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How Fans May Improve Competitive Balance-
An Empirical Analysis of the German Bundesliga

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How Fans May Improve Competitive Balance- An Empirical Analysis of the German Bundesliga ‡

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Abstract

There is an on-going debate about the optimal degree of team solidarity in the German Professional soccer league. Support for a high degree of team solidarity has been coming from the theory of competitive balance and its prediction that fans would otherwise lose interest in sports due to diminished uncertainty of outcome. However, empirical observations show that core assumptions of this theory may not hold in the case of the German Bundesliga. Based on aggregate seasonal gate-attendance and different measures of competitive balance, this paper presents results using vector error correction models and Granger causality tests. Whereas the role of competitive balance for fan attendance remains unclear, we find a robust positive effect of fan attendance on competitive balance. Possible explanations of this effect, in particular its channel and lag structure are exposed in greater detail.

JEL Classification: C13, C32, L83

Keywords: competitive balance, sports leagues, Granger Causality, VEC models

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1 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) who first stated that “uncertainty of outcome is necessary if the consumer is to be willing to pay admission to the game”(p.246). Following Fort & Maxcy (2003), this statement, also known as the *uncertainty of outcome hypothesis*, is at the core of one of two 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 puzzles right in front of us. For example fan attendance has been growing during the last two decades in most European football¹ leagues despite of the fact that competitive balance did not increase. Figure 1 shows the rising number of spectators in the 1. Bundesliga in Germany since the mid-eighties. At the same time the C5-Index reveals the league to deviate strongly from its ideal competitive balance level of 100².

Moreover, important actors of the sports industry exhibit behavior, which is not consistent with the core assumptions of competitive balance theory. For example recently in German football, officials from FC Bayern München have been showing a growing resis-

¹Throughout this paper, we will use the terms *football* and *soccer* equivalently.

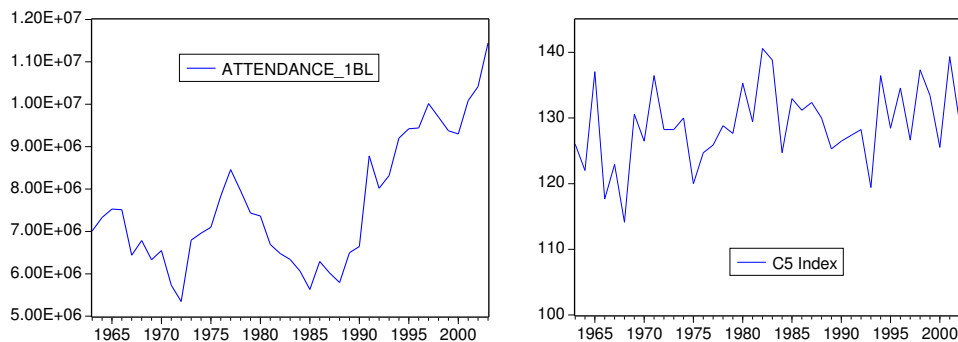
²The C5-Index displayed in Figure 1 is standardized to account for changes in team numbers. More details on the standardization are given in section 3.

tance 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 an European scale. In order to compete for the Champions league Championship against clubs as Real Madrid, Juventus Turin or FC Chelsea, club officials argue that they need two things³: 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 does not fear to loose 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 interest⁴ and ultimately harm Bayern München.

Both rising fan interest in the 1. Bundesliga despite persisting competitive imbalance and the push towards lower levels of redistribution by Bayern München would be less puzzling if the core assumptions of competitive balance theory would turn out to be invalid.

Figure 1: Seasonal Development: Fan Attendance and C5-Index in 1. Bundesliga 1963/64 - 2003/04



The purpose of this paper is, therefore, to analyze in more detail whether the core

³See the interview with Karl-Heinz Rummenigge, CEO of Bayern München, by Hoeltzenbein & Selldorf (2005)

⁴See e.g. the interview with Harald Strutz, President of Mainz 05, by Zitouni (2005).

assumptions of the theory of competitive balance hold for the case of the 1. Bundesliga. We will verify the empirical evidence for these assumptions by deriving results based on Granger causality tests for attendance and uncertainty variables.

Our approach is the following: It is well known that measuring uncertainty of outcome⁵ 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 emerged⁶: 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 horizon⁷.

Once the question how to measure competitive balance has been addressed, we turn to the core assumptions of competitive balance theory⁸, which state that an unequal distribution of resources for teams leads to unequal competition and, that fan interest declines when outcomes become less uncertain. Following a similar study by Davies, Downward & Jackson (1995), we choose Granger Causality Tests and Vector Error Correction Models (VEC) to analyze these claims simultaneously.

The empirical analysis is based on seasonal aggregate gate-attendance data for the First Division in Professional German football (1. Bundesliga) during the seasons 1963/64 to 2003/04. Using the Herfindahl-Index, C5-Index, relative entropy and standard deviation of win-loss percentages, we find that previous changes in fan demand Granger cause changes in last season's and current season's competitive balance. In contrast to that, the effect of competitive balance on fan attendance seems to be very weak. Regarding the first result, we hypothesize that an increase in aggregate fan demand for tickets from season $[t - i, t - (i - 1)]$ to season $[t - (i - 1), t - (i - 2)]$ will mainly be driven by an increase in the demand for weak teams. This would result in an assimilation of financial power for strong and weak teams. Based on correlation coefficients, this hypothesis seems to be supported.

