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I know what you did last summer – or do I? Introducing mental anchoring to the demand for sport

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I know what you did last weekend- or do I? Introducing Mental Anchoring to the Demand for Sport[‡]

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Abstract

Football matches are by no means homogenous goods. Rather, there are big differences in single match quality, which is *ex-ante* unobservable to consumers. We argue that quality uncertainty leads consumers to search for quality proxies which are observable in advance. Aggregate demand functions are shown to depend merely on prices, ex-ante quality perception and stochastic influence factors. Following the work by Kahneman, Tversky and Slovic, we suggest that consumer behaviour is to some extent driven by mental anchoring. Therefore, the usual approach to rely on absolute measures only, seems doubtful. The main focus of our empirical analysis is to introduce relative quality measures, which are based on different anchor levels. Besides seasonal-dynamic and seasonal-static anchors, this specification allows us to include absolute quality proxies as a special case. Applying median regression on a sample from over 2000 individual matches in the German Bundesliga, we find evidence for mental anchoring in the demand for sport. Our results indicate that consumers tend to compare current values for quality proxies to last season's indicator values instead of last match's indicator values.

JEL Classification: C14, C24

Keywords: mental anchor, censored median regression, fan demand

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1 Introduction

Many papers have been written about the demand for sport events[1]. However, besides the early paper[2] by Gärtner & Pommmerehne (1978), no other paper has tried to implement a soccer match's product nature into demand studies. Soccer matches are by no means homogenous goods. Rather, there are big differences in a single match's quality, which itself is *ex-ante* unobservable to consumers. Therefore, the decision to attend a specific match requires judgement under uncertainty. In this paper, we assume that quality uncertainty leads consumers to search for quality proxies which are known in advance. Aggregate demand is then merely a function of prices, ex-ante quality perception and stochastic influence factors.

If individuals are faced with judgement under uncertainty, we know from the influential work by Daniel Kahneman and Amos Tversky (Tversky & Kahneman (1982)) that they may rely on certain heuristics. Besides Representativeness and Availability, they also name the heuristic of Adjustment and Anchoring. In this paper we want to know, whether consumers in the 1. Bundesliga, who face a similar situation, evaluate quality proxies relative to a specific reference point, which we refer to as the mental anchor. The evaluation of a quality indicator relative to a reference point is modeled to be given by the difference between the indicator's current value and its anchor value.

To answer whether mental anchoring is present in the demand for sport, we analyze three different Models, each with a different reference point. Model 1 contains only "level" values of the quality proxies which corresponds to a reference point of zero. This is done to include the standard approach in sports economics as a special case in our model. The anchors in Model 2 and Model 3 are motivated by our interest in the fan-memory's time horizon. In other words, we want to know, how fast / sluggishly consumers react to changes in match quality, i.e. are they more myopic or longer-term oriented in their attitude towards quality indicators.

In Model 2, which incorporates the longer-term orientation, all quality proxies are evaluated relative to last season's finishing and average values. The reliance on "just-happened" differences in quality indicators is implemented in Model 3, where quality proxies are eval-

[1]See e.g. Borland & Macdonald (2003), Garcia & Rodriguez (2002).
[2]We thank Bruno S. Frey for bringing this paper to our attention.

uated relative to last match's quality proxies. Here, we allow for different anchors for home and visiting consumers. Whereas home fans are modeled to compare current quality indicators to the corresponding values of last home match, visiting fans are assumed to do the same relative to the values of their team's last away match.

For our empirical analysis, we use individual match attendance data on over 2000 matches from the first division of professional German Football (Soccer) in the period 1996-2004. Due to the European league system of promotion and relegation, our data contains information on home and away matches of 28 different teams.

Based on this data set, we estimate censored median models with fixed, but individual, censoring points. This is done to avoid distributional assumptions on the error-term in our econometric model. For benchmark purposes, we also present results from ordinary least squares estimation. Our results indicate that mental anchoring is actually present in the demand for German Football. In addition, we find evidence for longer-term orientation of consumers. A possible reason for this finding may come from the higher reliability of seasonal anchors as these anchors contain information from 34 matches. Therefore, consumers could infer that stochastic components, such as luck, should play a minor role in the anchor of Model 2 than in the anchor in Model 3.

The remainder of this paper is structured as follows: The next section presents a literature review on the demand for sport, describes our modelling approach and shortly discusses the concept of mental anchoring. In section 3 we present the empirical framework of our analysis. Section 4 contains our empirical results and section 5 concludes.

2 The Demand for Sport

2.1 Related Literature

Over the last decade, there has been a huge variety of academic research[3] about the demand for sports. However, it is crucial to distinguish (at least) two different kinds of demand, namely television demand and stadium attendance demand. The fact that consumer groups as well as "consumption environments" do substantially differ across these kinds of demand,

[3]For excellent overviews see Borland & Macdonald (2003) and Szymanski (2003).

has important consequences for econometric modeling, such as the (non-)adoption of censored regression models or the choice of the relevant set of regressors. Given that our data contains information about match attendance figures only, we will focus on the literature about attendance demand[4].

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 overview about 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

Given that we are analyzing a sample from German soccer, it seems appropriate to discuss the determinants of soccer match attendance. 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 costs 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 attendance.

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

[4] For studies concerning television demand for Football see e.g. Forrest, Simmons & Buraimo (2005).

ticket demand.

Last but not least, we want to give the results for the paper by Gärtner & Pommmerehne (1978), which we already mentioned in the introduction. Similar to our approach[5], they start from the quality uncertainty aspect in Football, although they choose a completely different modelling approach afterwards. Their results indicate that quality indicators seem to be the most important influence factors in the demand for sport. Furthermore, they were able to detect the expected signs on all quality variables.

However, the study by Gärtner & Pommmerehne (1978) suffers from several shortcomings. First, their data contains information on one club, namely the Hamburger SV in the period 1969 until 1975, only. The club was chosen to avoid the application of censored regression models. Thus, the question of representativeness and generalization of their results arises. Furthermore, the authors do not account for season ticket holders. It is well known that this group of consumers will attend (almost) each match within a season. This might lead to biased estimates.

Having discussed several demand studies for football, we will now derive our modeling approach for admission ticket demand.

2.2 From quality uncertainty to the demand for soccer matches

Imagine that you are attending a conference and the program contains the opportunity to attend a soccer match between two teams, which are not very well known to you. Obviously, you are not interested in watching a boring match, but how are you to know? On which information are you going to base your decision? Perhaps, you would ask some "experts" or take a look into the internet to check for the teams' current performances and/or star players in the roosters. In other words, you want to use observable proxies for the future quality of the match. Throughout this paper, we assume that a consumer who intends to attend a match does exactly the same.

