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Exploring determinants of football stadium attendance in Germany using panel data[1]

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Abstract

This thesis examines the sensitivity of long-term stadium attendance for professional football in Germany in the period of 1981-2018 to a number of club-specific factors, along with several domestic (socio-)economic factors and international spillovers. A replication of the analyses performed by Van Ours (2021) is conducted, who studies attendance in the Netherlands using panel data analysis based on the fixed effects method. We extend the methodology by alternative panel estimators, such as random effects and first differences. When choosing between these estimators, tests are applied to investigate endogeneity, heteroskedasticity, and serial correlation. The econometric results for Germany using the first-difference estimator indicate that within seasons attendance is affected by stadium capacity, club performance, and league level. Furthermore, national developments such as GDP per capita and the reunification have a positive effect. Lastly, the association between stadium attendance in Germany seems to be stronger with neighbouring countries than with the top leagues.

[1] The views stated in this thesis are those of the author and not necessarily those of the supervisor, second assessor, Erasmus School of Economics or Erasmus University Rotterdam.

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1 Introduction

The recently announced plans of twelve major football clubs to form a 'Super League', as a substitution for the Champions League, should have resulted in a huge stream of income for the participating clubs and was also thought of as an innovative project to make football more attractive. However, the withdrawal of several clubs after fan protests illustrated the misconception that clubs had about what supporters desire. Remarkably, only two out of the five leading football leagues, also known as the Big Five and including England, France, Germany, Italy and Spain, had no representatives in the new league. It concerns the German Bundesliga and the French Ligue 1. The absence of German clubs has sparked our interest in what determines football demand in Germany for the long-term, as exemplified by stadium attendance.

Even though attending a football match is a form of consumer behaviour for which the determinants are well-studied already, there are substantial deviations on the supply side due to the characteristics of sports. This peculiar economics of professional sports is examined by Neale (1964), who finds that in the sports industry it is unfavorable to pursue a monopoly in terms of business, which contradicts classical economics. The literature on determinants of attendance at professional sports leagues is pretty extensive and, therefore, no attempt is made to give a full overview of studies regarding stadium attendance. However, Borland and MacDonald (2003) do provide an overview of more than 60 studies that conducted research about this topic for a number of different sports, countries, and estimation methods. They identified five main categories of determinants of demand for sporting events attendance and advise to be careful with making inferences based on the literature beyond certain sports and countries. These main categories are: consumer preferences, economic factors, quality of viewing, characteristics of a sporting contest and the supply capacity.

So far, many of these studies have concentrated on the attendance per match, focusing only on a limited number of seasons. Several examples are given by Falter and Pérignon (2000) who study football in France with cross-sectional data for one season, Forrest and Simmons (2002) who study football in England with cross-sectional data for also just one season, and García and Rodríguez (2002) who study football in Spain with panel data for four seasons. Potential determinants of attendance that are estimated for match-level data in these studies are economic variables (prices, real income per capita, unemployment, and population), variables proxying expected match quality (recent performance, budgets, and match importance), match uncertainty (betting odds), and opportunity costs (weather and substitutes).

In contrast to the numerous short-term studies, there are only a few studies about the determinants of long-term developments using seasonal averages at club or league level. Dobson and Goddard (1995) investigated football attendance in England and Wales over a period of almost 70 years. Among their findings are a significant price effect and evidence for both a history and loyalty effect. Van Ours (2021) explores attendance in the Netherlands by considering national developments and international trends in football over a period of 63 years. He finds club-specific factors (stadium capacity, club performance, and league level) and season-specific determinants (unemployment and international attendance). Simmons (1996) performs a club-level analysis for clubs in England over a period of 30 years and finds that increases in real price have a significant negative long-term effect on attendance. In addition, other important determinants of attendance, such as position, goals scored, and promotion/relegation are identified.

However, none of these long-term studies have investigated the determinants for stadium attendance in Germany, except for Van Ours (2021) who uses a model with the unemployment rate, a time trend, and the average attendance in other leagues. In general, most European studies about determinants of stadium attendance are focused on England. Just a few studies have been conducted for stadium attendance in Germany, some of which are briefly discussed to illustrate the range of potential determinants.

The most complete study of the German Bundesliga is the work of Feddersen et al. (2006) who find a significant positive effect of the (re)construction of a stadium on attendance using a multivariate panel data regression over 60 seasons. Furthermore, they identify significant effects for income (positive), weekend games (positive), final position (negative), and the number of Bundesliga rivals within a certain radius (negative). More variables were studied, such as the number of inhabitants of the hometowns and winning a cup, but none were significant. Pawlowski and Anders (2012) identify, based on match-level data for one season, the chance of the home and/or away team to win the championship as a positive determinant. Moreover, having a strong brand as an away team, which indicates a great image and/or the perceived performance, increases stadium attendance. Another example is the study by Schreyer et al. (2016) regarding game outcome uncertainty for the decision-making of season ticket holders of a club in the Bundesliga. They find that uncertainty of the match outcome has a positive effect on stadium attendance in general, and in particular on season ticket holders with high coordination costs.

The current research is relevant for policy makers of clubs and members of football associations that are responsible for the redevelopment of stadiums and the improvement of league structures. The goal is to identify determinants for football stadium attendance in Germany from different angles by inspecting domestic club-specific, season/year-specific factors, and international spillovers. To achieve this goal, the following research questions are developed: *"To what extent can the long-term developments in football stadium attendance in Germany be explained by domestic (socio-)economic and performance determinants?"* and *"How is football stadium attendance in Germany related to international attendance?"*. To answer these questions, we inspect a set of determinants proposed by Van Ours (2021) and extend his research by considering alternative panel estimators and additional variables.

The analysis constructs a panel data set which follows 11 clubs in the top two tiers of professional football in Germany from season 1981/82 to 2018/19. Information on club level characteristics, such as stadium capacity, club performance, and league level are obtained to examine developments in stadium attendance. In addition, the following set of season/year-specific club-invariant determinants is also suggested to influence attendance: GDP per capita, the reunification of Germany, the club performance in European tournaments, the unemployment rate, and cinema attendance. Moreover, the average stadium attendance in the Bundesliga is related to the average stadium attendance in the top leagues of the Big Five and four neighbouring countries of Germany (Belgium, Denmark, the Netherlands, and Switzerland).

The general set-up of the analysis in this thesis is provided by Van Ours (2021), who studies long-term developments in stadium attendance in professional football in the Netherlands. To do this, a two-stage method of empirical analysis is performed: (1) the effects of club-specific variables are determined with a fixed effects (FE) model for panel data (2) seasonal effects from the first stage are examined using

Ordinary Least Squares (OLS). An additional analysis is performed to relate international spillovers to domestic stadium attendance. This set-up is applied to the set of variables central in this research and we extent the analysis by considering a different panel estimation model, namely the random effects (RE) model. Furthermore, the essence of an FE model is that it performs within transformation to remove unobserved heterogeneity, which can be done in multiple ways, two of which are considered: demeaning and first differencing (FD). The Hausman specification test, which tests the assumption of no endogeneity between the unobserved and explanatory variables, is conducted to select either the FE or RE model (Hausman (1978)). Subsequently, the Wooldridge test for serial correlation in panel data models is applied to choose between the FE and FD estimators (Wooldridge (2002)). Ultimately, we test each regression for serial correlation and heteroskedasticity and adjust the possibly biased standard errors.

The Hausman test to choose between the FE and RE estimator was found to be uninformative. Therefore, we decided to implement the less restrictive fixed effects estimator, which allows for unobserved heterogeneity to be correlated with the regressors. After controlling for heteroskedasticity and serial correlation, the same results for the determinants of attendance in the Netherlands were found as in Van Ours (2021), except for the variables goal difference and ranking. Then, the FD estimator for the within season analysis for Germany was implemented and showed significant effects for stadium capacity, club performance, and league level. In addition, the between seasons attendance is affected by national developments such as GDP per capita and the reunification of Germany. Finally, the association with international trends in neighbouring countries seems stronger than with the top European leagues.

We contribute to the literature by expanding the knowledge on determinants for long-term developments in football stadium attendance. In addition, the topic of long-term stadium attendance in Germany has not been examined thoroughly from different perspectives. The findings of this research can be used as a starting point for future research to further develop more complicated models for major leagues based on club-specific and season-specific factors. Especially the integration of econometric analyses with economic theory regarding economic factors could improve the fit of long-term development predictions.

The structure of this thesis is as follows. In Section 2, we discuss how the data is collected and the several determinants. Thereafter, in Section 3, the model specification, estimation methods, selection procedure, and points of concern are outlined. Subsequently, Section 4 presents the results of the empirical analysis. Finally, our research question is answered in Section 5.