Given that correlation coefficients only provide a hint but not a true test for the hypothesis, we propose an additional explanation, which is independent of the distribution of increases in overall fan demand. Teams compete according to a contest-success function and face positive, but decreasing marginal productivity of player talent. It follows that the impact of investing an additional money unit into player talent is smaller for strong teams than for weak teams. Obviously, in this setting the league may become more balanced even

⁵From now on, we will equivalently speak of measuring competitive balance.

⁶See e.g. Quirk & Fort (1997), Czarnitzki & Stadtmann (2002) and Borland & Macdonald (2003)

⁷We refer to the study of Humphreys (2002) as support for choosing this time horizon.

⁸See section 2.

if the increase of demand is not concentrated on the weak teams any more.

However, both effects can only be found to improve competitive balance with a lag of one season. This could be due to the fact that teams already start investing into new players before the end of the current season. Formally, this results in a positive effect of increases in aggregate fan demand from season $[t - 3, t - 2)$ to season $[t - 2, t - 1)$ on competitive balance measures from season $[t - 1, t)$ to season $[t, t + 1)$.

If, as our analysis suggests, fan attendance drives competitive balance in the 1. Bundesliga and not vice versa, conventional wisdom regarding the design of adequate regulations at the league level needs to be reconsidered. Existing mechanisms of redistribution like the sharing of TV revenues have been advocated as devices that increase fan attendance by securing competitive balance. However, if fans do not react to competitive balance as assumed in the theory of competitive balance, then the push towards less team solidarity, as advocated by Bayern München, will not have any harmful effects on fan attendance at the league level.

The remainder of the paper is organized as follows: Starting from the basic assumptions of the theory of competitive balance Section 2 provides general insights into the demand for sport. In section 3 we shortly discuss different measures of competitive balance and present our empirical results. We explain our findings in section 4 and section 5 concludes.

2 Competitive Balance and the Demand for Sport

As already mentioned we will concentrate on the two core assumptions of the theory of competitive balance, which we took out from the set of three assumptions identified by Szymanski (2003). These core assumptions state that:

1. Inequality of resources leads to unequal competition.
2. Fan interest declines when outcomes become less uncertain.

Before performing our own analysis of these claims, we shortly present evidence from previous empirical studies.

The first claim is analyzed in more detail in Hall, Szymanski & Zimbalist (2002). The authors perform Granger Causality tests between team performance and payroll for Major League Baseball (MLB) clubs and English soccer teams. Whereas Granger Causality runs in both directions for MLB teams since 1995 but not so prior to that year, payroll does

Granger cause performance in English soccer⁹.

The facts that financial power does indeed determine the success of a team and that financial power differs significantly among teams in the same league, make it necessary to develop measures for the degree of (un)equal competition [competitive balance]. Otherwise, an empirical analysis of fans' sensitivity to changes in competitive balance, which will be discussed in the next subsection can not be performed.

Regarding the second claim, we have to turn to the theory of demand for sport.

Over the last decade, there has been a huge variety of academic research¹⁰ about the demand for sports. Generally speaking, it is common knowledge that the demand for sports is affected by many different factors such as income, population, possible substitutes and other variables alike. Borland & Macdonald (2003) provide a comprehensive analysis of factors influencing the demand for sport. They distinguish five different groups of factors affecting the demand for sport:

1. Consumer Preferences
2. Economic Factors
3. Quality of Viewing
4. Sporting Contest
5. Supply Capacity

In the terminology of Borland and MacDonald, competitive balance, which is the focus of our analysis, is incorporated in the factor Sporting Contest. Their judgement on the quality of empirical evidence regarding competitive balance measures is noteworthy. Whereas they view the evidence for match-level uncertainty as “[...] relatively weak [...] there is much stronger evidence of an effect of season-level uncertainty on attendance”¹¹. However, these findings relate to the relationship between attendance at a certain match and its significance for promotion and/or relegation and not to seasonal aggregate fan attendance and seasonal measures of competitive balance. They conclude: “One lesson is that uncertainty of outcome - but only intra-seasonal or inter-seasonal - does seem to affect

⁹A study by Frick (2004) shows that in German soccer, pay rolls do significantly influence team success, too.

¹⁰See e.g. Simmons (1996), Dobson & Goddard (1992), Wilson & Sim (1995) and the recent work by Owen & Weatherston (2004).

¹¹See Borland & Macdonald (2003), p.486 .

demand. *This suggests that sporting-league administrators may have a basis for imposing rules and regulations that seek to achieve competitive balance.* However, those regulations can only be justified on a public-benefit basis where they can be demonstrated to address issues of longer-term competitive balance¹².

Since we are working with the aggregate seasonal fan attendance, it is exactly this longer-term competitive balance which we want to address in this paper.

Given that we are analyzing a sample from German soccer, it seems appropriate to discuss the determinants of soccer match attendance¹³. Garcia & Rodriguez (2002) analyze match attendance in the First Division in the Spanish football league. They estimate a demand function incorporating economic variables, variables proxying the expected quality of the match, uncertainty measures and opportunity cost of match attendance. Their main findings include the following: The group of variables measuring expected quality of a game seems to be the most important for match attendance followed by the group of opportunity cost variables. They conclude with the finding that the home team's and the visiting team's quality do not significantly differ in the effect on fan attendance¹⁴.

Another study, which is based on the First German football Division was done by Czarnitzki & Stadtmann (2002). They analyze match attendance for all teams in the seasons 1996/97 and 1997/98 and basically find out that neither the short-term nor the medium-term measures of uncertainty have a significant influence on match attendance. Their results point at the dominating influence of a team's reputation and its fans' loyalty on ticket demand.