Let us now formulate this idea more rigorously: In the remainder of this paper let c_t denote the stochastic quality of a match at time t. Furthermore, we assume this quality c_t to be a function of K observable, deterministic quality indicators $\tilde{\pi}_i, i = 1, ..., K$, stacked

[5] See subsection 2.2.

in the $(K \times 1)$ column vector $\tilde{\pi}$, and a stochastic quality component ϵ. Formally,

$$c_t = c_t(\tilde{\pi}_{\mathbf{t}}, \epsilon_t). \tag{1}$$

Based on this relationship, we can write the *aggregate* demand for a match at time (fixture) t, denoted by D_t, as a function of the seasonal price level p and the quality c_t:

$$D_t = D_t(p, c_t) = D_t(p, c_t(\tilde{\pi}_{\mathbf{t}}, \epsilon_t)), \tag{2}$$

where it is assumed that

$$\frac{\partial D_t(\cdot)}{\partial p} < 0 \quad \text{and} \quad \frac{\partial D_t(\cdot)}{\partial c_t} > 0. \tag{3}$$

In principle, we could now continue with an empirical analysis of this demand equation. However, the goal of our study is to introduce the idea of mental anchoring to the demand for sport. This concept has been an important idea in the field of psychology and behavioral finance since the 1980s. In our case, mental anchoring might help to understand the method by which quality proxies are evaluated, i.e. the functional form through which quality proxies enter the demand equation. The next subsection shortly discusses the idea behind the concept of mental anchoring and shows how the concept is incorporated in our empirical analysis.

2.3 The Concept of Mental Anchoring

The concept of mental anchoring states that people tend to compare information relative to specific reference points. Slovic, Fischhoff & Lichtenstein (1982), p. 481, describe anchoring as "one of the most general of presentation artifacts is the tendency of judgments to be anchored to initially presented values."

Although this concept seems quite intuitive, it is not straightforward to implement this concept in a non-experimental empirical analysis. Unfortunately, the term "anchored to initially presented values" exposes the researcher to (at least) two questions. First, we have to decide *which functional form* we should specify for the heuristic of anchoring. However, we will soon discuss the underlying idea behind our approach. The second questions seems to be even trickier: *Which* "*initially presented values*" should we include in our analysis?

Regarding the functional form for the anchoring process, we make the following assumption.

$$\tilde{\pi}_i = \pi_i - \pi_i^{Al}, \tag{4}$$

where $l = 1, 2, 3$ denotes the different anchor models (see below) and $\pi_i^{Al}, i = 1, \ldots, K$ denotes the relevant "initially presented values". Equation (4) is the simplest functional form for a mental anchor: Consumers compare the current value of an observed quality proxy, π_i, to the corresponding initially presented value simply by subtracting the latter.

Let us now turn to the question of which anchors to include in our study. Based on the functional form in (4), we will consider three different processes for $\pi_i^{Al}, i = 1, \ldots, K$. For reasons of comparability to previous studies, we start by setting $\pi_i^{A1} = 0, \forall i = 1, \ldots, K$. The anchors in Model 2 and Model 3 are motivated as follows: If consumers of sports events are subject to mental anchoring, the question arises, whether consumers are myopic or longer-term oriented. We analyze this question by introducing a season-static in Model 2 and a season-dynamic anchor in Model 3. If consumers were to base their attendance decisions merely on quality indicators relative to last season's average value for quality proxies[6], improved short-term team performance would not result in an increase in fan demand *until last season's corresponding value was to be outperformed.* In Model 3, the mental anchors consist of the relevant quality proxies' values before the last match. Here, we allow for different anchors for home and visiting fans. Whereas home fans are modeled to compare current quality indicators to the corresponding values of last home match, visiting fans are assumed to do the same relative to the values of their team's last away match. For reasons of simplicity, in the following, we will drop the distinction between last home match and last away match and simply refer to these anchors as the relevant value before last match.

Having exposed the justification for our anchoring approaches, we now turn to the empirical framework of our analysis.

[6]For positioning, we use the finishing value of last season for each team.

3 Empirical Framework

The purpose of this section is to provide the reader with an understanding of our estimation approach, namely the theory of censored quantile regression. We start with a description of our data.

3.1 The Data

Our data contains information on over 2000 individual matches in the first division of professional German soccer within the period 1996-2004. Thus, we are able to study demand for soccer over eight consecutive seasons[7]. Besides the overall number of spectators, we are also able to account for a variety of influence factors such as weather variables, entertainment proxies and team quality proxies. However, we have decided to include only a very limited number of regressors in our analysis. This is done for two reasons: In section 2.2, we proposed that people search for easily accessible quality proxies. Perhaps the best accessible information sources are league standings and team roosters. The second reason lies in the diminishing returns to information: It is simply implausible that a consumer would base her decision to attend a match on more than 10 - 15 influence factors.

Throughout our empirical analysis, we will use logarithmic match attendance as the dependent variable[8]. We are able to account for the number of season-ticket holders for each team in each season. In order to avoid biases due to different numbers of season-ticket holders, we subtract these consumers from observed attendance figures. Of course, this is equivalent to the assumption that all season-ticket holders attended each match within a certain season. Although this assumption may be criticized, it is the only feasible adjustment method for our data[9].

Table 1 contains our chosen quality proxies. Whereas most of these variables are self-explaining, few require some words on the underlying idea.

We will refer to the outcome uncertainty for a match of team i playing at home against team j in season τ as UOO_{τ}^{ij}. This measure is based on the approach by Forrest et al.

[7] To the best of our knowledge, this is the largest sample on individual match data ever analyzed in German soccer.

[8] See also subsection 3.2.

[9] Furthermore, Feehan, Forrest & Simmons (2002) provide evidence from the Premier League that season ticket holders do indeed attend almost every season match.