2 Data

The long-term developments of football stadium attendance in the Bundesliga, the highest professional football league in Germany, are examined with two analyses. For the first analysis, domestic factors are used to investigate whether trends within Germany can explain stadium attendance. To do this, a set of club-specific determinants related to performance and stadium capacity is inspected and a set of season/year-specific determinants that capture general developments by which all clubs are affected. Furthermore, the second analysis of stadium attendance examines a possible relation with average attendance in other European football leagues. This section starts with an explanation of the league structure in

Germany and continues with the description of the sets of determinants for the first and second analysis. An overview of the variable definitions and their sources can be found in Table 16 in Appendix D.

2.1 League structure in Germany

As mentioned before, in this research the stadium attendance for clubs playing at the highest professional football level, the Bundesliga, is investigated. The composition of clubs in this league changes every year and depends on a system of promotion and relegation to the second tier of professional football, which is called the 2. Bundesliga. When the top and second tier were established in 1963 and 1974, respectively, only clubs from West Germany took part and this lasted until the reunification of Germany in 1990. Thereafter, clubs from East Germany were also allowed to participate, but they could not keep up with the clubs from West Germany. For this reason we assume that the Bundesliga, which during its existence mainly consisted of west German clubs, represents the stadium attendance in Germany.

Furthermore, the number of participating clubs has not been constant since the founding. During the first two seasons, starting in 1963/64, only 16 clubs were included, while for the 26 consecutive seasons there were 18 teams. As an exception, two clubs from East Germany were added to the Bundesliga after the German reunification, thereby increasing the number of participants for only one season to 20. The 2. Bundesliga originally started with 40 clubs during the season of 1974/75, but this number has been reduced to 20 clubs from season 1981/82.

In this research, we consider clubs playing in either one of the top two tiers for a period of 38 years: from the last structural change in 1981/82 to 2018/19 which was the last season without Covid-19 regulations. These regulations forced clubs to play without attendants. To create a balanced panel of professional football clubs, we select clubs in almost the same way as Van Ours (2021) did in his research for the Netherlands with the following criteria: (1) the club played in the Bundesliga or 2. Bundesliga during all seasons (2) the club played at least one season in the Bundesliga.

This selection results in a data set that contains the data of 11 clubs, for which several summary statistics, such as the number of seasons in a league, average stadium attendance, and average stadium capacity are presented in Table 1.

Table 1: Summary statistics per club for 1981/82 - 2018/19.

	Club	Number of Seasons		Attendance (1000)	Capacity (1000)
		Bundesliga	2. Bundesliga		
1	1. FC Köln	29	9	33.6	49.9
2	Bayer 04 Leverkusen	38	0	20.8	25.2
3	Bayern München	38	0	53.8	70.5
4	Borussia Mönchengladbach	35	3	33.3	42.2
5	Borussia Dortmund	38	0	57.7	65.5
6	Eintracht Frankfurt	32	6	32.5	51.5
7	FC Schalke 04	33	5	46.4	62.7
8	Hamburger SV	37	1	38.8	55.7
9	VfB Stuttgart	37	1	37.2	57.4
10	VfL Bochum	24	14	19.6	32.2
11	Werder Bremen	38	0	31.6	39.3
	Average	34	4	36.8	50.2

As can be seen in Table 1, only the following four clubs have never relegated from the Bundesliga during the observed period: Bayer 04 Leverkusen, Bayern München, Borussia Dortmund, and Werder Bremen. The other clubs spent only a few seasons in the 2. Bundesliga, with the exception of 1. FC Köln and VfL Bochum, which played respectively 9 and 14 seasons in the second tier. The attendance represents the average number of attendances during all the seasons of a club of which data was collected for this study. This average ranges between 19,600 (Vfl Bochum) and 57,700 (Borussia Dortmund). The seasonal capacity is estimated for each club by the game with the highest attendance in that season, and the average over time ranges between 25,200 (Bayer 04 Leverkusen) and 70,500 (Bayern München).

To better inspect and put into perspective the developments of the 11 clubs, we display in Figure 1 the average stadium attendance for the set of clubs and the Bundesliga. These time series do not necessarily have to be the same as the former corresponds to a fixed set of clubs regardless of which league they play in, while the latter represents the development of football at the highest professional level. Naturally, the series do have similarities because the majority of clubs play most of the time in the Bundesliga.

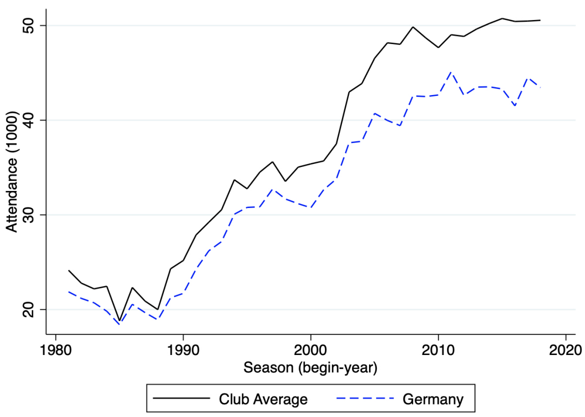

Figure 1: Average stadium attendance for selected clubs and Germany during 1981/82 - 2018/19.

Over the years, there has been an upward trend in the average stadium attendance for both the selected clubs and the Bundesliga. A period of small decline in the early years around 1981-1988 and a period of moderate stagnation since 2009 can be observed in Figure 1. It is shown that the club average lies above the national average for the whole period. We conclude that the balanced panel either represents a set of more popular clubs and/or the selection criteria lead to a set of clubs with a more stable performance and therefore systematic higher attendance.

2.2 Domestic determinants

There are 418 observations for each club-specific determinant, emerging from 38 seasons with 11 clubs, and 38 observations for each season/year-specific determinant. Table 2 shows several descriptive statistics of the two sets of determinants and the attendance, which are discussed in the following subsections.

Table 2: Statistical features of attendance and domestic determinants for 1981/82 - 2018/19.

	Variable	Mean	St.dev	Minimum	Maximum	Observations
Club-specific	Attendance	36,849	17,274	9,382	81,178	418
	Capacity	50,187	15,659	14,500	83,000	418
	2. Bundesliga	0.09	0.29	0	1	418
	Goal difference	9.28	20.97	-38	80	418
	Points	52.17	13.04	21	91	418
	Ranking	7.33	4.93	1	18	418
Season/year-specific	Unemployment (%)	6.87	2.03	3.38	11.17	38
	GDP	35,331	8,597	23,289	52,630	38
	Cinema (mln)	129.39	18.14	101.60	177.93	38
	UEFA coefficient	10.77	3.66	3.50	18.08	38

2.2.1 Club-specific determinants

The first club-specific variable is the stadium capacity, which is proxied by the highest attendance to a match for a club in a particular season. Clubs can vary the stadium capacity in a number of ways, such as by interchanging seats and standing places, renovating the stadium, or by building a new stadium. The capacity is often expanded to provide more seats for fans but there are also cases in which capacity was reduced because of regulations. A reduction happened for instance in 1992 when the Signal Iduna Park, the home stadium of Borussia Dortmund, converted most of its standing places into seats due to UEFA regulations. Furthermore, there are huge differences between clubs in terms of capacity. Namely, the smallest stadium can accommodate only 14,500 people while the largest stadium provides almost 6 times more places (83,000).

Furthermore, the following determinants of success and entertainment are included as proxies for club quality: a dummy variable indicating the competition level, goal difference, number of points, and the ranking. According to Simmons (1996), no sharp distinction between success and entertainment is made and both measures may be labeled as imperfect proxies of club quality. Dobson and Goddard (1995) bring up playing style as a potential better determinant of whether a club is viewed as entertaining but this determinant is not applicable for this study due to the absence of a suitable measure. Based on the third row of Table 2, it is clear that for only 9% of the observations, a club is part of the 2. Bundesliga. The goal difference ranges between a low of -38 and a high of 80. The number of achieved points has been adjusted to a three-points-for-a-win system, unlike the previous two-points system that was used until season 1994/95, and ranges between 21 and 91.

2.2.2 Season/year-specific determinants

Although many studies on stadium attendance have been able to identify determinants using short-run match-level data, there are only a few studies devoted to analysing determinants for the long-term stadium attendance using season/year-specific variables. According to Boyd and Krehbiel (2003), attention in the literature has generally been given to economic factors that affect sports attendance, such as income, population, and gross national product. More economic factors that are expected to influence demand are mentioned in the literature review of demand for sport by Borland and MacDonald (2003). Some of which are the unemployment rate, gross domestic product (GDP), and working hours. In this analysis, the GDP per capita and the unemployment rate are considered. To measure the impact of economic growth more accurately, we convert nominal GDP per capita to real GDP per capita using the GDP deflator for Germany.[2] Furthermore, it is difficult to come up with a priori reasoning corresponding to the expected sign of the unemployment rate. The reason why this is difficult is that the few studies on the relationship between unemployment and stadium attendance are not enlightening. For example, a positive effect is suggested by Turner and Sandercock (1981) but negative effects are found in Buraimo et al. (2021) and Reade and Van Ours (2021).