Thus, we may summarize the presented empirical evidence on the core claims of competitive balance theory as follows: Empirical studies support the idea that inequality of resources leads to unequal competition, as payroll Granger causes performance. The hypothesis that fan interest declines when outcomes become less uncertain, however, seems to crucially depend on the data aggregation level.

¹²See Borland & Macdonald (2003), p.491 ; emphases are our own.

¹³Although we will concentrate on seasonal aggregate fan attendance, which only denotes a share of total demand, we think that it is important to provide the reader with an idea of what affects the demand for sport in general.

¹⁴This further supports our focus on the first two core claims, as they state that "the necessary conditions for revenue sharing having an effect on competitive balance do not seem to be satisfied" (p.32).

3 Empirical Analysis

3.1 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. Over the years an almost uncountable number of measures has been developed. Two main types of measures can be distinguished, static and dynamic ones. Given that most previous studies have been performed with static measures¹⁵, we adopt this approach in our study. As we want to make sure that our results are robust and not due to the choice of a specific measure, we work with several measures of competitive balance in the empirical analysis.

3.1.1 Standard Deviation of Win-Loss Percentages

Measuring seasonal competitive balance by the 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. The calculation of this measure is given by

$$\sigma_{WL} = \frac{1}{N} \sum_{i=1}^N (WL_i - 0,5)^2, \quad (1)$$

where WL_i and N denote the Win/Loss-percentage¹⁶ of team i and the number of games played by each team within the season, respectively. Instead of σ_{WL} we will simply write WL% in the empirical part.

Michie & Oughton (2004) point to the drawbacks of measuring competitive balance by the standard deviation of winning percentages. The main problem of applying this measure in an European soccer framework lies in the existence of possible draws between contenders. Whereas in American sports draws only happen very rarely, it is a common figure for European soccer teams to end a season with a significant number of draws.

Still, we regard it the benchmark case for measuring competitive balance.

¹⁵See e.g. Quirk & Fort (1997), Horowitz (1997), and Michie & Oughton (2004).

¹⁶This percentage is simply calculated by dividing the number of team i 's games won by the total number of games played by each team.

3.1.2 The C5 Index of Competitive Balance

The C5-Index 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 .

Formally, the index is calculated as follows:

$$C5_t = \sum_{i=1}^5 s_{it}, \quad (2)$$

where s_{it} denotes team i 's ($i = 1, \dots, 5$) share of points in season t .

3.1.3 The Herfindahl Index

The problem of the C5-Index lies in its disability to capture imbalance changes within the groups of the top 5 and the rest of the teams. This is the reason for applying the Herfindahl Index to our data set. 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:

$$H_t = \sum_{i=1}^N s_{it}^2, \quad (3)$$

where N denotes the number of firms and s_i 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. The higher the value for H_t , the higher the imbalance in season t .

As can be seen from equation 3 and 2, H_t and $C5_t$ depend on the absolute number of teams. To circumvent this problem, we will work with a standardized version of these indexes proposed by Michie & Oughton (2004), where H_t [$C5_t$] is multiplied by $100/(1/N)$ [$100/(5/N)$]. For both measures, a perfectly balanced league would then exhibit a value of 100.

3.1.4 Relative Entropy

So far, the measure of relative entropy has not been used very often. Probably the best known exception is the study by Horowitz (1997). She uses relative entropy to analyze changes in competitive balance in Major League Baseball.

Formally, the measure of entropy is calculated as

$$E_t = - \sum_{i=1}^N s_{it} \log_2(s_{it}), \quad (4)$$

again s_{it} is team i 's percentage account of the league's total victories in season t . Let E_M denote the maximum possible entropy level for a season with N teams.

The measure of relative entropy is then calculated as

$$R_t = \frac{E_t}{E_M}. \quad (5)$$

It has to be mentioned that, among all measures applied in our study, this is the only measure, where an increase in R_t is equivalent to an improvement in competitive balance.

3.2 The Vector Autoregressive Model

Competitive balance theory assumes that competitive balance influences fan attendance. In contrast to the suspected theoretical modelling, in which demand is the dependent variable, we start without a decision of exogeneity and endogeneity and choose to estimate a vector autoregressive (VAR) model¹⁷. In this section we mainly follow the idea by Davies et al. (1995) who estimate a VAR model for fan attendance and club success for five clubs in the British rugby league. However, instead of looking at individual team success, we choose fan attendance and competitive balance measures as variables.

In order to estimate vector autoregressive models, we have to be assured of the series' stationarity.

3.2.1 Stationarity and Cointegration

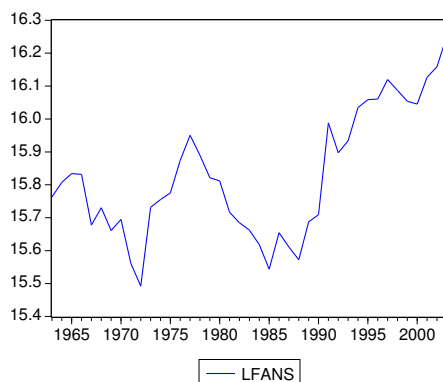
Figure 2 exposes the logarithmic seasonal development of fan attendance¹⁸ in the 1. Bundesliga since its beginning in the season 1963/64 until 2003/04.

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

¹⁷For an introduction on VAR estimation see e.g. Hamilton (1994).

¹⁸As should be clear by now, throughout this paper, by seasonal fan attendance we equivalently mean *aggregate stadium fan attendance*.

Figure 2: Logarithmic Seasonal Development of Fan Attendance in 1. Bundesliga 1963/64 - 2003/04



detailed view on the variables used in this study, descriptive statistics for all competitive balance measures are included as well.

