to competitive balance but not vice versa; increases in fan attendance lower competitive balance in the subsequent season. However, this effect is only significant on a 10% level of significance. In comparison to that, we do not find any significant relationship between competitive balance and fan attendance. This is also true for the Italian Serie A. For the French league, we find that changes in fan demand improve competitive balance afterwards and that fan attendance reacts to changes in competitive balance. Thus, there are significant differences across countries with respect to the relationship between competitive balance and fan attendance.

Regarding our results for the English Championship Division and the Italian Serie B, we find no clear cut pattern: Whereas the results of the Serie B correspond to our findings for the Serie A, i.e. there is no significant relationship between these variables, the second tier in England reveals strong differences in comparison to the English Premier League. Here, we also find evidence for an influence from fan attendance to competitive balance, similar to our results for the German 1. Bundesliga. Noteworthy is the fact that this is the only league, where, based on the *ISD*, we find evidence for the proposed influence from competitive balance to attendance.

Based on our empirical results, it may seem that fans do not always put as much emphasis on competitive balance as theory predicts. However, it is important to note that our analysis does not automatically proof the uncertainty of outcome hypothesis to be wrong: Given the time period of more than forty years for our study, it seems reasonable to suspect that several factors affecting demand may have changed, which could not been controlled for[32] in our study. Still, we regard it noteworthy to state that our results hint at the fact that the influence of competitive balance may be dominated by other influence factors.

This point might further be strengthened by the existence of certain institutional peculiarities associated with European football leagues, which might render competitive balance less important: On purely theoretical grounds European football leagues should be able to deal with a greater imbalance of their teams without losing fan interest than typical US Major Leagues. Due to the fact of promotion and relegation European leagues may capture fan interest by presenting two competitions simultaneously. Less endowed teams at the bottom of the league may activate fan interest by competing with each other against being relegated. At the same time the top teams compete to qualify for promotion to the next higher league or to international club competitions like the Champions league or the UEFA Cup. By providing several focal points for fan interest, European football leagues are less likely to become boring even if competitive imbalance is high. The result, that competitive balance does rarely drive fan attendance may, in part, follow from this peculiarity of European leagues.

In spite of these limitations, we believe that there are important lessons to be learned from our results for professional European Soccer: Recall that this paper was motivated by the on-going debate about team-solidarity in Professional European soccer. Our results show that, on a seasonal level, a need for team solidarity (for example, increased TV revenue sharing) can not be justified by resorting to the theory of competitive balance. In other words, our results indicate that critics of FC Bayern München or Juventus Turin may be overreacting. We do not find support that the popularity of the sport is at stake if these teams become more dominant in their domestic leagues. It seems that there is no need to act for the governing bodies of football.

In contrast, we believe our findings of a significant influence from attendance to competitive balance to support previous research on market design issues. In a recent paper Buraimo, Forrest and Simmons [2005] show the strong influence from a team's market size to team success. Therefore, based on our results, it seems reasonable to expect that a more homogenous distribution of team market sizes might improve a league's degree of competitive balance.

Regarding future research goals, we would like to mention that our study faces some statistical limitations. First, using seasonal average match attendance data prevents us from taking the advent of club heterogeneity into account. Moreover, we have no possibility to adjust for seasonal ticket holders or to distinguish seated from standing viewing accommodation[33] (as proposed by Dobson and Goddard [1992]). Incorporating these aspects in future research, possibly in association with new analytical tools such as unit root tests with break points (see, for example, Fort and Lee, [2006]), seems to be a promising extension of our study.

APPENDIX

Within the Appendix we give the results from the ADF, KPSS and DF-GLS unit root tests for England, Italy and France. In addition, we also show the VAR/VEC estimation results for these countries.