Adding to these economic variables, two other determinants are included: the performance of German clubs in major European tournaments and leisure activity preferences. These determinants are represented by respectively the UEFA coefficient of Germany and the total number of cinema visits per year. The UEFA coefficient, an average based on the performance of clubs in European tournaments, is included in the analysis to inspect whether international performance has an effect on domestic stadium attendance. A similar measure of international success as a determinant for football attendance in Chile is examined by Ferreira and Bravo (2007), but no significant effect was found. Lastly, a causal relation between cinema and stadium attendance is not necessarily suspected but a change in leisure preferences might be identified. This potential change is also investigated for the Netherlands by Van Ours (2021), but a significant positive effect was only found for a specific period and a certain set of variables.

As shown in Table 2, the unemployment rate equals 3.38% at its lowest point and 11.17% at the peak, with an average of 6.87%. The average GDP per capita is approximately equal to $35,000. Table 2 also reports that German cinemas receive approximately 130 million visitors on average per year. The mean value of the UEFA coefficient is 10.77, putting Germany in the top 5 best performing countries of Europe. The minimum and maximum number of points are 3.50 and 18.08, respectively.[3]

The left panel of Figure 2 displays the time series of GDP per capita and the unemployment rate. This panel shows that the former has been increasing throughout the period, while the latter presents an increasing trend up to 2005 and a decreasing trend thereafter.

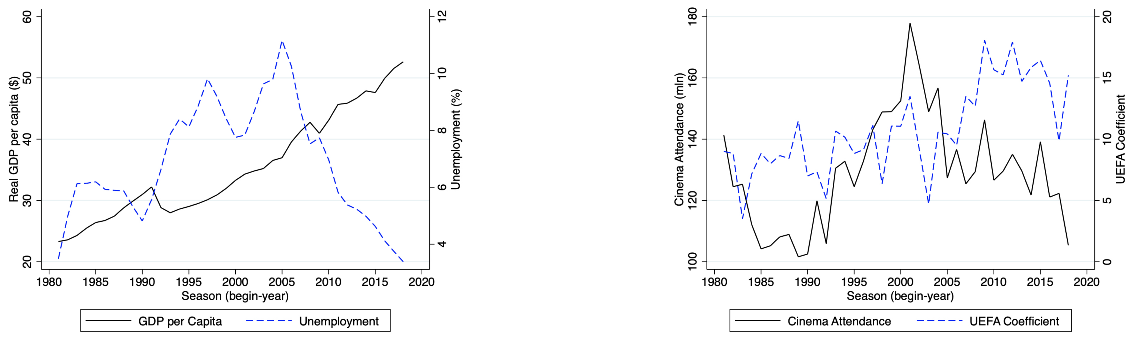

Figure 2: Graphs displaying the season/year-specific determinants GDP per capita and unemployment (Left) and cinema attendance and UEFA coefficient (Right).

[2] See GDP deflator Germany for 1981-2018 with 2015 as base year.

[3] See https://kassiesa.net/uefa/data/

The right panel of Figure 2 displays the time series of the cinema attendance and the UEFA coefficient. The development of cinema attendance moves towards a minimum during the end of the 1980s, just like the football attendance, but experiences a revival up to the beginning of the 2000s and then undergoes a prolonged fall. On the other hand, the UEFA coefficient shows an increasing trend with some ups and downs through the years.

To conclude, the division of Germany until 1990 makes it necessary to be precise about the specification of the aforementioned variables. To elaborate, East and West Germany were ruled as two different countries, resulting in differences in the data. In this research, the data on cinema attendance and unemployment prior to 1991 refer to West Germany and data from 1991 to reunified Germany. The same holds for GDP per capita and the UEFA coefficient from 1992 onwards. This choice is made because the Bundesliga was the professional football league for West Germany and as there was no free travel allowed between the two countries, it suffices to examine the data from West Germany.

2.3 International determinants

A possible association between stadium attendance in Germany and attendance in other European countries is investigated using two main groups of interest: (1) the other Big Five countries (2) Germany's four neighbouring countries with the biggest football leagues. Figure 3 in Appendix B provides an overview of the developments in stadium attendance for these groups.

The first group that includes England, France, Italy, and Spain is considered as their shared dominance in European football might lead to similar trends in stadium attendances across these countries. The second group seeks to explain attendance via international spillover effects between Germany and neighbouring countries. The following four countries are selected based on the large size, as measured in yearly revenue, of their league: Belgium, Denmark, the Netherlands, and Switzerland.[4] Table 3 provides an overview of the pairwise correlations in stadium attendance between the countries. A blue cell corresponds to the correlation between stadium attendance in Germany and one of the Big Five countries, while green corresponds to the correlation between Germany and a neighbouring country.

Table 3: Correlations between average stadium attendance per year for European countries.

	England	France	Germany	Italy	Spain	Belgium	Denmark	Netherlands
France	0.95***							
Germany	0.95***	0.88***						
Italy	-0.84***	-0.79***	-0.87***					
Spain	0.13	-0.12	0.30	-0.40**				
Belgium	0.80***	0.74***	0.82***	-0.78***	0.15			
Denmark	0.87***	0.84***	0.89***	-0.84***	0.52***	0.70***		
Netherlands	0.97***	0.91***	0.97***	-0.86***	0.18	0.88***	0.88***	
Switzerland	0.82***	0.69***	0.88***	-0.85***	0.34*	0.84***	0.74***	0.86***

Note: Correlations for 1981/82-2018/19 with exception of Spain from 1992/93;
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

[4] The aggregate revenue per league for European countries can be found in UEFA (2020). Although France borders Germany, it is not included in the set of neighbours to create two distinct sets of countries.

Except for the low correlation with Spain, there are no major differences in the magnitudes of the already high correlations between Germany and the countries in the first or second group. However, Italy is considered to be an outlier because its significant negative correlation with the other countries is opposite to the general positive trend. The observations of Italy are therefore disregarded in further analyses. Van Ours (2021) finds a similar, high correlation in attendances between several European leagues. He suggests that socio-economic developments, spillover effects in interest to attend a match, and copycat behaviour among football hooligans, might serve as potential explanations for the previously mentioned high correlation.

3 Methodology

To identify whether long-term developments in stadium attendance can be explained by certain club-specific and season/year-specific variables, a longitudinal analysis is performed that uses panel data. More specific, as the data consists of multiple time series for the same clubs, different panel data estimation methods are considered. The paper of Van Ours (2021) shows that long-term developments in professional football stadium attendance in the Netherlands are influenced by club-specific factors and season-specific factors. The validity of these results is questioned because the motivation for and shortcomings of the estimation procedure are not discussed. His empirical two-stage and exploratory analyses are therefore replicated. In order to do this, econometric tests are applied. These econometric tests may indicate a preference for a different estimation method or correction for the standard errors, depending on the characteristics of the data. Thereafter, the research is extended to Germany for two different periods and with extra variables.

In this section, the set-up of the analysis is described, the specification and selection of the models used for the analyses are explained, and potential complications regarding the estimation results of the corresponding methods are addressed. All statistical analyses are performed with the program Stata, version 16.1.

3.1 Set-up of the analysis

A set-up similar to the one used in the analysis of Van Ours (2021) is implemented and adjusted to the key variables of interest in this thesis. We perform two different analyses: (1) club attendance with club-specific and season/year-specific determinants (2) league attendance with international spillover effects. A detailed overview of all variables used in the analyses with the corresponding sources is provided in Table 16 in Appendix D.

3.1.1 Club attendance

The general demand equation for the dependent variable A_{it}, which is the stadium attendance of club i in season t, is estimated in two stages because there is a different number of observations available for the club-specific and season/year-specific variables. The first stage equation is calculated with 418 observations of the club-specific variables, while for the second stage equation there are 38 observations.

After taking the log of both the dependent variable and a regressor and adding club-fixed effects and a disturbance term, the first stage equation is given by

$$\ln(A_{it}) = \alpha_i + \beta_0 + \beta_1 DIV_{it} + \beta_2 RK_{it} + \beta_3 GD_{it} + \beta_4 PT_{it} + \beta_5 \ln(CAP_{it}) + \gamma_t D_t + \varepsilon_{it}, \tag{1}$$

where α_i are club-specific fixed effects that control for time-invariant characteristics of clubs, β_0 is a constant, $\beta_1, ..., \beta_5$ coefficients of club-specific time-varying determinants, γ_t a vector of seasonal fixed effects, and ε_{it} the disturbance term. Furthermore, DIV_{it} is a dummy variable that equals 1 when club i plays in the 2. Bundesliga in season t and 0 otherwise, RK_{it} is the end-of-season ranking divided by 100, GD_{it} is the end-of-season goal difference divided by 100, PT_{it} is the end-of-season number of points divided by 100, CAP_t is the stadium capacity, and D_t a vector of seasonal dummy variables that indicate to which year each observation belongs.