Table 1: Descriptive Statistics

| | Log(Attendance) | Herfindahl | C5 | WL% | Entropy |
|----------------|-----------------|------------|--------|------|---------|
| Mean | 15.83 | 105.62 | 129.25 | 0.18 | 0.98 |
| Median | 15.81 | 105.12 | 128.44 | 0.18 | 0.98 |
| Max | 16.25 | 109.61 | 140.59 | 0.21 | 0.99 |
| Min | 15.49 | 101.42 | 114.12 | 0.15 | 0.97 |
| Std. Deviation | 0.19 | 2.01 | 6.18 | 0.02 | 0.006 |

From Figure 2 the strong increase in fan attendance is immediately revealed. In order to verify our impression of non-stationarity, we perform the Augmented-Dickey Fuller (ADF) test for unit-roots on the series. Based on the ADF test statistic for the original series, displayed in Table 2, we can not reject the null hypothesis that there is a unit root.

The results from Table 2 further reveal that we have to transform (trend elimination, first differences) the attendance series in order to obtain a stationary series¹⁹. Regarding the competitive balance measures, we see that for all original series, the existence of a unit-root can not be rejected. However, for these series, trend elimination already leads to

¹⁹From now on, for reasons of simplicity, we will speak of fan attendance instead of fan attendance first differences.

Table 2: Test-Statistics from Unit-Root Tests

| | Log(Attendance) | Herfindahl | C5-Index | WL% | Entropy |
|-------------------------------------|-----------------|------------|-----------|----------|----------|
| Level (None) | 0.87 | 0.16 | 0.18 | 0.14 | -0.26 |
| Level (Intercept + Trend) | -1.66 | -7.88*** | -6.91*** | -6.91*** | -8.53*** |
| 1st Differences (None) | -6.62*** | -7.75*** | -14.05*** | -8.99*** | -7.52*** |
| 1st Differences (Intercept + Trend) | -6.88*** | -7.59*** | -13.72*** | -8.94*** | -7.33*** |

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

stationary series.

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

$$\Delta(Fans)_t := Fans_t - Fans_{t-1}. \quad (6)$$

This has important consequences for our interpretation of the estimation results²⁰.

Before presenting our results, let us shortly explain the procedure of a VAR estimation. Formally, a VAR specification can be expressed as

$$CB_t = \alpha_{10} + \sum_{i=1}^j \beta_{1i} CB_{t-i} + \sum_{i=1}^j \gamma_{1i} Fans_{t-i} \quad (7)$$

$$Fans_t = \alpha_{20} + \sum_{i=1}^j \beta_{2i} CB_{t-i} + \sum_{i=1}^j \gamma_{2i} Fans_{t-i}. \quad (8)$$

where CB_{t-i} , $i = 1, \dots, j$ 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. In this paper, we choose the Akaike Information Criterion (AIC). 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.

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

²⁰See section 3.

account for: Cointegration of the series²¹.

Simply spoken, cointegration describes the fact that for two series that are non-stationary²², there is a linear combination, given by the cointegrating vector, of the series which is stationary. The important consequence from cointegration is that there exists a long-run relationship between both variables.

Applying the cointegration test²³ proposed by Johansen (1988) as it is implemented in EViews 5, we are able to reject the cointegration hypothesis for the C5-Index and Herfindahl-Index, but can not do so for the standard deviation of winning percentages and relative entropy. The detailed results are given in Table 3, where the test accounts for our knowledge about the competitive balance measures to be trend stationary.

Table 3: Results for Tests on Cointegration between $\log(\text{attendance})$ and ...

| | C5 | Herfindahl | WL% | Entropy |
|--------------------|-------|------------|-------|---------|
| None:* | | | | |
| Eigenvalue | 0.34 | 0.35 | 0.54 | 0.63 |
| Trace Statistic | 21.01 | 21.69 | 35.40 | 43.32 |
| 5% Critical Value | 25.87 | 25.87 | 25.87 | 25.87 |
| p-Value | 0.18 | 0.15 | 0.00 | 0.00 |
| At most 1:* | | | | |
| Eigenvalue | 0.12 | 0.12 | 0.11 | 0.12 |
| Trace Statistic | 4.77 | 5.00 | 4.72 | 5.05 |
| 5% Critical Value | 12.52 | 12.52 | 12.52 | 12.52 |
| p-Value | 0.63 | 0.60 | 0.64 | 0.59 |

*: Refers to number of cointegrated equations under the null-hypothesis.

Fortunately, the VAR approach can slightly be adjusted to account for these results: An error correction term²⁴ is incorporated for each equation, resulting in an vector error correction (VEC) model. We will discuss the corresponding results in the next subsection.

²¹For an introduction to Cointegration see e.g. Greene (2003) and Hamilton (1994).

²²Recall from Table 2 that this situation applies here, otherwise the test would not be valid.

²³It should be noted that these tests are performed on the original series.

²⁴We do not discuss this term here any further.

3.2.2 Estimation Results for the VEC models

Table 4 and Table 5 contain our estimation results²⁵ on the corresponding lag structures for the dependent variable CB. Based on the AIC, most measures of competitive balance reveal a VEC(2)²⁶.