(2005)[10] and calculated as follows

$$\text{UOO}_{\tau}^{ij} = \mid \text{PPG}_{\tau}^{i} + \text{IHA}_{\tau}^{i} - \text{PPG}_{\tau}^{j} - \text{IAA}_{\tau}^{j} \mid, \tag{5}$$

where PPG_{τ}^{i} and PPG_{τ}^{j} denote the points per game records for home team i and visiting team j in season τ before the match, respectively. IHA_{τ}^{i} (Individual Home Advantage) and IAA_{τ}^{j} (Individual Away Advantage) refer to team specific home and away advantages. These values are derived as follows: For each team, $i = 1, \ldots, 18$, we calculate the PPG at home, (PPG (Home)) and the PPG as visiting team (PPG (Away)) *in the previous season*, $\tau - 1$. Next we calculate the difference between these values and define IHA_{τ}^{i} as :

$$IHA_{\tau}^{i} = \begin{cases} \text{PPG}_{\tau-1}^{i}(\text{Home}) - \text{PPG}_{\tau-1}^{i}(\text{Away}) & : \quad \text{PPG}_{\tau-1}^{i}(\text{Home}) - \text{PPG}_{\tau-1}^{i}(\text{Away}) > 0 \\ 0 & : \quad \text{PPG}_{\tau-1}^{i}(\text{Home}) - \text{PPG}_{\tau-1}^{i}(\text{Away}) \leq 0 \end{cases}$$

and IAA_{τ}^{j} by

$$IAA_{\tau}^{i} = \begin{cases} PPG_{\tau-1}^{i}(\text{Home}) - PPG_{\tau-1}^{i}(\text{Away}) & : \quad PPG_{\tau-1}^{i}(\text{Home}) - PPG_{\tau-1}^{i}(\text{Away}) < 0 \\ 0 & : \quad PPG_{\tau-1}^{i}(\text{Home}) - PPG_{\tau-1}^{i}(\text{Away}) \geq 0 \end{cases}$$

As can be seen, each team can only have one thing at a time: *Either* a home advantage *or* an away advantage. Another important aspect relates to teams which have recently been promoted. For these teams, individual home advantage is given by the league's average home advantage in the previous season. Given the fact that most teams in the German Bundesliga are more successful at home, an away advantage is ruled out for recently promoted teams.

Regarding the interpretation of our results on this variable, it is important to understand the underlying idea of this measure: The greater the value of this measure, the *less uncertain* the outcome of the match is. An ex-ante perfectly balanced match should show an UOO_{τ}^{ij}-value of 0. For reasons of readability, we will drop the subindexes on UOO in the remainder of this paper.

[10] This measure was also applied by Simmons & Forrest (2005). However, the authors did not find a significant influence on logarithmic match attendance.

Table 1: Variable Description

Variable	Source	Description
Home: Standing	League Standings	Home: league position before match
Away: Standing	League Standings	Away: league position before match
Home: PPG	League Standings	Home: points per game
Away: PPG	League Standings	Away: points per game
Home: GLG	League Standings	Home: goals last match
Away: GLG	League Standings	Away: goals last match
Home: National Players	Rooster	Home: number of national players
Away: National Players	Rooster	Away: number of national players
Temperature	Control	Temperature on match day (in .10°C)
Rain	Control	Dummy=1, if rain on match day
UOO	Control	Measure of match uncertainty
Distance	Control	Distance between cities (in 100 km)
Price	Control	Admission Price (in 10€)
Away: FCB, BVB, HSV	Control	Dummy=1, if Away is Bayern Munich, Dortmund or Hamburg
Herfindahl	Control	Herfindahl-Index before match
Derby	Control	Dummy=1, if match classifies as derby
Unemploy Rate	Control	Unemployment rate (in %)
Male Population	Control	Male Population (in 100'000)
Fixture	Control	Fixture within Season
Friday	Control	Dummy=1, if match is on a Friday
Saturday	Control	Dummy=1, if match is on a Saturday
Sunday	Control	Dummy=1, if match is on a Sunday

The calculation of prices needs some explanation, too. Due to an increase in price transparency over the last years, we had to rely on the average admission prices, which were calculated in the following way. For each category, i.e. seating or standing accommodation, we obtained the highest and lowest admission prices[11]. Based on these prices, we calculated the average price for seating and standing accommodation, which were then weighted by

[11] We are grateful to Christian Müller from the German Bundesliga for providing us with this information.

the percentage share of seating and standing places in the stadium. Of course, this measure has two important shortcomings: First, changes in stadium capacity will effect the measure to the extent that is incorporates changes in the relative shares of standing and seating accommodation and second, this measure is not able to absorb changes in prices caused by "Match of the Day" surcharges. Still, we believe that this measure has been obtained in an appropriate way.

Although this measure is often applied in the sports economics literature, we will briefly discuss the derivation of Herfindahl, the Herfindahl index, which is included in our model to control for the possibility of diminished fan interest due to a lower degree of competitive balance in the league as a whole[12]. We will first define the H-Measure, which is calculated as

$$\mathrm{H}_{t\tau} = \sum_{i=1}^{18} s_{it\tau}^2, \tag{6}$$

where $s_{it\tau}^2$ denotes the squared share of points of team i (team i's points divided by overall points in the league) at fixture t in season τ. The higher the value of H, the lower the degree of competitive balance in the league. We also apply the following standardization procedure[13] on the measure, which results in an index-value of 100 for a perfectly balanced league:

$$\mathrm{Herfindahl}_{t\tau} = \mathrm{H}_{t\tau} * \frac{100}{1/N}, \tag{7}$$

where N denotes the number of teams within the season[14].

As can be seen from Table 1, our data does not contain information on live broadcasting of a match, as we have not been able to obtain this information, yet[15]. However, recall that we are interested in the "procedure", by which consumers evaluate quality indicators. The

[12] The idea that the closer the teams' playing strengths the higher the interest of spectators was first introduced by Rottenberg (1956). Since then, the influence of competitive balance (or openness of outcome) on attendance has been widely analyzed by researchers. See e.g. Humphreys (2002), Schmidt & Berri (2001).

[13] This procedure has been proposed by Michie & Oughton (2004).

[14] Within our sample, each season there were 18 teams in the first division of professional German Football.

[15] See e.g. Forrest, Simmons & Szymanski (2004) and the recent paper by Buraimo, Forrest & Simmons (2006) for an analysis of this relationship.

heuristic of mental anchoring is expected to be applied in situations which require judgement under uncertainty. In our opinion, whether a situation requires judgement under uncertainty from the consumers or not, does not depend on the status of live broadcasting. Thus, we do not expect negative impacts on our quality indicators' estimates due to the lack of controlling for this effect.

In Table 2, we give descriptive statistics for our variables. The reader might wonder about the negative minimum value for APPG. This value was caused by 1. FC Kaiserslautern, who was punished by subtraction of three points for failed licence compliance in the season 2003/04. As a result, the club started the season with -3 points.