TABLE 10
Test-Statistics from Unit-Root Tests for the English Premier League

	Log (Attendance)	CR^5	ISD
Augmented Dickey Fuller			
Level (None)	0.568637	0.188695	0.143947
Level (Constant)	-0.620393	-3.408239**	-4.293044***
Level (Const. + Trend)	-0.607350	-3.402507*	-4.518660***
1st Differences (None)	-5.164381***	-9.377577***	-9.042787***
1st Differences (Const.)	-5.128317***	-9.272693***	-8.968361***
1st Differences (Const. + Trend)	-5.227903***	-9.240496***	-6.559261***
KPSS			
Level (Constant)	0.177059	0.258201	0.299574
Level (Const. + Trend)	0.178094**	0.175172**	0.123188
1st Differences (Const.)	0.247674	0.164525	0.162644
1st Differences (Const. + Trend)	0.136695*	0.114770	0.148855**
Dickey Fuller GLS			
Level (Constant)	-0.699252	-3.458751***	-4.218231***
Level (Const. + Trend)	-0.772363	-3.432846**	-4.565615***
1st Differences (Const.)	-5.166253***	-7.668936***	-8.872436***
1st Differences (Const. + Trend)	-5.282730***	-8.944963***	-9.063925***

*, ** and *** denote significance on $\alpha = 10\%$, $\alpha = 5\%$ and $\alpha = 1\%$ significance levels, respectively

TABLE 11
Test-Statistics from Unit-Root Tests for the English Championship Division

	Log (*Attendance*)	*CR*[5]	*ISD*
Augmented Dickey Fuller			
Level (None)	0.072791	-0.322628	0.345831
Level (Constant)	-1.583221	-3.198452**	-3.975165***
Level (Const. + Trend)	-1.330773	-3.599676**	-4.145979**
1st Differences (None)	-6.545462***	-8.790966***	-7.313785***
1st Differences (Const.)	-6.470169***	-8.669400***	-7.249008***
1st Differences (Const. + Trend)	-6.045348***	-8.566316***	-7.168273***
KPSS			
Level (Constant)	0.213170	0.500262**	0.194053
Level (Const. + Trend)	0.197999**	0.137247*	0.117118
1st Differences (Const.)	0.378897*	0.397113*	0.237668
1st Differences (Const. + Trend)	0.150859**	0.389394***	0.156278**
Dickey Fuller GLS			
Level (Constant)	-1.403400	-2.574900**	-3.872640***
Level (Const. + Trend)	-1.398958	-3.681827**	-4.162556***
1st Differences (Const.)	-5.878282***	-6.107712***	-1.221731
1st Differences (Const. + Trend)	-6.100900***	-7.418655***	-6.480862***

*, ** and *** denote significance on $\alpha = 10\%$, $\alpha = 5\%$ and $\alpha = 1\%$ significance levels, respectively

TABLE 12
Test-Statistics from Unit-Root Tests for the Italian Serie A

	Log (*Attendance*)	*CR*[5]	*ISD*
Augmented Dickey Fuller			
Level (None)	-0.062930	-0.278467	0.095658
Level (Constant)	-1.865786	-2.582092	-6.092617***
Level (Const. + Trend)	-1.660773	-2.756882	-6.479658***
1st Differences (None)	-5.959556***	-11.69921***	-12.43022***
1st Differences (Const.)	-5.882693***	-11.54982***	-12.26968***
1st Differences (Const. + Trend)	-6.828967***	-11.49553***	-12.22049***
KPSS			
Level (Constant)	0.218376	0.499636**	0.330291
Level (Const. + Trend)	0.218591***	0.059020	0.160488**
1st Differences (Const.)	0.476524**	0.334976	0.404684*
1st Differences (Const. + Trend)	0.182760**	0.184410**	0.500000***
Dickey Fuller GLS			
Level (Constant)	-1.249955	-1.789269*	-2.410867**
Level (Const. + Trend)	-1.347619	-2.800305	-3.237825**
1st Differences (Const.)	-5.057299***	-11.70600***	-12.30990***
1st Differences (Const. + Trend)	-6.360664***	-10.62196***	-10.98142***

*, ** and *** denote significance on $\alpha = 10\%$, $\alpha = 5\%$ and $\alpha = 1\%$ significance levels, respectively

TABLE 13
Test-Statistics from Unit-Root Tests for the Italian Serie B

	Log (*Attendance*)	*CR*[5]	*ISD*
Augmented Dickey Fuller			
Level (None)	-0.214249	-0.647177	0.307889
Level (Constant)	-2.631546*	-4.125552***	-6.473080***
Level (Const. + Trend)	-2.840559	-5.591397***	-6.543284***
1st Differences (None)	-8.768859***	-6.469792***	-6.060574***
1st Differences (Const.)	-8.686281***	-6.439975***	-6.003170***
1st Differences (Const. + Trend)	-8.707028***	-6.402514***	-5.933901***

TABLE 13 (continued)
Test-Statistics from Unit-Root Tests for the Italian Serie B