Table 4: VEC results: dependent variable $\Delta(\text{Fans})$

| | Lagged indep. variable | Twice Lagged indep. variable | Lagged dep. variable | Twice lagged dep. variable | Error Correction Term |
|-----------------------------|---------------------------|---------------------------------|-------------------------|-------------------------------|--------------------------|
| Measure | CB | CB | Attendance | Attendance | CointEq1 |
| $\Delta(\text{Entropy})$ | -2.813389 (-0.52485) | 1.308870 (0.42362) | -0.058585 (-0.34136) | 0.068553 (0.37129) | 5.634983 (0.76955) |
| $\Delta(\text{WL})\%$ | 0.671926 (0.67378) | - - | -0.065896 (-0.38153) | - | -1.335568 (-0.85765) |
| $\Delta(\text{Herfindahl})$ | 0.003930 (0.31303) | -0.008363 (-1.01121) | -0.135056 (-0.75433) | 0.000298 (0.00171) | -0.015034 (-1.03375) |
| $\Delta(\text{C5-Index})$ | 0.002015 (0.49439) | -0.002639 (-0.96104) | -0.160085 (-0.93329) | 0.013028 (0.01075) | -0.006747 (-1.47528)* |

(t-values in parentheses)

The comparison between Table 4 and Table 5 shows that fan attendance has a significant influence on competitive balance. For competitive balance, we do not find any significant influence on fan attendance. Furthermore, previous increases in fan attendance seem to improve current competitive balance relative to the previous season, which is revealed through the negative coefficients for $\Delta(\text{Fans})(-2)$ ²⁷: If $\Delta(\text{Fans})(-2) > 0$, i.e. if there are more fans in season $t - 2$ than in season $t - 3$, changes in competitive balance measures from season $t - 1$ to season t are negatively (for entropy: positively) affected, i.e. the competitive balance improves²⁸.

²⁵For all estimations, we included a constant which never proved to be significant. Therefore, we do not report it here.

²⁶Values for the AIC are not given in this paper.

²⁷Here, (-2) denotes the twice lagged variable.

²⁸In subsection 4.1.2 we will perform a more detailed analysis of this result.

Table 5: VEC results: dependent variable $\Delta(\text{CB measure})$

| | Lagged indep. variable | Twice Lagged indep. variable | Lagged dep. variable | Twice lagged dep. variable | Error Correction Term |
|-----------------------------|---------------------------|---------------------------------|-------------------------|-------------------------------|----------------------------|
| Measure | Attendance | Attendance | CB | CB | CointEq1 |
| $\Delta(\text{Entropy})$ | -0.020596 (-2.29195)** | 0.015192 (1.57142)* | 0.567648 (2.02241)** | 0.261275 (1.61495)* | -1.945290 (-5.07353)*** |
| $\Delta(\text{WL})\%$ | 0.089857 (3.51309)*** | - - | 0.139087 (0.94180) | - - | -1.433009 (-6.21398)*** |
| $\Delta(\text{C5-Index})$ | -1.942659 (-0.19489) | -29.20610 (-2.97096)*** | 0.056858 (0.24007) | 0.225996 (1.41629)* | -1.044763 (-3.93093)*** |
| $\Delta(\text{Herfindahl})$ | 0.147189 (0.04335) | -8.417634 (-2.54344)*** | -0.095229 (-0.40000) | 0.045458 (0.28986) | -0.995404 (-3.60927)*** |

(t-values in parentheses)

It turns out that it was justified to apply the VEC methodology to the C5-Index and Herfindahl-Index, too. This can be seen from the significance of the error correction terms for both. We will discuss the significance of the error correction term in section 4.

Note from Table 5 that, for WL% and relative entropy, there is a significant negative influence from $\Delta(\text{Fans})(-1)$ on competitive balance. We will come back to this finding in section 4.

To derive a better understanding of these results, we perform Granger Causality Tests on these relationships.

3.3 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 of values of y . The big advantage of Granger Causality tests is the possibility to explicitly address the direction of interaction.

In Table 6, we give our estimation results on Granger Causality tests based on fan attendance and measures of competitive balance. Note that the given "Lags" in the Table

denote the lag order of the corresponding VEC model.

Table 6: Output from Pairwise Granger Causality Tests on Fan Attendance and Competitive Balance Measures

| Null Hypothesis | Lags | F-Statistic | Prob. |
|---|------|-------------|-----------|
| $\Delta(Fans)$ does not Granger Cause $\Delta(\text{Entropy})$ | 2 | 8.390415 | 0.0151** |
| $\Delta(\text{Entropy})$ does not Granger Cause $\Delta(Fans)$ | 2 | 3.242126 | 0.1977 |
| $\Delta(Fans)$ does not Granger Cause $\Delta(\text{Herfindahl})$ | 2 | 6.685674 | 0.0353** |
| $\Delta(\text{Herfindahl})$ does not Granger Cause $\Delta(Fans)$ | 2 | 4.178835 | 0.1238 |
| $\Delta(Fans)$ does not Granger Cause $\Delta(\text{C5-Index})$ | 2 | 8.921588 | 0.0116** |
| $\Delta(\text{C5-Index})$ does not Granger Cause $\Delta(Fans)$ | 2 | 4.872095 | 0.0875* |
| $\Delta(Fans)$ does not Granger Cause $\Delta(\text{WL}\%)$ | 1 | 12.34178 | 0.0004*** |
| $\Delta(\text{WL}\%)$ does not Granger Cause $\Delta(Fans)$ | 1 | 0.453978 | 0.5005 |

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

The results in Table 6 support our findings from the VEC estimation; for all measures we are able to reject the null that fan attendance does not Granger cause competitive balance. Interesting is the result that we also find Granger Causality from the C5-Index to fan attendance. The C5-Index is the only measure for which we obtain this direction of interaction. The results from Table 6 also explain the significance of the error correction terms in Table 4 and Table 5. As fan attendance may now be viewed as the exogenous variable, it is the competitive balance measure, which reacts to the long-term equilibrium error, i.e. the error correction term. In the case of the C5-Index, however, the error correction term is significant for both equations, which is reflected in the Granger Causality results.