Table 2: Descriptive Statistics

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
log(Day Attendance)	9.56	0.62	6.22	11.06	2372
Home: Standing	9.64	5.21	1	18	2374
Away: Standing	9.31	5.17	1	18	2374
Away: FCB, BVB, HSV	0.17	0.37	0	1	2374
Home: GLG	1.70	1.35	0	7	2302
Away: GLG	1.16	1.13	0	9	2230
Distance	4.06	2.13	0	8.76	2374
Price	1.77	0.47	0.68	3.91	2374
Home: National Players	3.51	3.76	0	19	2374
Away: National Players	3.51	3.76	0	19	2374
Home: PPG	1.34	0.53	0	3	2373
Away: PPG	1.39	0.54	-3	3	2373
UOO	0.83	0.60	0	3.82	2372
UOO^2	1.05	1.44	0	14.62	2372
Herfindahl	115.36	18.77	104.01	282.42	2374
Derby	0.03	0.16	0	1	2374
Male Population	2.95	3.48	0.10	16.60	2374
Unemploy. Rate	12.34	3.89	3.10	20	2374
Temperature	93.18	60.85	-86	309	2374

Continued on next page...

... table 2 continued

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
Rain	0.36	0.48	0	1	2374
Fixture	18.01	9.52	2	34	2374
Friday	0.10	0.30	0	1	2374
Saturday	0.65	0.48	0	1	2374
Sunday	0.16	.37	0	1	2374

Now, that the nature of our data set has been explored, we turn to the development of the econometric model for our empirical analysis.

3.2 Estimation Approach

Recall from section 2.2 that the quality of a match is modelled to be given as

$$c_t = c_t(\tilde{\pi}_{\mathbf{t}}, \epsilon_t). \tag{8}$$

For the empirical analyis, we specify the quality to be a linear function of the deterministic quality indicators and the stochastic quality component, such that

$$c_t = \tilde{\pi}_{\mathbf{t}}{}'\beta + \epsilon_t, \tag{9}$$

where β is a $(n \times 1)$ parameter vector. Plugging equation (9) in (2), we obtain the following regression equation

$$D_t = \tilde{\pi}_{\mathbf{t}}{}'\beta - \gamma p + u_t \tag{10}$$

where u_t denotes the error-term of the model and is given by the sum of the "quality error-term", ϵ, and a "demand error-term component, η.

As we postulated a positive effect of quality indicators on demand, Table 3 contains the expected signs for the quality indicators in our models. In case that both signs are theoretically possible, we write $(+/-)$.

Table 3: Expected Signs for β- Coefficients

Variable	Expected Sign
Home: Standing	$(-)$
Away: Standing	$(-)$
Away: FCB, BVB, HSV	$(+)$
Home: GLG	$(+)$
Away: GLG	$(+)$
Distance	$(-)$
Price	$(-)$
Home: National Players	$(+)$
Away: National Players	$(+)$
Home: PPG	$(+)$
Away: PPG	$(+)$
UOO	$(+)$
UOO^2	$(-)$
Herfindahl	$(-)$
Derby	$(+)$
Male Population	$(+)$
Unemploy. Rate	$(+/-)$
Temperature	$(+)$
Rain	$(-)$
Fixture	$(+)$
Friday	$(+)$
Saturday	$(+)$
Sunday	$(+)$

The fact that the expected sign for "Unemploy. Rate" can not be determined ex-ante is due to the following reasoning: On the one hand, a higher unemployment rate is associated with a lower income, which should result in less spending on football match admission. On the other hand, being unemployed comes with less opportunity costs of attending. The sign for the coefficient depends on which effect dominates the other.

Having presented our regression equation (10) for the median regression[16] and the expected signs on the quality indicators, we will now turn to the discussion of the theoretical aspects of quantile regression.

3.3 Censored Quantile Regression

In principle, the ideas behind ordinary least squares and quantile regression do not differ very much: Both approaches rely on a linear specification for parameters of the conditional distribution of a dependent variable, say y, given a set of regressors, say $x_1, \ldots, x_K$. Furthermore, both estimators are derived from an optimization problem. However, there are two crucial differences: Whereas OLS makes use of the conditional mean function, quantile regression works on conditional quantile functions. Besides, the functional form of the optimization problem is different: While the OLS estimator minimizes the sum of squared residuals, the quantile regression estimator minimizes a weighted sum of the absolute residuals.

As our empirical analysis is based on attendance figures for individual matches in German Football, we have to account for the existence of top coding values[17]. For each match, these values are given by the capacity constraint of the corresponding home team's stadium.

In the presence of censoring from above, the conditional θ^{th} quantile of y_i given x_i can be written as

$$\text{Quant}_\theta(y_i|x_i, \beta_\theta) = \min\{y_i^0, x_i'\beta_\theta\}, \tag{11}$$

where y_i^0 denotes the top coding value of observation i. Note that we have to allow for individual censoring points.

Based on (11) we can write the censored quantile regression model as a *latent variable model*:

$$\begin{aligned} y_i^* &= x_i'\beta_\theta + u_{\theta i} \\ \text{Quant}_\theta(u_{\theta i}|x_i) &= 0 \end{aligned} \tag{12}$$

[16] Recall that the median is simply the 0.5 quantile.

[17] It is well documented in econometric textbooks that ordinary least squares (OLS) will be biased in the presence of censoring, see e.g. Wooldridge (2003).

and

$$y_i = \begin{cases} y_i^* & : \quad y_i^* < y_i^0 \\ y_i^0 & : \quad y_i^* \geq y_i^0 \end{cases}$$

The estimator $\tilde{\beta}_\theta$ is given by

$$\tilde{\beta}_\theta = \text{argmin} \frac{1}{N} \sum_{i=1}^{N} \rho_\theta(y_i - \min\{y_i^0, x_i'\beta\}), \tag{13}$$

where ρ_θ denotes the *check function* introduced by Koenker & Bassett (1978) and is given by $\rho_\theta(\lambda) = \theta|\lambda|\mathcal{I}(\lambda \geq 0) + (1-\theta)|\lambda|\mathcal{I}(\lambda < 0)$. Here, $\mathcal{I}(\cdot)$ denotes the indicator function.

The optimization problem can be written as

$$\min_{\beta \in \mathcal{B}_\theta} Q_N(\beta), \tag{14}$$

where

$$Q_N(\beta) = \frac{1}{N} \left\{ \sum_{i=1}^{N} (\theta - \frac{1}{2} + 1/2\text{sgn}(y_i - \min\{y_i^0, x_i'\beta\}))(y_i - \min\{y_i^0, x_i'\beta\}) \right\}. \tag{15}$$

The corresponding F.O.C. for (13) is given by

$$\frac{1}{N} \sum_{i=1}^{N} \mathcal{I}(x_i'\tilde{\beta}_\theta < y_i^0)(\theta - 1/2 + 1/2\text{sgn}(y_i - x_i'\tilde{\beta}_\theta)x_i = 0. \tag{16}$$

Based on this estimation framework, we now turn to the question *how* this optimization problem may be implemented in statistical software packages.