	Log (*Attendance*)	CR^5	*ISD*
KPSS			
Level (Constant)	0.236548	0.666190**	0.193444
Level (Const. + Trend)	0.207199**	0.153295**	0.127353*
1st Differences (Const.)	0.349624*	0.188085	0.367353*
1st Differences (Const. + Trend)	0.210864**	0.187974**	0.276169***
Dickey Fuller GLS			
Level (Constant)	-2.433113**	-4.041623***	-5.945532***
Level (Const. + Trend)	-2.756281	-5.661744***	-6.507712***
1st Differences (Const.)	-6.856588***	-6.522659***	-10.32526***
1st Differences (Const. + Trend)	-8.502462***	-10.36777***	-10.39052***

*, ** and *** denote significance on α = 10%, α = 5% and α = 1% significance levels, respectively

TABLE 14
Test-Statistics from Unit-Root Tests for the French Ligue 1

	Log (*Attendance*)	CR^5	*ISD*
Augmented Dickey Fuller			
Level (None)	1.416405	-0.225967	-0.024430
Level (Constant)	-0.021322	-4.152422***	-6.018971***
Level (Const. + Trend)	-2.380571	-4.884150***	-5.930740***
1st Differences (None)	-5.471168***	-9.822652***	-10.56372***
1st Differences (Const.)	-5.710602***	-9.700552***	-10.46300***
1st Differences (Const. + Trend)	-5.715220***	-4.029245**	-10.41184***
KPSS			
Level (Constant)	0.696802**	0.420830*	0.142284
Level (Const. + Trend)	0.155844**	0.188688**	0.119543*
1st Differences (Const.)	0.187790	0.191399	0.240812
1st Differences (Const. + Trend)	0.049034	0.096673	0.180752**
Dickey Fuller GLS			
Level (Constant)	0.128790	-3.754024***	-2.437095**
Level (Const. + Trend)	-1.962840	-4.497469***	-5.023969***
1st Differences (Const.)	-4.718053***	-9.812787***	-10.43568***
1st Differences (Const. + Trend)	-5.630762***	-9.753633***	-10.32092***

*, ** and *** denote significance on α = 10%, α = 5% and α = 1% significance levels, respectively

TABLE 15
VAR results for the English Premier League

	Dependent Variable: Δ(*Fans*)			**Dependent Variable: Δ(*CB*)**		
Measure	**Lag (-1) indep. var. *CB***	**Lag (-1) dep.var. *Attendance***	**Constant**	**Lag (-1) indep. var. *Attendance***	**Lag (-1) dep. Var. *CB***	**Constant**
ISD	0.001991	0.193843	0.0000602	0.737003	0.287775	1.230945
	(0.03818)	(0.16031)	(0.06587)	(0.68722)	(0.16367)	(0.28237)
	[0.05216]	[1.20919]	[0.00913]	[1.07244]	[1.75825]	[4.35930]
CR^5	-0.166570	0.200589	0.120755	0.084519	0.508181	0.345327
	(0.29480)	(0.15870)	(0.20685)	(0.07728)	(0.14355)	(0.10073)
	[-0.56503]	[1.26394]	[0.58377]	[1.09367]	[3.54004]	[3.42831]
Herfindahl	0.000167	0.194521	0.004017	4.283387	0.219723	-0.015838
	(0.00588)	(0.15958)	(0.00960)	(4.47683)	(0.16493)	(0.26945)
	[0.02848]	[1.21896]	[0.41819]	[0.95679]	[1.33226]	[-0.05878]

Standard-errors in () and t-values in []

TABLE 16
VAR results for the English Championship Division

	Dependent Variable: Δ(*Fans*)			Dependent Variable: Δ(*CB*)		
	Lag (-1) indep. var.	Lag (-1) dep.var.		Lag (-1) indep. var.	Lag (-1) dep. Var.	
Measure	*CB*	*Attendance*	Constant	*Attendance*	*CB*	Constant
ISD	-0.170756	-0.034372	0.268431	0.722080	0.440033	0.880760
	(0.08166)	(0.15228)	(0.12752)	(0.24469)	(0.13121)	(0.20491)
	[-2.09110]	[-0.22572]	[2.10499]	[2.95098]	[3.35353]	[4.29827]
$\Delta(CR^5)$	-0.246135	-0.117885	0.003514	0.057521	-0.216696	-0.000125
	(0.69812)	(0.18382)	(0.01573)	(0.04138)	(0.15716)	(0.00354)
	[-0.35257]	[-0.64130]	[0.22337]	[1.38997]	[-1.37879]	[-0.03519]
Δ(*Herfindahl*)	-0.017988	0.029665	0.004107	5.009752	-0.266932	0.096737
	(0.01370)	(0.16298)	(0.01604)	(1.76334)	(0.14823)	(0.17359)
	[-1.31301]	[0.18202]	[0.25596]	[2.84105]	[-1.80083]	[0.55726]