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 statement by Borland & Macdonald (2003) from section 2, it seems that the requested long-term effect of competitive balance on fan demand can not be verified on an aggregated 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.

Furthermore, we obtain another interesting result: Changes in competitive balance can be forecasted more precisely if we use former changes in competitive balance *and* incorporate changes in fan demand. This leads us to question the channel through which changes in fan demand might affect competitive balance. For the remainder of this paper, we will focus on answering this question and explaining the corresponding VEC estimation results.

4 Possible Explanations for the Empirical Results

Within this section, we present some explanations why it should rather be fan attendance that affects competitive balance than vice versa in the 1. Bundesliga. Our main statements refer to the *channel* through which fan attendance influences competitive balance and *the lag structure* which determines the time passed until the effect is observed.

4.1 The Channel: Heterogeneous Patterns in Fan Demand

4.1.1 Theory

Recall from section 2 that Hall et al. (2002) found Granger causality from payrolls to performance. Based on their results, 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 budget²⁹. Thus, we analyze the different sources of team revenues in the 1. Bundesliga. Basically, we can distinguish between ticket sales, advertising, merchandise, transfers and TV revenues. For the seasons 2001/2002 to 2003/2004 the combined share³⁰ of ticket sales, advertising (and merchandise³¹) 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 & 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

²⁹This argument lies at the core of the revenue sharing system in the USA, which was implemented to improve competitive balance.

³⁰Source Straub & Müller (2005), own calculations.

³¹Although 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.

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 equal distribution of clubs' fan attendances leads to a better competitive balance. Changes in fan attendance are viewed as exogenous shocks in our analysis. These shocks should influence competitive balance, because they lead to the assimilation of financial resources (budgets) and/or 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 (as clubs can afford to invest similar amounts of money) can be expected in this case.

The marginal productivity argument goes as follows: Competition in professional team sports leagues is generally³² described using a so-called contest success function for the clubs³³. In its simplest form, we can write the logit specification of a contest success function as

$$p_A = \frac{t_A}{t_A + t_B}, \quad (9)$$

where p_A ³⁴ 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 talent³⁵, in other words:

$$\frac{\partial p_A}{\partial t_A} > 0, \quad \frac{\partial^2 p_A}{\partial t_A^2} < 0 \quad (10)$$

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, he faces a smaller marginal impact of investing another Euro into player talent than the weak club.

Formally, it can easily be seen that

$$\frac{t_B}{(t_A + t_B)^2} = \frac{\partial p_A}{\partial t_A} > \frac{\partial p_B}{\partial t_B} = \frac{t_A}{(t_A + t_B)^2}, \quad \text{iff} \quad t_B > t_A; \quad t_B, t_A > 0. \quad (11)$$

³²See e.g. El-Hodiri & Quirk (1971), Dietl, Franck & Roy (2003) or the detailed review by Szymanski (2003).

³³For the sake of simplicity, let us assume that there are only two clubs A and B.

³⁴ p_B is given by $1 - p_A$.

³⁵See e.g. Dietl et al. (2003).

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 won³⁶. 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 attendance³⁷.

Summarizing, we state that both discussed effects will lead to a higher degree of competitive balance. Unfortunately, we can not empirically investigate the assimilation of playing strength based on our data. We will therefore focus on our hypothesis regarding financial budgets:

Hypothesis: Increases in fan attendance are mainly driven by demand for tickets of small clubs.

4.1.2 Empirical Evidence

Although we speak of a hypothesis, we do not perform statistical tests to validate it. Rather, we only use simple correlation coefficients as a first step towards validation. Given the league's organization with promotion and relegation, we face a problem regarding a team's continuity in the First Division. To circumvent this problem, we have to change the time period of our investigation: We choose five teams in the period 1965/66-1994/95 that took part in each season, namely FC Bayern München (FCB), 1.FC Köln (KOLN), Borussia Mönchengladbach (MBACH), Eintracht Frankfurt (FRANK) and 1.FC Kaiserslautern (FCK).

Having derived the relationship between the individual demand for the five clubs and the aggregate demand for all teams, we next take a look at the rank order of these teams. To determine this rank order the following procedure is applied: For each team we calculate the median rank over the seasons 1965/66 until 1994/95 and assume that the smaller a team's median rank is, the higher the team's quality has been. In case that two teams share the same median rank, the standard deviation is taken as an additional criterium. Here, we argue that a higher standard deviation reveals a less constant playing strength. The resulting quality rank order is presented in the Table 8.

A comparison of Table 8 and Table 7 shows that the relative size of the correlation

³⁶It should be mentioned that this reasoning is in line with empirical results by Dobson & Goddard (1998) who, based on Granger Causality tests, find that (p.1641) "[...] the dependence of performance on revenue seems to be greater for smaller clubs than for the larger"

³⁷We explicitly exclude the case, where one team faces *all* additional demand.