3.3.1 The Iterative Linear Programming Algorithm

The Iterative Linear Programming Algorithm (ILPA) was introduced by Buchinsky (1991) and Buchinsky (1994). The underlying idea is as follows[18].

> [...] if one had known in advance the set of observations for which $x_i'\beta_\theta \geq y_i^0$, then these could have been excluded from the estimation. The Barrodale-Roberts algorithm (as well as other LP algorithms) would then yield a local

[18] See Buchinsky (1991), pp. 30-32.

minimizer $\tilde{\beta}_\theta$ to the problem in (13). Of course this set of observations is not known in advance, but the suggested algorithm uses the idea in an iterative way.

Buchinsky (1991) defines the algorithm's structure as follows:

The Algorithm:

Let $\tilde{\beta}_\theta^{(0)}$ denote an initial estimate of β_θ. Usually, this estimate will have been obtained from least squares or quantile regression. Obviously, the closer this value is to β_θ, the fewer iteration steps are necessary to achieve convergence.

Step 1: For the j^{th} iteration, determine from the previous iteration the set $\mathcal{A}$ of observations with $x_i'\tilde{\beta}_\theta^{(j-1)} < y_i^0$, i.e.,

$$\mathcal{A}_{j-1} = \{i : x_i'\tilde{\beta}_\theta^{(j-1)} < y_i^0\}, \tag{17}$$

where y_i^0 is the censoring value of y_i. Only this set of observations is used in the next step of the iterations.

Step 2: Solve the linear programming problem for the set $\mathcal{A}_{j-1}$ of observations defined in Step 1. This step provides a new estimate for β_θ, say $\tilde{\beta}_\theta^{(j)}$.

Step 3: Define $\mathcal{A}_j$ as in (17) of Step 1.

i. If $\mathcal{A}_j = \mathcal{A}_{j-1}$ terminate the algorithm and set $\tilde{\beta}_\theta = \tilde{\beta}_\theta^{(j)}$.

ii. If $\mathcal{A}_j \neq \mathcal{A}_{j-1}$ repeat Step 2.

We implement this algorithm using `STATA 9.1`. However, there is a small modification regarding the definition of convergence. The number of iteration steps necessary to obtain convergence in the sense above need not be finite. Therefore, convergence is defined *either* as by Buchinsky (1991) above *or* if a certain number of iteration steps has been reached. The latter definition is based on the approach by Robert Vigfusson[19].

4 Empirical Results

In this section we present our empirical results on all three models. In all models, the logarithmic number of day-ticket holders will be used as dependent variable.

[19] His stata code can be obtained from http://gsbwww.uchicago.edu/fac/timothy.conley/research. However, we had to amend the code to account for individual censoring points.

As we are using new data for the German Bundesliga, a more detailed discussion of our results, especially for the Benchmark case (Model 1) seems justified.

4.1 Model 1

Our results for the benchmark model can be seen from Table 4. As team and season effects are not our main concern in this study, we have decided not to give these results in the following Tables[20]. As we can see from the Table, most results are similar for median regression and OLS and most coefficients show the expected signs. In case that the results differ for both estimation procedures, we prefer to rely on the results from median regression. Let us now discuss the results from model 1 in more detail: As expected, our model detects a positive, albeit asymmetric, influence of a team's ranking on attendance. If a team is able to improve its ranking by 1, this would ceteris paribus result in an 0.8% increase in match attendance. Surprisingly, the same effect can not be detected for the visiting team.

Another asymmetry lies in the results for the influence of national players. Whereas the number of national players for the home team does not significantly influence attendance figures, the corresponding number of the visiting team does positively affect (4.5%) attendance. Given that we are using data on individual matches, this result should come as a surprise. Within our data, the number of national players for a team does not change within a season. Thus, the number of the home team's national players should not decide about attendance for a *specific match*. In turn, each visiting team may only be watched once within a season[21], thereby significantly affecting consumers' attendance decision. This result is also in line with previous results from Garcia & Rodriguez (2002) and Roy (2004).

[20] Team and Season Dummies were included in each model and turned always out to be significant. The results are available from the authors on request.

[21] Here, we abstract from the possibility that the home team might play against a certain other team at home in the domestic FA cup, too.

Table 4: Estimation Results (Model 1)

	Median Regression		Ordinary Least Squares	
Variable	**Coefficient**	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**
Home: Standing	-0.008†	(0.004)	-0.008*	(0.004)
Away: Standing	0.001	(0.004)	0.000	(0.004)
Home: PPG	0.199**	(0.051)	0.139**	(0.044)
Away: PPG	0.174**	(0.046)	0.120**	(0.041)
Home: Nat. Playrs	-0.004	(0.006)	-0.033**	(0.004)
Away: Nat. Playrs	0.045**	(0.004)	0.021**	(0.003)
Home: GLG	0.018**	(0.006)	0.012*	(0.005)
Away: GLG	-0.010	(0.007)	-0.001	(0.006)
UOO	0.069	(0.045)	0.002	(0.040)
UOO^2	-0.025	(0.020)	0.005	(0.016)
Male Population	0.049**	(0.015)	0.021	(0.020)
Unemploy. Rate	-0.044**	(0.008)	-0.055**	(0.008)
Distance	-0.040**	(0.004)	-0.036**	(0.004)
Price	0.029	(0.032)	-0.023	(0.035)
Away: FCB, BVB, HSV	0.321**	(0.027)	0.205**	(0.021)
Herfindahl	0.002	(0.002)	0.003	(0.002)
Derby	0.638**	(0.089)	0.246**	(0.049)
Fixture	0.013**	(0.001)	0.008**	(0.001)
Temperature	0.002**	(0.000)	0.001**	(0.000)
Rain	-0.057**	(0.016)	-0.018	(0.015)
Friday	0.187**	(0.033)	0.191**	(0.037)
Saturday	0.286**	(0.026)	0.244**	(0.032)
Sunday	0.317**	(0.031)	0.282**	(0.034)
Intercept	9.148**	(0.333)	9.736**	(0.297)
N	1724		2227	
(Pseudo) R^2	0.458		0.711	

Continued on next page...

... table 4 continued

	Median Regression		Ordinary Least Squares	
Variable	**Coefficient**	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**
$F_{(56,2170)}$		.	141.544	

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

Interestingly, there are also symmetric effects of team quality variables. Perhaps the most important influence factors are the number of points per game (PPG) for both teams. Increasing the number of points per game for the home (visiting) team by 1 would ceteris paribus result in an increase of 19.9% (17.4%) in attendance figures.