The equation for the second stage with the seasonal fixed effects $\hat{\gamma_t}$ as dependent variable and the season/year-specific variables is estimated by Ordinary Least Squares (OLS) and given by

$$\hat{\gamma_t} = \delta_0 + \delta_1 \ln(GDP_t) + \delta_2 U_t + \delta_3 UEFA_t + \delta_4 \ln(UN_t) + \delta_5 \ln(CIN_t) + u_t, \tag{2}$$

where δ_0 is a constant and $\delta_1, ..., \delta_5$ are the coefficients of the club-invariant variables. Moreover, GDP_t is the real GDP per capita, U_t is a dummy that equals 1 for the years after the reunification in 1990 and 0 otherwise, $UEFA_t$ is the UEFA coefficient of Germany divided by 10, UN_t is the unemployment rate in Germany, CIN_t is the number of cinema visits, and u_t is the disturbance term.[5] Variables defined by calender year refer to the first year of each season. The log-transformation is applied to GDP_t, UN_t, and CIN_t.

3.1.2 League attendance

Van Ours (2021) finds in his analysis of international trends that for Germany the effect of the unemployment rate disappears when international spillovers are included. To further investigate the association between stadium attendance in Germany and in the countries listed in Section 2.3, an analysis is performed with two different measures of international attendance. Namely, the average attendance in the Big Five and four neighbouring countries. In addition, within this analysis the dependent variable is represented by the average stadium attendance per season in the Bundesliga, which is a more accurate indicator of developments in Germany than the club-specific stadium attendance from the previous analysis. However, Figure 1 shows the great resemblance between the time series, which allows us to use both analyses to explain stadium attendance in Germany.

The equation with (the log of) average attendance in the Bundesliga, B_t, as dependent variable is given by

$$\ln(B_t) = \theta_0 + \theta_1 \ln(GDP_t) + \theta_2 U_t + \theta_3 \ln(AA_t) + \kappa_t, \tag{3}$$

where θ_0 is the constant and θ_1, θ_2, and θ_3 are the coefficients of, respectively, the macroeconomic, reunification, and international spillover variables. Moreover, GDP_t is the real GDP per capita, U_t is the reunification dummy, AA_t the average attendance in the Big Five or the neighbouring countries, and κ_t the disturbance term.

Three versions of Equation 3 are estimated using OLS. In the first equation, only GDP per capita and the reunification dummy are included, the second and third versions include an equally weighted average of the average stadium attendance in, respectively, the other Big Five countries and the selected neighbouring countries of Germany.

[5] Another time series of the unemployment rate in Germany is used than in Van Ours (2021). In this study, the data before 1991 refers to West Germany and reunified Germany afterwards.

3.2 Model specification and selection

Since the cross-section of 11 football clubs observed over 38 years provides information across clubs and time, we have multiple options for constructing an econometric model that uses a balanced panel data structure to explain stadium attendance. Baltagi (2008) provides a comprehensive list of advantages and disadvantages of panel data compared to time-series or cross-sectional studies, some of which are addressed to motivate the use of panel data estimation procedures for our data.

Firstly, an important benefit of using panel data is that including club-specific fixed effects can control for unobserved heterogeneity caused by club-specific characteristics, such as tickets prices, club history, or cultural differences between the cities of the respective clubs. Secondly, changes over time can be inspected because multiple observations are available for the same clubs. Thirdly, panel data is associated with more variability and less collinearity due to the cross-sectional dimension of the variables. Some limitations of panel data, such as the data collection process and the time span, are of limited relevance for this study. On the other hand, the data may suffer from endogeneity and/or cross-section dependence.

To investigate the relation between stadium attendance and the explanatory variables, we use two types of models, with their corresponding estimators, that are often used in the context of panel data: the fixed effects (FE) model and random effects (RE) model. Both models allow for the inclusion of the club-specific effects from Equation 1, but differ in the consistency and efficiency of the corresponding estimates. If the club-specific effects are correlated with the time-varying explanatory variables, the estimates of the FE model are unbiased and consistent under certain assumptions, while the RE estimates are biased and inconsistent. On the other hand, if the club-specific effects are uncorrelated with the explanatory variables, then the coefficients can be consistently estimated in both the FE and the RE model, but the latter is more efficient (Baltagi (2008)). To choose between these models, we use the Hausman specification test, which can be used to test the assumption of no correlation between the club-specific effects and the explanatory variables (Hausman (1978)).

In Van Ours (2021), the FE model is used to determine the effects of the variables, some of which are also used in this thesis, without substantiating the choice for this model. Therefore, as part of the replication, we investigate whether his conclusions are still valid when another estimation method is used or when the standard errors are adjusted if the residuals violate the assumptions of homoskedasticity and no serial correlation.

3.2.1 Fixed Effects

FE models are especially useful for panel data because they can provide unbiased estimates, under certain assumptions, even if time-constant characteristics of the clubs are not observed or correlated with the regressors. Directly estimating a regression model with OLS would not be appropriate since the unobserved club-specific effects cause endogeneity. Fortunately, the FE model allows a limited form of endogeneity by leveraging the panel structure, whereby the explanatory variables may be correlated with the club-specific effects but not with the disturbance term. In the FE framework, the data is transformed to extract variation within clubs over time, while variation across clubs is removed (Brüderl and Ludwig (2014)). For the regression analysis of Equation 1, two within estimators are considered: (1) the fixed effects (FE) estimator (2) the first-difference (FD) estimator.

Estimates in the FE model are obtained in three steps. In the first step, the temporal averages of both the dependent variable and the terms on the right side of Equation 1 are calculated. Then, the time-invariant fixed effects are eliminated by demeaning the equation with the individual means. Unobserved effects that are constant also disappear in this way. The FE transformed equation is given as

$$A_{it} - \bar{A}_i = (x_{it} - \bar{x_i})\beta + (\varepsilon_{it} - \bar{\varepsilon_i}), \tag{4}$$

where $\bar{A}_i = \frac{1}{T}\sum_{t=1}^{T} A_{it}$, $\bar{x}_i = \frac{1}{T}\sum_{t=1}^{T} x_{it}$, and $\bar{\varepsilon}_i = \frac{1}{T}\sum_{t=1}^{T} \varepsilon_{it}$. Furthermore, A_{it} denotes the dependent variable stadium attendance, x_{it} denotes the vector of explanatory variables, β is the corresponding vector of parameters and ε_{it} the disturbance term. Although not displayed, the seasonal dummy variables are also demeaned. Finally, OLS is applied to the within-model of Equation 4.

Even after the transformation, the following assumption of strict exogeneity of the explanatory variables conditional on the unobserved fixed effects is maintained

$$\mathbb{E}[\varepsilon_{it}|x_i, \alpha_i] = 0, t = 1, 2, ..., T. \tag{5}$$

In addition, the following rank condition on the matrix of the demeaned regressors is necessary to establish the well behaved asymptotic properties of the FE estimator (Wooldridge (2010))

$$\text{rank}(\sum_{t=1}^{T} \mathbb{E}[\ddot{x}'_{it}\ddot{x}_{it}]) = \text{rank}(\mathbb{E}[\ddot{X}_i{}'\ddot{X}_i]) = K, \tag{6}$$

where $\ddot{x}$ is the vector of demeaned regressors, $\ddot{X}$ the matrix of demeaned regressors for all time periods, and K the number of regressors. This assumption is violated if time-invariant regressors are included in the FE analysis, but this is not the case for our data set. It also rules out perfect collinearity among the regressors. The FE estimator can be expected to produce unbiased and consistent estimators under these assumptions. In addition, it is shown in Wooldridge (2010) that unbiased and consistent standard errors can be obtained conditional on the regressors if the disturbance terms are homoskedastic and serially uncorrelated.

An alternative to the FE estimator is given by the FD estimator, which also uses within transformation to eliminate the time-invariant characteristics of clubs. The FD estimates are obtained by first differencing Equation 1 so that the constant terms disappear, and performing OLS on the first differenced equation

$$\Delta A_{it} = \Delta x_{it}\beta + \Delta\varepsilon_{it}, \tag{7}$$

where $\Delta A_{it} = A_{it} - A_{it-1}$, $\Delta x_{it} = x_{it} - x_{it-1}$, and $\Delta\varepsilon_{it} = \varepsilon_{it} - \varepsilon_{it-1}$. Again, x_{it} represents the vector of explanatory variables, β is the corresponding vector of parameters, and ε_{it} is the disturbance term. The first difference of the seasonal dummy variables is also taken. The FD estimator is unbiased and consistent under the same assumptions as the FE estimator but less efficient. An alternative assumption for the FD estimator is that the first difference of the disturbance terms are serially uncorrelated, which implies serial correlation in the original disturbances. This is the opposite of the assumption for the FE estimator.