Table 7: Correlation Coefficients

| Club | $\rho(\text{Aggregate Demand, Club})$ |
|---------------------|---------------------------------------|
| FC Bayern München | 0.178356 |
| FC Koeln | 0.397743 |
| Bor. M'Gladbach | 0.634124 |
| Eintracht Frankfurt | 0.670010 |
| FC Kaiserslautern | 0.688943 |

Table 8: Rank Order of Teams

| "Quality Rank" | Club | \emptyset Rank | Median Rank | $\sigma(\text{Rank})$ |
|----------------|--------------------------|------------------|-------------|-----------------------|
| 1. | FC Bayern München | 3.3 | 2 | 3.05 |
| 2. | 1.FC Köln | 6 | 5 | 3.57 |
| 3. | Borussia Mönchengladbach | 5.8 | 5 | 4.08 |
| 4. | Eintracht Frankfurt | 7.8 | 7.5 | 4.17 |
| 5. | 1.FC Kaiserslautern | 8.3 | 8 | 4.21 |

coefficient for each team corresponds to each team's relative quality rank. This is what our hypothesis predicts.

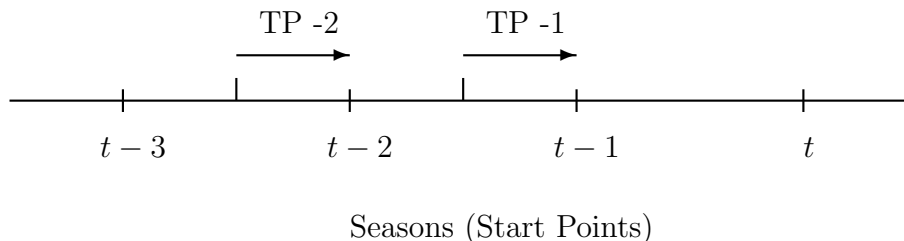
4.2 The Lag Structure: The Timing of Transfers

At this point, let us take a closer look at the time structure of our results, which is given in Figure 3.

We denote each season $[t, t + 1)$ by t , i.e. the season's starting year³⁸. Our hypothesis is that an increase in fan attendance from season $t - 3$ to season $t - 2$ can only positively

³⁸This notational convention can also be found in Simmons (1996).

Figure 3: Time Line



influence competitive balance with a lag of one season. This can be explained from Figure 3: Let $TP -i$, $i = 1, 2$ denote the *transfer window before the start of season $t-i$* . This accounts for the fact that clubs usually invest into new players *before* the end of the current season. As a consequence, the amount of ticket revenues (and potentially, advertising revenues for the next season) is not deterministic³⁹. Thus, they may not be able to increase their budget immediately. Consider as an example the season from $[t - 3, t - 2)$. The complete ticket revenues will only be known at the end of the season. But $T - 2$ does already start *during* the second half of this season. At this time, the club can only use its current advertising revenues (based on last seasons fan attendance) and a (small) fraction of the current ticket revenues, which depends on the timing of the transfer.

Thus, the competitive balance can not improve in the subsequent seasons, only in the next but one *relative* to the previous season. The lag structure detected by C5-Index, Herfindahl-Index and relative entropy displays exactly this effect.

However, one may also imagine an 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

³⁹It would be very interesting to perform Granger Causality tests on attendance and success for the Bundesliga as Davies et al. (1995) did for the English Rugby league. If attendance drove success, the randomness of revenues could then be even higher, as attendance in the remaining games might decide about the club's ability to qualify for international contests in the next season. For example, for FC Schalke, the direct qualification for the Champions league season 2005/06 is expected to create revenues of at least 12-15 Mio. Euro.

balance in the next season might actually be worse than in the subsequent season (where the budget will then be assimilated). However, a look at Table 5 reveals that the empirical evidence on this effect is not that clear cut as only two of four measures seem to detect it.

5 Conclusion

Whereas theory tells us that fans care about uncertainty of outcome in sports, reality seems to contradict this idea on a seasonal level for the 1. Bundesliga in German soccer. Here, fans do not put as much emphasis on competitive balance as theory predicts. Instead, there is strong empirical evidence for an effect of fan attendance on competitive balance.

As to the *channel* through which changes in fan attendance influence competitive balance it seems that changes in aggregate demand from season to season are primarily driven by changes in the demand for weak teams. This improves the distribution of financial power between teams. Although correlation coefficients support this idea of an unequal distribution of shocks in fan demand, we emphasize that our estimation results can also be explained by a contest-success function argument. A second important finding is the existence of a *lag structure* in this context. This is related to the fact that an increase in a team's seasonal ticket revenues can not be exploited immediately: Usually, the transfer period for the subsequent season already starts before the end of the current season, i.e. before the full dimension of additional ticket revenues is revealed. Furthermore, as mentioned by Czarnitzki & Stadtmann (2002) this relationship goes beyond ticket revenues and is highly correlated with advertising revenues in the next season.

At this point, it is necessary to emphasize that we are aware of some limitations of our study. In our opinion, these can mainly be separated into two groups: Statistical limitations and limitations due to institutional peculiarities of European soccer leagues.

Regarding statistical limitations, one may criticize the high level of aggregation in our data. Using aggregated seasonal data not only implies a relatively small sample size for our study. In addition, we are not able to account for the advent of club heterogeneity. Moreover, we have no possibility to adjust for seasonal ticket holders or to distinguish seated from standing viewing accommodation⁴⁰ (as proposed by Dobson & Goddard (1992)).

Besides those, our study faces limitations due to institutional peculiarities associated with European football leagues. On purely theoretical grounds European football leagues

⁴⁰The latter two being due to a lack of access to the corresponding data.

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 not drive fan attendance may, in part, follow from this peculiarity of European leagues.

Another limitation applies to the described channel structure. It is a fact that each club in the 1. Bundesliga still possesses spare capacity for additional ticket demand, at least for some matches⁴¹. As a result, weak teams in the 1. Bundesliga are indeed able to absorb additional ticket demand. Of course, this would no longer be true for a league exhibiting sold out matches, only⁴².