Concerning the number of goals in the last match for the home team, there is clear evidence that consumers rely on this indicator. The more goals the home team scored in the previous match, the more fans will decide to attend.

Noteworthy are also our results on the match uncertainty and competitive balance measures: None of the variables turns out to significantly affect the demand for tickets. We will come back to this point once we have presented the results for model 2 and model 3.

Regarding the results for our control variables, we find the expected for Distance, Friday, Saturday, Sunday, Derby, Temperature, Rain, Away: FCB, BVB, HSV and Fixture. As a greater distance between home and visiting team is associated with higher opportunity costs for traveling away supporters, a negative sign for Distance is what we expected. In comparison to normal weekdays, matches on the weekend can generally be viewed easier as many people do not have to work on Saturday afternoons or Sundays. Derbies seem to possess the greatest influence on attendance: The fact that a match is classified as a Derby, increases attendance figures by roughly 64%. Although this effect seems extraordinarily high, it is not too far away from the results by Garcia & Rodriguez (2002) whose estimates range from 45% to 49%. However, it seems as if this result is to a large extent driven by 1860 Munich. For this team, the median attendance figure within our sample period was 13050 for non-derbies. For derbies, the median attendance was 55150. Thus, the true derby effect should be much smaller.

Besides derbies, special visiting teams such as Bayern Munich [FCB], Borussia Dortmund [BVB] (the two most successful teams in the period) and Hamburger SV [HSV] (the only team, that has always been participating in the Bundesliga since its foundation in 1963/64.) have a positive influence on demand as they possess a special reputation.

Weather influences, which might be viewed as indirect quality factors[22] also show the expected influence: If there is rain on the match day before the kick-off, attendance will be lower by 5.7%. In comparison, an increase of 1 $°C$ in the average temperature before kick-off will result in 2% more consumers in the stadium.

Concerning our economic variables, we come up with the following results: A higher unemployment rate in the home team's area significantly lowers attendance figures. It seems as if the lower income effect would dominate the positive effect of more spare time. The admission price does not show to be significant in this Model. However, given the fact that we have to rely on average prices, which do not change within a season, this result should be interpreted very carefully.

Note that besides these various effects on demand, there is also a positive trend within seasons. Although some authors[23] argue that average contest uncertainty is decreasing with the number of matches played, it seems to us that the struggle for winning the championship (participating in the UEFA Cup and/or avoiding relegation) is most interesting close to the end of the season. The following Table 5 contains the timing of the most interesting decisions in German Football: The winner of the championship and the 3 teams, which will be relegated at the end of the season. The numbers refer to the *fixtures after which* the decisions were made[24]. Each season, there were 34 fixtures.

[22]See Gärtner & Pommmerehne (1978).
[23]See Gärtner & Pommmerehne (1978).
[24]For relegation, uncertainty is assumed to persist as long as not *all three* teams have been determined.

Table 5: "Seasonal Decisions (Fixture)"

Season	**Championship**	**Relegation**
1996/97	33	33
1997/98	33	34
1998/99	31	34
1999/00	34	34
2000/01	34	34
2001/02	34	33
2002/03	30	34
2003/04	32	34

As we can see from Table 5, usually, it takes until the last match to decide about relegation and the winner of the championship. This in turn will positively affect the demand for matches towards the end of a season. We view this in line with our results for the time trend within seasons.

We would like to point out once more that the previously presented results resemble the common modeling approach for the demand for sport. Based on these results it seems that the German Bundesliga exhibits many effects known from previous studies.

Let us now turn to the core results of our empirical analysis, i.e. the results for Model 2 and Model 3.

4.2 Model 2

This subsection contains our estimation results on the season-static anchors. To avoid the introduction of new variable names, we will write all season static anchored variables in CAPS. In other words, HERFINDAHL will denote the anchored value of "Herfindahl" with respect to the season-static anchoring value. An overview of the anchored variables as well as the belonging anchoring value can be found in Table 6.

Table 6: Season-static anchored variables and anchors

Anchored variable	Anchoring value
HOME: STANDING	Finishing position of home team in previous season
AWAY: STANDING	Finishing position of away team in previous season
HOME: PPG	League average of points per games in previous season
AWAY: PPG	League average of points per games in previous season
HOME: NAT. PLAYERS	League average of national players per team in previous season
AWAY: NAT. PLAYERS	League average of national players per team in previous season
HOME: GLG	League average of team goals per game in previous season
AWAY: GLG	League average of team goals per game in previous season
UOO	Average match uncertainty in previous season
HERFINDAHL	Average value for Herfindahl-Index in previous season

As can be seen from Table 6, except for the teams' finishing positions, away and home supporters are assumed to rely on the same anchoring values[25]. Regarding last season's finishing positions, we face the problem that promoted teams did not participate in the first division last season. We choose the following approach to circumvent this problem: Within our sample period there were always 18 teams in the first division. As only the three best performing teams in the junior division are promoted, we use the ranks 19, 20 and 21 to refer to last season's ranking for promoted teams.

In Table 7 the results for Model 2 are displayed. As we can see, most quality variables retain their significance, such as HOME: STANDING, HOME: PPG, AWAY: PPG, AWAY: NAT. PLAYERS and HOME: GLG. In addition, the median regression now shows a significant positive influence of AWAY: STANDING, too. This result makes intuitive sense: If a team's current position is better than at the end of last season, this attracts fans from home, as well as from the visiting team.

[25]Unfortunately, this assumption prevents us from testing between the different models. This is why we rely on the adjusted (pseudo) R^2. We will loosen this assumption for Model 3 in the next subsection.

Perhaps the most interesting result is the coefficient on HERFINDAHL. If the league is currently less balanced than in the previous season on average, this will result in less match attendance. This result is in line with standard sports economic theory. Implications of this result will be discussed in section 5.