With an additional analysis, it is possible to determine whether the FE or the FD estimator is more appropriate to use, except when T=2 because in that case, the estimates of the coefficients are identical. The estimates can differ substantially depending on the degree of serial correlation in the original disturbance terms if more time periods observed. The FE estimator assumes that no serial correlation occurs in the disturbances, while the FD estimator assumes no serial correlation in the transformed disturbances, which is the same as a strong correlation in the original errors (Brüderl and Ludwig (2014)). Under the assumption of no serial correlation, the FE estimator is preferred over the FD estimator as the estimates of the standard errors are more efficient. However, the FD estimator is more efficient if the disturbance terms follow a random walk (Wooldridge (2010)).

3.2.2 Random Effects

The RE model assumes strict exogeneity of the disturbance terms with the club-specific fixed effects and the explanatory variables, and exogeneity of the club-specific terms with the explanatory variables. These assumptions are defined in Wooldridge (2010) as[6]

$$\mathbb{E}[\varepsilon_{it}|x_{it}, \alpha_i] = 0, t = 1, ..., T, \tag{8}$$

$$\mathbb{E}[\alpha_i|x_{it}] = \mathbb{E}[\alpha_i] = 0. \tag{9}$$

In the RE model, the unexplained residual variance is split up in two levels, a higher-level variance between clubs and a lower-level variance across clubs and time, given by, respectively, α_i and ε_{it} (Bell and Jones (2015)). The RE model with both terms as the residual is given as

$$A_{it} = \beta_0 + \beta_1 x_{it} + \sum_{t=1}^{T} \gamma_t D_t + \alpha_i + \varepsilon_{it}, \tag{10}$$

$$\alpha_i \sim iid(0, \sigma_\alpha^2), \varepsilon_{it} \sim iid(0, \sigma_\varepsilon^2), \tag{11}$$

where β_0 is the constant, β_1 is a vector of parameters, γ_t are seasonal fixed effects, α_i the club-specific random effects, and ε_{it} the disturbance term. Furthermore, x_{it} denotes the vector of explanatory variables and D_t the vector of seasonal dummy variables. For consistent estimates, the club-specific effects and the explanatory variables should comply with the assumption of strict exogeneity.

3.2.3 Fixed effects versus random effects

In general, the Hausman specification test can be performed to compare a consistent and efficient estimator with an alternative estimator that is less efficient but still consistent. Under the null hypothesis of no correlation between the club-specific effects and the explanatory variables, the RE estimator ($\hat{\beta}_{RE}$) and the FE ($\hat{\beta}_{FE}$) estimator hold these properties and should be similar. Therefore, the Hausman specification test can be useful for detecting a violation of the assumption of no endogeneity. In fact, the test statistic is a measure of the difference between these estimators, for which the result should show zero asymptotic covariance between the efficient (RE) estimator and the difference between the RE and the asymptotically inefficient (FE) estimator (Hausman (1978)). The test distribution under the null hypothesis is the chi-square distribution with the number of explanatory variables as degrees of freedom. The test statistic is given by

$$H = (\hat{\beta}_{RE} - \hat{\beta}_{FE})'[V(\hat{\beta}_{FE}) - V(\hat{\beta}_{RE})]^{-1}(\hat{\beta}_{RE} - \hat{\beta}_{FE}). \tag{12}$$

When the test results in a finding of $p < 0.05$, the estimators differ enough to reject the null hypothesis at a conventional significance level, and thus the consistent FE model is preferred. However, if the test fails to reject the null hypothesis ($p > 0.05$), it does not necessarily indicate that the RE model is preferred over the FE model. According to Clark and Linzer (2015), the Hausman test is not a necessary or sufficient tool for deciding between the two models because failure to reject the null hypothesis is probably due to the lack of statistical power and not because the assumption of zero correlation is true. Several limitations of the Hausman test can be pointed out. For instance, the assumption of an efficient estimator is violated if there is some form of misspecification or if the observations are clustered. Also, the difference in the estimated variances might not be positive definite in finite samples and, thus, the test is undefined. Lastly, the test does not aid in evaluating the bias-variance trade-off implied by the FE and RE estimators.

In Clark and Linzer (2015), a set of guidelines is derived for how to choose between both. They classify three dimensions of consideration: the extent to which variation in the explanatory variable is mostly within unit rather than across units, the size of the data set, and the researcher's goal. Under the conditions of our moderate-sized data set, 38 observations for each of the 11 clubs, the choice of an appropriate model can be guided by the goal of

[6] $\mathbb{E}[\alpha_i] = 0$ is without loss of generality if an intercept is included in x_{it}.

our research, which is identifying determinants for the long-term developments of football stadium attendance in Germany. Petersen (2004) has also given thought to the issue of preferring one model over the other. He advises researchers to think of the models as answering different questions. If one would be interested in predicting time-invariant variables, the RE model is preferred, but that is not the goal of this study.

3.3 Econometric problems

As Certo and Semadeni (2006) note, the use of panel data often creates potential statistical problems for OLS regressions, as the error terms might contain heteroskedasticity or serial correlation. Serial correlation occurs when the disturbance term of a club at one point in time is correlated with the disturbance term of the same club at another moment. Ignoring the properties of the disturbances could have serious consequences for inference, to the extent that the assumption of independent and identically distributed error terms is violated. Estimating the model under the assumption of homoskedasticity and no correlation, when in fact these are present, results in biased standard errors of the panel coefficients (Heij et al. (2004)). Moreover, in the context of a spurious regression, Granger and Newbold (1974) warn against misspecification and problems with the interpretation of coefficients, if there is a strong serial correlation in the residuals of a regression with economic variables. They recommend to include a lagged dependent variable, which creates a dynamic panel model, or to take the first difference of the variables in the regression.

In practice, when dealing with clubs of different sizes, the assumption of constant variance might be too restrictive. To test the null hypothesis of homoskedasticity, we perform the conventional White test (White (1980)). The following 3-step approach is taken to apply the test: (1) perform the original regression (2) perform an auxiliary regression of the squared residuals on a constant, the original regressors, and the squared regressors (3) under the null hypothesis have $nR^2 \overset{asy}{\sim} \chi^2(p-1)$, with p the number of estimated parameters in step 2. If $p < 0.05$, then the null hypothesis is rejected and panel-robust standard errors as described in Brüderl and Ludwig (2014) are used to correct for heteroskedasticity in the first stage.

Nevertheless, these do not account for serial or contemporaneous correlation and our analysis of the errors is therefore continued. The OLS standard errors are incorrect under serial correlation and depending on the extent of the correlation and endogeneity, the coefficient estimates could become inconsistent (Chudik and Pesaran (2013)). To identify serial correlation, we use the Wooldridge test for serial correlation in panel data (Wooldridge (2002)). More powerful and parameterised tests for serial correlation are discussed in Baltagi (2008), but we choose the Wooldridge test because it requires less assumptions, which makes it more robust according to Drukker (2003). Wooldridge's method performs an OLS regression of the first differences to obtain the residuals $\Delta\hat{e}_{it}$. Under the assumption of no serial correlation, it should hold that Corr($\Delta\varepsilon_{it}$, $\Delta\varepsilon_{it-1}$) = -0.5, which is examined by regressing the estimated residuals $\Delta\hat{e}_{it}$ from the aforementioned regression on their lags $\Delta\hat{e}_{it-1}$. A Wald test is performed to test whether the coefficient of the lagged residual differs significantly from -0.5. If the Wooldridge test indicates serial correlation, we use the Driscoll and Kraay (1998) standard errors, which correct for heteroskedasticity, first-order serial correlation, and contemporaneous correlation.

For the time series data in the second stage and the league attendance analysis, the Breusch-Godfrey test for serial correlation is performed (Breusch (1978); Godfrey (1978)). The following 3-step approach is taken to apply the test: (1) perform the original regression (2) perform an auxiliary regression of the residuals on the original regressors and the lagged residual (3) under the null hypothesis have $nR^2 \overset{asy}{\sim} \chi^2(p)$, with p the number of lagged residuals included. If the p-value is smaller than 0.05, the null hypothesis is rejected and Newey-West standard errors are used, which are heteroskedasticity and serial correlation consistent (Newey and West (1987)).

3.3.1 Endogeneity

The FE and FD estimators allow a limited form of endogeneity between the fixed effects and explanatory variables, but endogeneity between the explanatory variables and disturbance terms causes the OLS estimates of all estimators to be inconsistent. As explained in Heij et al. (2004), endogeneity may arise through the following three channels: (1) omitted variables (2) measurement errors (3) simultaneity. The first issue is dealt with by the FE and FD estimators, which eliminate club-specific unobserved characteristics that are time-invariant and not included in other variables. Furthermore, endogeneity may arise when the explanatory variables are observed with an error, but we have no reason to assume that this is the case for the data set. Lastly, some regressors might not be exogenous to stadium attendance, such as the stadium capacity and performance measures. However, we assume that the capacity within a season is unaffected by demand that might be high, as clubs only vary capacity between seasons. In addition, although the crowd size affects performance via the home advantage (Goumas (2014), the variable of interest is seasonal performance and only half of the matches are played at home.