Standard-errors in () and t-values in []

TABLE 17
VAR results for the Italian Serie A

	Dependent Variable: Δ(*Fans*)			Dependent Variable: Δ(*CB*)		
	Lag (-1) indep. var.	Lag (-1) dep.var.		Lag (-1) indep. var.	Lag (-1) dep. Var.	
Measure	*CB*	*Attendance*	Constant	*Attendance*	*CB*	Constant
ISD	0.083896	0.011882	-0.151431	-0.026449	-0.043659	1.908183
	(0.06348)	(0.16542)	(0.11601)	(0.46078)	(0.17682)	(0.32315)
	[1.32165]	[0.07183]	[-1.30535]	[-0.05740]	[-0.24692]	[5.90518]
$\Delta(CR^5)$	0.042387	0.046754	0.001655	-0.046527	-0.626604	-0.000774
	(0.40220)	(0.16892)	(0.01294)	(0.05958)	(0.14185)	(0.00457)
	[1.05388]	[0.27678]	[0.12789]	[-0.78095]	[-4.41733]	[-0.16947]
Δ(*Herfindahl*)	0.016211	0.131544	0.000778	4.180071	-0.121305	0.148296
	(0.00834)	(0.18244)	(0.01261)	(3.58506)	(0.16397)	(0.24786)
	[1.94281]	[0.72102]	[0.06165]	[1.16597]	[-0.73980]	[0.59831]

Standard-errors in () and t-values in []

TABLE 18
VAR results for the Italian Serie B

	Dependent Variable: Δ(*Fans*)			Dependent Variable: Δ(*CB*)		
	Lag (-1) indep. var.	Lag (-1) dep.var.		Lag (-1) indep. var.	Lag (-1) dep. Var.	
Measure	*CB*	*Attendance*	Constant	*Attendance*	*CB*	Constant
ISD	0.079446	-0.290366	-0.117790	-0.216494	-0.060948	1.454615
	(0.10356)	(0.15200)	(0.14310)	(0.24293)	(0.16552)	(0.22871)
	[0.76711]	[-1.91031]	[-0.82311]	[-0.89118]	[-0.36822]	[6.36002]
CR^5	0.415472	-0.303492	-0.289171	-0.019292	0.396172	0.405558
	(0.74602)	(0.15149)	(0.50282)	(0.03019)	(0.14866)	(0.10020)
	[0.55692]	[-2.00341]	[-0.57510]	[-0.63908]	[2.66492]	[4.04753]
Herfindahl	-0.016171	-0.373418	-0.009323	0.575912	-0.112156	0.086440
	(0.01990)	(0.16707)	(0.02289)	(1.41010)	(0.16799)	(0.19323)
	[-0.81249]	[-2.23512]	[-0.40725]	[0.40842]	[-0.66765]	[0.44735]

Standard-errors in () and t-values in []

TABLE 19
VAR results for the French Ligue 1

	Dependent Variable: Δ(*Fans*)			Dependent Variable: Δ(*CB*)		
	Lag (-1) indep. var.	**Lag (-1) dep.var.**		**Lag (-1) indep. var.**	**Lag (-1) dep. Var.**	
Measure	***CB***	***Attendance***	**Constant**	***Attendance***	***CB***	**Constant**
ISD	0.118711	0.133182	-0.162405	-0.828164	-0.031656	1.611009
	(0.05612)	(0.15007)	(0.08714)	(0.38771)	(0.14499)	(0.22513)
	[2.11537]	[0.88750]	[-1.86374]	[-2.13605]	[-0.21834]	[7.15581]
CR^5	0.367542	0.128205	-0.238371	-0.111728	0.337822	0.466221
	(0.39298)	(0.15781)	(0.27632)	(0.05874)	(0.14627)	(0.10285)
	[0.93526]	[0.81241]	[-0.86267]	[-1.90220]	[2.30958]	[4.53322]
Herfindahl	0.023448	0.095342	-2.435977	-3.345487	0.078677	96.67701
	(0.00902)	(0.14582)	(0.94457)	(2.50156)	(0.15471)	(16.67701)
	[2.60006]	[0.65382]	[-2.57893]	[-1.33736]	[0.50856]	[5.96636]