Table 7: Estimation Results (Model 2)

	Median Regression		Ordinary Least Squares	
Variable	**Coefficient**	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**
HOME: STANDING	-0.015**	(0.002)	-0.008**	(0.002)
AWAY: STANDING	-0.006**	(0.002)	-0.001	(0.001)
HOME: PPG	0.088**	(0.032)	0.128**	(0.029)
AWAY: PPG	0.112**	(0.028)	0.111**	(0.025)
HOME: NAT. PLAYERS	0.003	(0.007)	-0.030**	(0.004)
AWAY: NAT. PLAYERS	0.048**	(0.004)	0.022**	(0.003)
HOME: GLG	0.016*	(0.006)	0.012*	(0.005)
AWAY: GLG	-0.008	(0.008)	-0.001	(0.006)
UOO	0.052	(0.047)	0.019	(0.039)
UOO^2	-0.002	(0.021)	0.001	(0.016)
HERFINDAHL	-0.003**	(0.001)	0.003	(0.002)
Male Population	0.030†	(0.016)	0.022	(0.019)
Unemploy. Rate	-0.052**	(0.009)	-0.057**	(0.008)
Distance	-0.041**	(0.004)	-0.036**	(0.004)
Price	0.094**	(0.034)	-0.001	(0.035)
Away: FCB, BVB, HSV	0.315**	(0.028)	0.210**	(0.021)
Derby	0.761**	(0.122)	0.248**	(0.049)
Friday	0.199**	(0.034)	0.184**	(0.038)
Saturday	0.287**	(0.028)	0.243**	(0.032)
Sunday	0.315**	(0.033)	0.281**	(0.034)
Fixture	0.011**	(0.001)	0.008**	(0.001)
Temperature	0.002**	(0.000)	0.001**	(0.000)
Rain	-0.060**	(0.017)	-0.019	(0.015)

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... table 7 continued

	Median Regression		Ordinary Least Squares	
Variable	**Coefficient**	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**
Intercept	10.039**	(0.179)	10.278**	(0.159)
N	1733		2227	
(Pseudo) R^2	0.466		0.714	
$F_{(56,2170)}$	.		141.034	

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

On the control variables, our results do not change very much with the notable exception of admission prices. Within the specification of Model 2, the admission price is found to positively influence match attendance. However, as previously mentioned, the results on the price variable should be interpreted very carefully.

The reader should note that for both estimation procedures, i.e. Median Regression and OLS, Model 2 seems to provide the slightly better goodness of fit (measured by the adjusted (pseudo) R^2). Although we are aware of the small scale of the changes in this measure and of the weakness of this measure itself, we still believe this model to provide very interesting results, which are in line with our theoretical predictions. Altogether, we view these results as an indication for the presence of mental anchoring in the demand for sport. However, recall from subsection 2.3 that we also wanted to analyze the time-persistence of an anchor. This can only be done through a comparison of model 2 and model 3, to which we turn now.

4.3 Model 3

Within this subsection, we present our empirical results on the dynamic anchoring model. Here, the anchor is defined as the value of each quality proxy at the time of the last home (away) game. In other words, it is assumed that, for each home (away) game, home (away) consumers compare current indicator values to the situation before the last home (away) game. This is done for the following reason: Team behaviour in home and away matches does usually differ with respect to the degree of offensiveness, i.e. most teams show a more offensive playing strategy at home. Thus, information on a team's last home match may not be especially useful for consumers of the team's next away game. A consequence of this approach is that we allow for different anchors of home and visiting consumers.

Similar to our notation convention in Model 2, we merely change the typeface for the season-dynamic anchored variables, which we will write in `Verbatim`. In other words, `Herfindahl` will denote the anchored value of "Herfindahl" with respect to the season-dynamic anchoring value. A complete overview of the relevant anchors in Model 3 is given in Table 8.

Table 8: Season-dynamic anchored variables and anchors

Variable	Description
`Home: Standing (Home)`	Home Position before last Match (Home Perspective)
`Home: Standing (Away)`	Home Position before last Match (Away Perspective)
`Away: Standing (Home)`	Away Position before last Match (Home Perspective)
`Away: Standing (Away)`	Away Position before last Match (Away Perspective)
`Home: PPG (Home)`	Home PPG before last Match (Home Perspective)
`Home: PPG (Away)`	Home PPG before last Match (Away Perspective)
`Away: PPG (Home)`	Away PPG before last Match (Home Perspective)
`Away: PPG (Away)`	Away PPG before last Match (Away Perspective)
`Home: Nat. Players (Away)`	Home National Players last Match (Away Perspective)
`Away: Nat. Players (Home)`	Away National Players last Match (Home Perspective)
`Home: GLG (Home)`	Home GLG before last Match (Home Perspective)
`Home: GLG (Away)`	Home GLG before last Match (Away Perspective)
`Away: GLG (Home)`	Away GLG before last Match (Home Perspective)
`Away: GLG (Away)`	Away GLG before last Match (Away Perspective)
`UOO (Home)`	Match uncertainty before last match (Home Perspective)
`UOO (Away)`	Match uncertainty before last match (Away Perspective)
$\texttt{UOO}^2$ `(Home)`	Square of `UOO (Home)`

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Variable	Description
UOO^2 (Away)	Square of UOO (Away)
Herfindahl (Home)	Herfindahl-Index before last match (Home Perspective)
Herfindahl (Away)	Herfindahl-Index before last match (Away Perspective)

Our estimation results, which are given in Table 9, reveal significant differences in comparison with Model 1 and Model 2. Our results show the expected signs for `Home: Standing (Home)`, `Home: PPG (Away)`, `Away: PPG (Home)` , `Away: Nat. Players (Home)` and `Home: GLG (Away)` . If the home team's current ranking is better by one than its ranking before last home game, this will increase fan demand from home supporters by roughly 2%. For the away supporters, the home team's points per game seem to be the more important information - a better ranking than that of last away match's home team does not seem to influence the demand of supporters for the visiting team. Note that, from the home supporters perspective, the corresponding effect is found for the visiting team's points per game and standing, as well. Another interesting result is the positive influence of a larger number of national players from the visiting team. In other words, teams with a large number of national players create a positive external effect for the home team when playing away. If the visiting team in this match possesses one more national player than the visiting team in the previous home match for the home team, this will increase attendance by 0.9%. Interestingly, visiting fans seem to prefer watching matches with several goals (see the positive coefficient for `Home: GLG (Away)` although this should be associated with a lower winning probability for the supported team.

In comparison to these results, the negative coefficient for `Home: PPG (Home)` does not seem plausible. Although a positive value on this variable would indicate a higher quality, an improved point efficiency of the home team would actually lower ticket demand.

Interestingly, similar to our results for Model 1, neither the league's current degree of competitive balance or the match uncertainty measure do affect the demand for match attendance. This similarity also holds for the results on our control variables (see Table 4.