4 Results

In this section, the results of the model selection procedure for the first stage analysis in the article of Van Ours (2021) and this thesis are described. Furthermore, some of the analyses of Van Ours (2021) are re-estimated and compared with the original results. Finally, the parameter estimates for the club, season, and league analyses for Germany are given.

4.1 Model selection

In order to investigate how the dependent and exploratory variables are related, we first apply the model selection procedure, as explained in Section 3.2.3, to select a model that deals with the characteristics of the data and complies with the goals of our research. The Hausman specification test should validate the use of either the FE or RE model for the first stage of the club attendance analysis in Van Ours (2021) and this thesis. These analyses are quite similar, given that in both cases four regressions are performed with the aim of explaining club stadium attendance, in the Netherlands or Germany, by a set of identical club-specific regressors. The first two regressions cover the time period of 1956/57-2018/19 in the Netherlands and 1981/82-2018/19 in Germany, while the last two regressions cover 1987/88-2013/14 and 1991/92-2018/19, respectively. Expanding the range of possible models and running the analysis again, enables a better examination of this set of variables and the results might be of interest for explaining stadium attendance in other leagues, in this thesis the Bundesliga.

The Hausman test statistic does not reject the null hypothesis of a systematic difference in coefficients between the FE and RE estimator for the first two regressions in Van Ours (2021), as both p-values are equal to 1, but it does for the third regression with $p = 0.00$. The test statistic is uninformative for the fourth regression because the data fails to meet the asymptotic assumptions. Normally, this would point towards the RE model for the first two regressions and the FE model for the third regression. There is reason, though, to question this result because the matrix of the difference of the estimated variances is not positive definite for the three tests, which could be due to the finite sample. Hence, the test statistic is undefined and we select a model in a different way. To avoid the restrictive assumption of no correlation between the unobserved heterogeneity and the regressors, we favor the FE model. Similar finite sample problems arise when applying the test to the regressions for our data set. Thus, we again use the FE model for the first stage analysis.

The FE model can deal with unobserved heterogeneity in various ways, for example, by demeaning the variables to eliminate the constant terms or by using the first differences, resulting in the FE and FD estimators. As explained in section 3.2.1, the preference for a model depends on the assumption of no serial correlation in the error terms. When the first stage regressions in Van Ours (2021) are performed using the FE estimator, the Wooldridge test rejects the null hypothesis of no serial correlation in each of the four regressions, with $p = 0.00$. With the FD estimator, the null hypothesis is rejected for the first two regressions at a 5% significance level, with $p = 0.02$ for both, but not for the last two regressions. Thus, neither of the two estimators is more efficient and the FE estimator is, eventually, selected for simplicity. Nevertheless, it is still necessary to correct for serial correlation and possible heteroskedasticity. The Wooldridge test for the regressions in the first stage analysis for Germany indicates significant serial correlation in the error terms with the FE estimator and no serial correlation with the FD estimator. Hence, the FD estimator is selected for the first stage analysis.

4.2 Replication

To verify the usefulness of certain club-specific variables as determinants for stadium attendance, we performed the same first stage regressions as those given in Van Ours (2021) Table 4, using the FE estimator. The results are presented in Table 12 in Appendix C and are briefly discussed. Instead of the robust standard errors, we use the Driscoll-Kraay standard errors to adjust for serial correlation and heteroskedasticity, which both happen to be present in the data. The coefficient results are identical and the standard errors are very similar overall, but some deviations in the shorter period cause the goal difference to become insignificant and the ranking to be significant only at the 10% level if points are excluded. The main findings do not change much when lagged regressors are included. In addition, the variance inflation factor (VIF) is used to identify whether the explanatory variables are affected by multicollinearity. This appears to be the case for the performance indicators, see Table 15 in Appendix C. To isolate the effect of each individual variable, it is wise not to include all performance measures in a single model. Overall, the stadium capacity, performance of the club, and the league level influence stadium attendance in the Netherlands and might also be pertinent to Germany.

Furthermore, the second stage regressions (Van Ours (2021) Table 5) are also replicated and the OLS regression results can be found in Table 13 in Appendix C. The Newey-West standard errors are applied to the longer period to adjust for serial correlation and heteroskedasticity. Both are present as indicated by the Breusch-Godfrey test and White test. This adjustment is not necessary for the shorter period as the null hypotheses of no serial correlation and homoskedasticity are not rejected. The same coefficient estimates are found and no changes in significance occurred after applying other standard errors. Robustness tests with lagged regressors show that the effect of cinema disappears in both periods. The other variables are also somewhat affected. Nevertheless, the developments in countries can have various causes, so the variables may still be informative for attendance in Germany.[7]

Finally, the exploratory analysis of international trends regarding Germany (Van Ours (2021) Table 6) is replicated with Newey-West standard errors to adjust for serial correlation and heteroskedasticity. This yielded the same results for unemployment, calender time effects, and the international spillovers, which can be found in Table 14 in Appendix C. However, a striking result is obtained when only the subperiod after the German reunification is considered: the effect of unemployment reverses and becomes significantly positive, while international spillover effects become negative. Nevertheless, when the calender time effects are disregarded, the signs of the variables

[7] The time variable is not considered due to the high correlation with GDP per capita (0.98). Also, the effect of Premier League attendance for Germany is already investigated by Van Ours (2021). Finally, hooliganism cannot be investigated because no arrest data is available for Germany.

reverse again. Consequently, because of the sensitivity of these results, which vary widely in sign and magnitude for different sets of variables, we refrain from hard conclusions about the effects of the variables. In addition, not the unemployment rate but the GDP per capita is used in our analysis of international spillover effects.

4.3 Parameter estimates club attendance

Table 4 shows the FD parameter estimates of the club-specific variables from the first stage. The log-linear model with the log-transformed dependent variable and log-transformed stadium capacity was preferred over a linear model because it resulted in a substantially better statistical fit for the FD estimator. Furthermore, the coefficient of stadium capacity is interpreted as the elasticity. The null hypothesis of no serial correlation is not rejected by the Wooldridge test, while the White test for heteroskedasticity indicates heteroskedastic disturbances in each regression. Thus, the robust standard errors are displayed. For each regression, the null hypothesis of an equal constant term across the clubs is rejected at the 1% significance level, which is in accordance with the assumption of club-fixed effects. The overall explanatory power is decent and similar across periods. Columns (3) and (4) cover the period from 1992 but the FD estimator takes into account the observations from 1991 and onwards.

Table 4: FD parameter estimates (log) stadium attendance; first stage - club-specific effects.

	1981/82 - 2018/19		1992/93 - 2018/19	
	(1)	(2)	(3)	(4)
2. Bundesliga	-0.32***	-0.32***	-0.27***	-0.27***
	(0.03)	(0.03)	(0.03)	(0.03)
Log Capacity	0.55***	0.55***	0.61***	0.61***
	(0.04)	(0.04)	(0.06)	(0.06)
Ranking/100	-0.28	-0.46**	-0.12	-0.22
	(0.23)	(0.18)	(0.22)	(0.17)
Goal difference/100	0.09	0.13***	0.09	0.12**
	(0.06)	(0.05)	(0.06)	(0.05)
Points/100	0.14		0.08	
	(0.10)		(0.10)	
Observations	407	407	297	297
R-squared	0.728	0.727	0.751	0.751

Note: Fixed effects for clubs, a constant, and time dummies are included;
R-squared is within; Robust SE in parentheses;
$^{**}p < 0.05$, $^{***}p < 0.01$

Based on the FD results, the impact of the competition level is found to be significant and playing in the 2. Bundesliga instead of the Bundesliga reduces attendance with roughly 30%. Furthermore, the marginal effect of stadium capacity is significant, positive, and quite similar across the periods considered. Lastly, the results of the three performance indicators are insignificantly different from zero in both periods for the full model, which is probably due to the high pairwise correlations between points and ranking (-0.93) and points and goal difference (0.95). For a complete overview of pairwise correlations, see Table 7 in Appendix A. In addition, pinpointing the effect of each performance indicator might be difficult due to collinearity between these variables. So to ensure that the model finds true patterns in the data, the amount of collinearity is inspected using the VIF. For the variable points, the VIF of 16.11, see Table 10 in Appendix A, appears to be higher than thresholds that are considered in the literature as problematic for separating out the individual effects, such as 2.5 in Johnston et al. (2018) or 10 in Allison (1999). Therefore, points is removed from further analyses. The goal difference is regarded as a more subtle indicator for entertainment than points, which is in line with the article of Van Ours (2021).

Columns (2) and (4) display the results obtained after removing points. The coefficient of goal difference becomes significantly positive and implies that an extra goal increases attendance by about 0.1%. The effect of final ranking differs a lot across the two time periods. The estimate over the whole period is significant and implies that a rise of one place in the ranking results in an increase of 0.5% in stadium attendance, while the effect over the shorter period is almost halved and insignificant.