Standard-errors in () and t-values in []

NOTES

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1. Actually, there exists another string, which analyzes different institutional arrangements, such as gate revenue sharing, free agency and salary caps with respect to their influence on competitive balance. See, for example, Booth [2004] and Fort [2003].
2. Throughout this paper, we will use the terms football and soccer equivalently.
3. It has to be mentioned that Rottenberg did not specify increases in fan attendance to be exclusively due to a greater degree of uncertainty of outcome. The displayed increase in fan attendance might also be the result of changes in other influence factors. However, the graphical illustration allows for the possibility that competitive balance may only be a second order effect for attendance decisions.
4. This is the ISD version proposed by Cain and Haddock [2006]. The exact derivation of this measure is discussed in section "Empirical Analysis".
5. The reasoning for this *inverse relationship* is given in the next section.
6. See Scully [1995]. Thus, this research field may still be considered a rather young one.
7. We are currently aware of only four exceptions, namely Simmons [1996], Davies, Downward and Jackson [1995], Dobson and Goddard [1998] and the recent paper by Hoon Lee [2006]. See Fort and Lee [2006] for a short review of this literature.
8. This argument lies at the core of the revenue sharing system in the USA, which was implemented to improve competitive balance.
9. Although it seems intuitive that the more shirts of a team are sold, the more fans attend games in a season, we also give the numbers of advertising and ticket sales, only.
10. Unfortunately, we are unable to empirically investigate the assimilation of playing strength based on our data.
11. For the sake of simplicity, let us assume that there are only two clubs A and B.
12. p_B is given by 1-p_A.
13. It should be mentioned that this reasoning is in line with empirical results by Dobson and Goddard [1998, 1641] who, based on Granger causality tests, find that "[…] the dependence of performance on revenue seems to be greater for smaller clubs than for the larger".

14. We explicitly exclude the case, where one team faces all additional demand.
15. From now on, we will equivalently speak of measuring competitive balance.
16. We refer to the study by Humphreys [2002] as support for choosing this time horizon.
17. Under a 3-point system, equation (4) becomes $\sqrt{1.71N}$.
18. In fact, applying this index in a sports framework is likely to result in a flawed measurement of competitive balance. Whereas it is possible in an industry framework for a firm to capture the whole market, no single team within a league can win all league matches. We are grateful to an anonymous referee for bringing this point to our attention.
19. For an introduction on VAR estimation, see, for example, Hamilton [1994].
20. As the Herfindahl-Index is not our main concern in this study, we do not give the detailed results.
21. From now on, for reasons of simplicity, we will speak of fan attendance instead of fan attendance first differences.
22. The included constant merely reflects the non-zero mean of the series.
23. For an introduction to co-integration. See, for example, Greene [2003] and Hamilton [1994].
24. For *ISD* and *Herfindahl*, co-integration could be ruled based on our results from Table 2.
25. Values for the SC are not given in this paper.
26. Although the Ligue 1 is not as renowned as the Spanish Primera Division, the latter had to be left out as the relevant data could not be obtained.
27. The unit root test results for England, Italy and France are given in the Appendix.
28. See Table 16 in the Appendix. Note that we do not show the coefficients on the error correction term throughout this paper.
29. Recall from section “Empirical Analysis” that a positive sign refers to a negative effect on the degree of competitive balance.
30. The results are given in Table 17 in the Appendix. Except for the Herfindahl-Index, no co-integration could be found on a 5% level of significance. As a consequence, we specified a VEC model for the Herfindahl-Index.
31. Very recently, there has been another scandal in the Serie A, which resulted in Turin being relegated to the Serie B, denial of championship titles and exclusion from international competitions.
32. Unfortunately, we have not been able to obtain data, such as admission prices or disposable income, on these factors for all countries over the sample period. The robustness of our results with respect to these factors would be an important task for future research.
33. The latter two being due to a lack of access to the corresponding data.

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