Table 9: Estimation Results (Model 3)

	Median Regression		Ordinary Least Squares	
Variable	**Coefficient**	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**
`Home: Standing (Home)`	-0.019**	(0.006)	-0.013*	(0.005)
`Home: Standing (Away)`	-0.005	(0.004)	-0.003	(0.003)
`Away: Standing (Home)`	0.003	(0.004)	0.004	(0.003)
`Away: Standing (Away)`	0.000	(0.006)	-0.003	(0.005)
`Home: PPG (Home)`	-0.246**	(0.080)	-0.147**	(0.056)
`Home: PPG (Away)`	0.094*	(0.043)	0.080*	(0.037)
`Away: PPG (Home)`	0.119**	(0.039)	0.099**	(0.033)
`Away: PPG (Away)`	-0.087	(0.070)	-0.055	(0.059)
`Away: Nat. Players (Home)`	0.009**	(0.003)	0.010**	(0.002)
`Home: Nat. Players (Away)`	-0.004	(0.003)	-0.018**	(0.002)
`Home: GLG (Home)`	-0.007	(0.006)	-0.009†	(0.005)
`Home: GLG (Away)`	0.012*	(0.006)	0.014**	(0.005)
`Away: GLG (Home)`	-0.010	(0.007)	-0.006	(0.006)
`Away: GLG (Away)`	0.010	(0.007)	0.006	(0.006)
`UOO (Home)`	-0.012	(0.045)	0.013	(0.040)
`UOO (Away)`	-0.018	(0.042)	-0.020	(0.035)
$\texttt{UOO}^2$ `(Home)`	0.019	(0.021)	0.000	(0.015)
$\texttt{UOO}^2$ `(Away)`	-0.023	(0.018)	-0.003	(0.015)
`Herfindahl (Home)`	0.002	(0.007)	0.004	(0.007)
`Herfindahl (Away)`	-0.005	(0.007)	-0.004	(0.008)
Male Population	0.053**	(0.018)	0.030	(0.021)
Unemploy. Rate	-0.044**	(0.009)	-0.054**	(0.009)
Distance	-0.042**	(0.005)	-0.039**	(0.004)
Price	0.040	(0.037)	0.008	(0.038)
Away: FCB, BVB, HSV	0.462**	(0.031)	0.269**	(0.023)
Derby	0.683**	(0.094)	0.263**	(0.054)
Friday	0.203**	(0.039)	0.177**	(0.041)

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... table 9 continued

Variable	Median Regression Coefficient	(Std. Err.)	Ordinary Least Squares Coefficient	(Std. Err.)
Saturday	0.313**	(0.032)	0.259**	(0.035)
Sunday	0.360**	(0.038)	0.285**	(0.037)
Fixture	0.012**	(0.001)	0.007**	(0.001)
Temperature	0.002**	(0.000)	0.002**	(0.000)
Rain	-0.065**	(0.019)	-0.019	(0.017)
Intercept	9.837**	(0.175)	10.236**	(0.174)
N	1636		2059	
(Pseudo) R^2	0.431		0.688	
$F_{(65,1993)}$	.		103.338	

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

The reader should note that both estimation methods reveal the smallest value for the adjusted (pseudo) R^2 in all three models.

We will now turn to the implications of our findings, which are exposed in the following section.

5 Concluding Discussion

The purpose of this paper was to analyze the procedure by which consumers of Professional German Football evaluate quality indicators in the presence of quality uncertainty. Whereas all previous studies rely on absolute values for this indicators, we base our analysis on an analogy to the situations analyzed by Kahneman and Tversky in their famous paper on decision under uncertainty (Tversky & Kahneman (1982)). Assuming that a similar reasoning may apply to quality variables for the demand for sport, we focused on the "Adjustment and Anchoring" heuristic. In particular, we asked, whether consumers of German football are subject to mental anchoring. In order to answer this question, we analyzed three different reference points, which might serve as mental anchors.

To compare our results to those from previous studies, we also included a reference point of "zero", which resulted in a model of absolute quality indicators. We want to point out that our results for this model specification are in line with previous results from the literature.

Our main focus, however, lay on two different reference-points. In Model 2 we used average values from the previous season as reference points. This may be viewed as a season-static mental anchor, which is updated once a year, only. In comparison to this, Model 3 contained a dynamic process for mental anchors: Before each home game, consumers were modeled to compare current indicators for the match to those from the previous home match. Here, we also included different anchors for home and visiting consumers.

Based on our findings we conclude that the heuristic of "Adjustment and Anchoring" is indeed present in the demand for professional German Football. Furthermore, regarding the question, whether consumers change their anchoring values from fixture to fixture, or whether they stick to a certain anchoring value more continuously, we find evidence for the latter: The adjusted (pseudo) R^2 in Model 2 is consistently higher for Median Regression and OLS than in our benchmark model. Model 3, however, consistently reveals a lower adjusted (pseudo) R^2 than Model 1[26].

In addition, we tested for the specification of home and away standing: For these variables, we re-estimated Model 1, this time including the corresponding anchoring values for home and away standing. If our approach to rely on the difference between an indicator variable and its anchor was correct, the following two parameter restrictions should be fulfilled:

$$\beta_{\text{Home:Standing}} + \beta_{\text{Home:Standing(Anchor)}} = 0 \quad \text{and} \quad \beta_{\text{Away:Standing}} + \beta_{\text{Away:Standing(Anchor)}} = 0. \tag{18}$$

Performing a Wald-Test on these two restrictions, we came up with the following results: For the season-static anchors, (Model 2), we obtained a p-Value of 0.43, meaning that we

[26]This is not merely due to the anchors for visiting fans. We also estimated a model specification without visiting fans' anchors. Therefore, we have decided to present the model with both groups of anchors in this paper.

can not reject the null hypotheses in (18) on any of the common levels of significance. Replacing the season-static anchors by the season-dynamic values from Model 3[27], resulted in a p-Value of 0.06 indicating that (18) can be rejected for Model 3 on a 10% level of significance. Although this is not a test of the complete model specification, it supports our results from above.

It should be noted that these results do not seem to be driven by "anomalies" in the data as in the benchmark model almost all quality indicators, as well as control variables showed the expected signs. The results on the coefficients are comparable to those in Model 2.

A possible explanation for consumers' adoption of seasonal anchors may be the following: Reference-points within a season may suffer from a lack of reliability. This means that a below average position in the first half of the season may be due to bad injury luck or a higher share of high quality opponents. However, over the season, these stochastic influences should tend to eliminate each other, such that the finishing position in the league mirrors the "true" quality of a team. Therefore, some consumers might prefer to rely on a season-static anchor.

Last but not least, the results for the Herfindahl-Index support the idea that the competitive balance in the German Bundesliga is rather high: Changes from fixture to fixture do not influence attendance. Here, it is the deviation from last season's average value that influences fan demand, indicating that consumers have a feeling for a leagues specific degree of competitive balance. Besides, this should encourage researchers in this field, who fail to derive the expected effect of competitive balance measures on attendance in the "standard" model specification (our Model 1).

[27]Here, home and away standing were tested with respect to the home team fans' anchoring values.

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