Table 5 presents the OLS parameter estimates of the season/year-specific variables from the second stage given by Equation 2, with the seasonal fixed effects from columns (2) and (4) in Table 4 as dependent variables. Newey-West standard errors are applied as serial correlation was found for columns (1), (2), and (4). Heteroskedasticity was found for columns (2) and (6). The R-squared values show that the explanatory power of the variables is good. The correlations and collinearity between the variables, as shown in Tables 8 and 11 in Appendix A, do not yield any findings worth mentioning.

Table 5: OLS parameter estimates (log) stadium attendance; second stage - season/year-specific effects.

	1981/82 - 2018/19			**1992/93 - 2018/19**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Log GDP	0.65***	0.79***	0.88***	0.69***	0.96***	0.96***
	(0.08)	(0.17)	(0.11)	(0.09)	(0.05)	(0.05)
Reunification	0.35***	0.26***	0.19**			
	(0.05)	(0.09)	(0.07)			
UEFA/10	0.06	0.07	0.03	0.02	0.03	0.03
	(0.07)	(0.06)	(0.03)	(0.06)	(0.02)	(0.02)
Log Unemployment (%)		0.15	0.11		0.24***	0.23***
		(0.11)	(0.09)		(0.04)	(0.02)
Log Cinema			0.38**			0.05
			(0.16)			(0.08)
Observations	38	38	38	27	27	27
R-squared	0.925	0.937	0.953	0.863	0.972	0.973

Note: Constant included; Newey-West SE in parentheses;
$^{**}p < 0.05$, $^{***}p < 0.01$

The coefficient of GDP per capita is significant, positive and similar across periods, but also moderately sensitive depending on which variables are included in the model. The significantly positive coefficient of reunification reveals that this historic event has been beneficial for stadium attendance. This finding might be explained by the fact that citizens from both parts of Germany were free to cross the border after the reunification, which allowed more people to attend matches. This right to travel broadened the football market in Germany and may have led to an increase in stadium attendance compared to the situation of a divided Germany. The performance of German clubs in European tournaments does not seem to have affected stadium attendance for clubs, as the coefficient, although positive, is not significant in any of the regressions. The effect of European success might be significant for an individual club, but the estimator assumes equal effects across all clubs. The estimates of the unemployment rate are positive but insignificant for the longer period, while the effect for the shorter period is significantly positive. This result is difficult to explain from an economic perspective, as it is not in line with the existing literature. It may be indicative of a model misspecification or a biased result due to endogeneity. Explanations can also be given from a social perspective, such as having more free time to attend matches and/or the function of a social outlet (Turner and Sandercock (1981)), but exploring the social nature of this phenomenon is beyond the scope of this thesis. Furthermore, column (3) shows that the coefficient of cinema attendance is significant and positive, which could indicate that stadium attendance benefits from an increase in recreational activities, represented by cinema attendance. However, over the shorter period, the coefficient is not significant.

A range of robustness checks is performed to examine the sensitivity of the coefficient estimates. For example, the performance indicator goal difference is replaced by the sum of goals for and against. As a result, the effect of ranking doubles and becomes significant in both periods, while sum of goals is not significant. Furthermore, the effect of ranking by league is tested with a variable for each league, which appear to be significantly different. For the Bundesliga, the magnitude is almost the same as before but for the 2. Bundesliga the effect of ranking is much higher, one place up yields about 2% additional stadium attendance. This finding implies that stadium attendance for lower quality football is more sensitive to changes in ranking. Cinema attendance is replaced by box office revenue, which refers to the money raised by movie ticket sales. Unemployment, measured by the number of unemployed persons rather than a percentage of the labour force, is introduced. Finally, the inclusion of lagged regressors in the first and second stage regressions is tested. The main findings of the first stage are not affected by the lagged variables. Contrary to this result, the findings of the second stage are quite sensitive to the inclusion of lagged variables. In brief, the coefficient of GDP per capita decreases to about 0.6 for the longer period and increases to 1.7 for the shorter period. In addition, the effect of cinema disappears for both periods. The main findings are not affected by the robustness checks, apart from the discussed changes.

4.4 Parameter estimates league attendance

Table 6 presents the OLS results for Equation 3 that tests the association with international attendance. The Breusch-Godfrey test rejects the null hypothesis of no serial correlation at the 5% level for the equations in columns (1), (3), and (5). The White test does not reject the null hypothesis of homoskedasticity at the 5% level for any regression. The Newey-West standard errors are thus presented to adjust for serial correlation.

Table 6: OLS parameter estimates (log) league attendance; average international attendance.

	1981/82 - 2018/19		**1992/93 - 2018/19**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Log GDP	0.75***	0.15*	0.77***	0.30***	0.59***
	(0.09)	(0.08)	(0.07)	(0.07)	(0.12)
Reunification	0.32***	0.21***			
	(0.05)	(0.03)			
Log Neighbours		0.67***		0.51***	
		(0.09)		(0.07)	
Log Big Five					0.43*
					(0.21)
Observations	38	38	27	27	27
R-squared	0.921	0.975	0.870	0.944	0.897

Note: Constant included; Newey-West SE in parentheses;
$^{*}p < 0.10$, $^{***}p < 0.01$

The first column shows the coefficient estimates of a parsimonious model with only GDP per capita and a reunification dummy. Both variables have a significant, positive effect on the average attendance in the Bundesliga. However, the effect of GDP drops sharply and becomes significant only at the 10% level when the average stadium attendance in neighbouring countries is included. This could be the result of an omitted variable bias as the latter is highly correlated with both the dependent variable and GDP, as displayed in Table 9 in Appendix A. The average attendance in the Big Five could not be calculated for the longer period, because attendance data for Spain is only available from 1992. The results for GDP in columns (3)-(5) show a similar pattern to the one in the first two columns. The coefficient in the model with GDP only has approximately the same value as in column

(1). Even though this effect seems high in absence of other variables, the impact decreases sharply if the average stadium attendance in neighbouring countries is included. The average attendance in Germany does not seem to be affected that much by the average attendance in the other top leagues, even though the effect is significant at 10% and positive. Overall, the explanatory power of the models is excellent and the international attendance has a significant effect.

5 Conclusion

The aim of this thesis was to identify domestic factors that influence the long-term developments in football stadium attendance in Germany and to analyse the association with other European football leagues.

To approach this, we first revisited the analyses by Van Ours (2021) and used the set-up and set of potential determinants for the Netherlands as a starting point for the analysis of stadium attendance in Germany. A panel data set of 30 clubs for 63 seasons with the club-specific and season/year-specific factors and the time series data for average attendance in Belgium, France, England, Germany, and the Netherlands was used for the replication. Next, to analyse whether the results of Van Ours (2021) were valid, we implemented the two-stage estimation procedure and extended the research by testing whether the original fixed effects (FE) model or a random effects model for panel data would be more appropriate for the first stage analysis. We found no clear preference and therefore implemented the same FE model. The regression diagnostics indicated the presence of serial correlation and heteroskedasticity, but after adjusting the standard errors, the same results were found. Only the significance of goal difference disappeared over the shorter period and ranking became significant at 10%.

Furthermore, for our panel data set that covers 11 German clubs over 38 years, the first-difference estimator was implemented for the first stage regressions. As the results show, the club-specific variables with a significant effect on stadium attendance are the league level, stadium capacity, and depending on the period considered, the ranking and the goal difference. The results from the second stage regressions, in which factors were considered that vary between seasons but affect all clubs equally, were fairly sensitive to the period of time and variables included in the model. Real gross domestic product (GDP) per capita, which proxies income, has a significant effect on stadium attendance. A dummy variable for the reunification of Germany was also found to be significantly positive. The analysis, however, did also report several factors without a significant effect, such as the performance in European tournaments and cinema attendance after the reunification. A remarkable result is that the unemployment rate has a positive effect on stadium attendance over the whole period and a significant positive effect after the reunification, which deviates from the negative effect found by Van Ours (2021) over a somewhat longer period.

Finally, a parsimonious model with only GDP and a reunification dummy if the whole sample is considered, showed that both the average attendance in the biggest football leagues and in neighbouring countries of Germany explain much of the variation in football stadium attendance in Germany. Although based on only 27 annual observations, the positive effect of the neighbouring countries seems bigger.

Clearly, there are some limitations to our research. Firstly, the FE model only allows a limited form of endogeneity to the extent that correlation between the fixed effects and regressors is accepted. We rely on certain assumptions to limit richer endogeneity, such as no substitution effects as a result of increased competition between the leagues and that performance and stadium capacity are exogenous to attendance. However, these assumptions should be investigated by further research, as endogeneity issues can change the regression results. One could for example replicate our results with a dynamic panel data estimator that accommodates the use of endogenous regressors. Secondly, the absence of data for stadium attendance in Spain before 1992, hooliganism related arrests, or measures to infer preferences for recreational activities, has limited us in explaining developments.