In spite of these limitations, we believe that there are important lessons to be learned from our results, especially for the 1. Bundesliga: Recall that this paper was motivated by the on-going debate about team-solidarity in Professional German soccer. Our results show that, on a seasonal level, a need for team solidarity (here: 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 may be overreacting. We do not find support that the popularity of the sport is at stake if Bayern München becomes more dominant in German football.

Moreover, our finding of Granger causality from fan attendance to competitive balance and the corresponding lag structure generates new insights for research in sports economics. Whereas prior research (e.g. the studies by Hall et al. (2002) and Dobson & Goddard (1998)) already detected Granger causality from revenues to performance, the results from our analysis provide new insights to the *mechanism* of *how* revenues, generated by fan attendance, may actually be translated into differing degrees of competitive balance. Our results also hint at heterogenous patterns in fan demand for weak and strong teams. Furthermore, to our best knowledge, we are the first to connect our results to the

⁴¹For the seasons 1996/97 to 2003/2004 no club was able to generate an attendance demand of 100% for *all* home matches.

⁴²However, we are currently not aware of any European football league, where our assumption does not hold.

theoretical concept of contest-success functions. Our empirical results are in line with the corresponding theoretical predictions.

References

- Borland, J. & Macdonald, R. (2003), 'Demand for Sport', *Oxford Review of Economic Policy* **19**(4), 478–502.
- Czarnitzki, D. & Stadtmann, G. (2002), 'Uncertainty of Outcome versus Reputation: Empirical Evidence for the First German Football Division', *Empirical Economics* **27**, 101–112.
- Davies, B., Downward, P. & Jackson, I. (1995), 'The Demand for Rugby League: Evidence from Causality Tests', *Applied Economics* **27**, 1003–1007.
- Dietl, H. M., Franck, E. & Roy, P. (2003), 'Überinvestitionsprobleme in einer Sportliga', *Betriebswirtschaftliche Forschung und Praxis* pp. 528–540.
- Dobson, S. & Goddard, J. (1998), 'Performance and Revenue in Professional League Football: Evidence from Granger Causality Tests', *Applied Economics* **30**, 1641–1651.
- Dobson, S. M. & Goddard, J. A. (1992), 'The Demand for Standing and Seated Viewing Accommodation in the English Football League', *Applied Economics* **24**, 1155–1163.
- El-Hodiri, M. & Quirk, J. (1971), 'An economic model of a professional sports league', *The Journal of Political Economy* **79**(6), 1302–1319.
- Fort, R. & Maxcy, J. (2003), 'Comment: "Competitive Balance in Sports Leagues: An Introduction"', *Journal of Sports Economics* **4**(2), 154–160.
- Frick, B. (2004), 'Die Voraussetzungen sportlichen und wirtschaftlichen Erfolges in der Fussball-Bundesliga', *Working Paper* .
- Garcia, J. & Rodriguez, P. (2002), 'The Determinants of Football Match Attendance Revisited', *Journal of Sports Economics* **3**(1), 18–38.
- Greene, W. H. (2003), *Econometric Analysis*, 5th edn, Prentice Hall.
- Hall, S., Szymanski, S. & Zimbalist, A. S. (2002), 'Testing Causality Between Team Performance and Payroll- The Cases of Major League Baseball and English Soccer', *Journal of Sports Economics* **3**(3), 149–168.
- Hamilton, J. D. (1994), *Time Series Analysis*, Princeton University Press.

- Hoeltzenbein, K. & Selldorf, P. (2005), 'Ich bin ein grosser Freund des Verdienstes', Interview with Karl-Heinz Rummenigge, *Süddeutsche Zeitung*, May 6th 2005.
- Horowitz, I. (1997), 'The Increasing Competitive Balance in Major League Baseball', *Review of Industrial Organization* **12**, 373–387.
- Humphreys, B. R. (2002), 'Alternative Measures of Competitive Balance in Sports Leagues', *Journal of Sports Economics* **3**(2), 133–148.
- Johansen, S. (1988), 'Statistical Analysis of Cointegrating Vectors', *Journal of Economic Dynamics and Control* **12**, 231–254.
- Michie, J. & Oughton, C. (2004), 'Competitive Balance in Football: Trends and Effects', *Football Governance Research Centre, Research Paper 2004 No. 2*.
- Owen, P. & Weatherston, C. R. (2004), 'Uncertainty of Outcome and Super 12 Rugby Union Attendance', *Journal of Sports Economics* **5**(4), 347–370.
- Quirk, J. & Fort, R. D. (1997), *Pay Dirt: The Business of Professional Team Sports*, Princeton University Press.
- Rottenberg, S. (1956), 'The Baseball Players' Labor Market', *The Journal of Political Economy* **64**(3), 242–258.
- Simmons, R. (1996), 'The demand for English league football: A club level analysis', *Applied Economics* **28**, 139–155.
- Straub, W. & Müller, C. (2005), Die wirtschaftliche Situation im Lizenzfussball 2005, Technical report, DFL Deutsche Fussball Liga GmbH.
- Szymanski, S. (2003), 'The Economic Design of Sporting Contests', *The Journal of Economic Literature* **41**(4), 1137–1187.
- Wilson, P. & Sim, B. (1995), 'The Demand for Semi-Pro League Football in Malaysia 1989-91: A Panel data Approach', *Applied Economics* **27**, 131–138.
- Zitouni, M. (2005), 'Umzug nach Frankfurt? Nicht ausgeschlossen', Interview with Harald Strutz, *Kicker*, July 7th 2005.