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Appendices

A Tables

Table 7: Correlations between dependent variable in the first stage analysis and club-specific variables.

	Attendance	Capacity	2. Bundesliga	Ranking	Goal difference
Capacity	0.72***				
2. Bundesliga	-0.24***	-0.24***			
Ranking	-0.17***	-0.14***	-0.17***		
Goal difference	0.19***	0.20***	0.11**	-0.89***	
Points	0.22***	0.20***	0.15***	-0.93***	0.95***

Note: The transformed variables as explained in Section 3.1 are used;

$^{**}p < 0.05$, $^{***}p < 0.01$

Table 8: Correlations between dependent variable in the second stage analysis and season/year-specific variables.

	Seasonal fixed effects	GDP	UEFA	Unemployment (%)
GDP	0.88***			
UEFA	0.66***	0.73***		
Unemployment (%)	0.16***	-0.19***	-0.20***	
Cinema (mln)	0.48***	0.15***	0.19***	0.49***

Note: The transformed variables as explained in Section 3.1 are used;

$^{***}p < 0.01$

Table 9: Correlations between dependent variable in the international analysis and explanatory variables.

	Germany	GDP	Neighbours
GDP	0.87***		
Neighbours	0.96***	0.89***	
Big Five	0.84***	0.75***	0.90***

Note: The transformed variables as explained in Section 3.1 are used;

$^{***}p < 0.01$

Table 10: Collinearity diagnostics of club-specific variables.

	Capacity	2. Bundesliga	Ranking	Goal difference	Points
VIF complete model	1.15	1.12	7.87	9.98	16.11
VIF reduced model	1.13	1.11	4.93	4.95	

Note: The transformed variables as explained in Section 3.1 are used.

Table 11: Collinearity diagnostics of season/year-specific variables.

	GDP	Reunification	UEFA coefficient	Unemployment (%)	Cinema (mln)
VIF	4.28	3.88	2.31	2.01	1.83

Note: The transformed variables as explained in Section 3.1 are used.

B Graphs

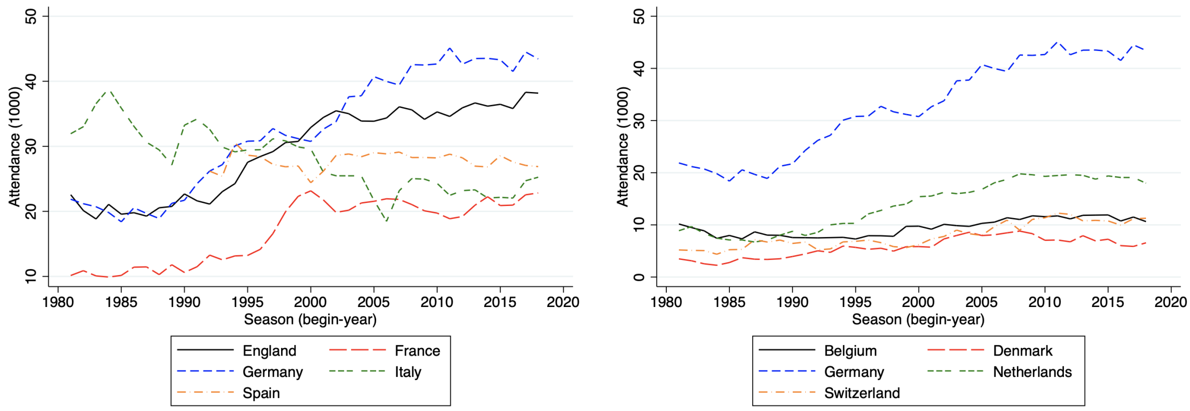

Figure 3: Graphs displaying the average stadium attendance for football at the highest level in the Big Five countries (Left) and in four neighbouring countries of Germany (Right).

C Replication

The estimation results of the analyses in Van Ours (2021) are displayed in Tables 12, 13, and 14. The original results are shown on the left side of a double column and our replication results on the right side. A single column means that the exact same regression was performed.

Table 12: FE parameter estimates stadium attendance; first stage club-specific effects. (Replication of Table 4 in Van Ours (2021))

	1956/57-2018/19				1987/88-2013/14			
	(1)		(2)		(3)		(4)	
First division	-0.31***	-0.31***	-0.31***	0.31***	-0.44***	-0.44***	-0.44***	-0.44***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)	(0.02)	(0.05)	(0.02)
Second division	-0.42***	-0.42***	-0.42***	-0.42***				
	(0.07)	(0.04)	(0.07)	(0.04)				
Ranking/100	-0.80**	-0.80**	-0.65***	-0.65***	-0.63	-0.63	-0.64**	-0.64*
	(0.37)	(0.36)	(0.23)	(0.23)	(0.44)	(0.52)	(0.30)	(0.33)
Goal difference/100	0.29***	0.29***	0.24***	0.24***	0.17**	0.17	0.18***	0.18
	(0.05)	(0.07)	(0.05)	(0.07)	(0.07)	(0.11)	(0.06)	(0.10)
Points/100	-0.13	-0.13			0.00	0.00		
	(0.16)	(0.18)			(0.18)	(0.25)		
Log stadium capacity	0.73***	0.73***	0.73***	0.73***	0.57***	0.57***	0.57***	0.57***
	(0.03)	(0.04)	(0.03)	(0.04)	(0.05)	(0.03)	(0.05)	(0.03)
Observations	1890	1890	1890	1890	810	810	810	810
R-squared	0.866	0.866	0.866	0.866	0.869	0.869	0.869	0.869

Note: Fixed effects for seasons and clubs and constant are included; R-squared is within; Driscoll-Kraay SE in parentheses;
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 13: OLS parameter estimates stadium attendance; second stage season/year-specific effects. (Replication of Table 5 in Van Ours (2021))

	1956/57-2018/19						1987/88-2013/14		
	(1)		(2)		(3)		(4)	(5)	(6)
Log Urate	-0.26***	-0.26***	-0.12***	-0.12***	-0.08***	-0.08***	-0.15***	-0.10***	-0.10***
	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
Time/10	0.14***	0.14***	0.08***	0.08***	0.09***	0.09***	0.27***	0.19***	0.19***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)
Log Premier League			0.56***	0.56***	0.41***	0.41***		0.35***	0.35***
			(0.07)	(0.09)	(0.06)	(0.08)		(0.10)	(0.11)
Log Cinema Visits					0.16***	0.16***			0.00
					(0.03)	(0.04)			(0.08)
Log Arrests							0.08***	0.03*	0.03
							(0.02)	(0.02)	(0.02)
Observations	63	63	63	63	63	63	27	27	27
R-squared	0.816	0.816	0.912	0.912	0.941	0.941	0.986	0.991	0.991

Note: Constant is included; Newey-West SE in parentheses for (1)-(3);
$^{*}p < 0.10$, $^{***}p < 0.01$

Table 14: OLS parameter estimates league attendance; average international attendance. (Replication of Table 6 column (3) in Van Ours (2021))

	1963/64 - 2018/19						1992/93 - 2018/19		
	(1)		(2)		(3)		(4)	(5)	(6)
Log Urate	-0.12***	-0.12***	-0.00	-0.00	0.00	0.00	0.20***	0.26***	0.30***
	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)	(0.02)	(0.04)	(0.03)
Time/10	0.20***	0.20***	0.11***	0.11***	0.08***	0.08***	0.26***	0.32***	0.35***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.03)	(0.02)
English PL			0.64***	0.64***				-0.26**	
			(0.09)	(0.11)				(0.11)	
Average other leagues					0.75***	0.75***			-0.34***
					(0.09)	(0.12)			(0.08)
Observations	56	56	56	56	56	56	27	27	27
R-squared	0.769	0.769	0.855	0.855	0.872	0.872	0.953	0.961	0.967

Note: Constant included; Newey-West SE in parentheses;
$^{**}p < 0.05$, $^{***}p < 0.01$

Table 15: Collinearity diagnostics of club-specific variables in Van Ours (2021)

	Capacity	First division	Second division	Ranking	Goal difference	Points
VIF complete model	3.16	2.78	1.32	6.28	10.07	10.19
VIF reduced model	3.15	2.76	1.29	5.29	5.58	

D Variables used in the analysis

Table 16: Overview of variables.

Variable	Description	Source
A_{it}	Attendance: it is the average seasonal stadium attendance for club i in season t; log transformation is applied to this variable.	League attendance
α_i	Club fixed effect: it is the club-specific fixed effect for club i.	-
B_t	Attendance: it is the average seasonal stadium attendance in the Bundesliga in season t; log transformation is applied to this variable.	League attendance
CAP_{it}	Capacity: it is the stadium capacity for club i in season t, which is estimated by the game with the highest attendance in that season; log transformation is applied to this variable.	League attendance
CIN_t^*	Cinema visits: it is the total number of cinema visits in Germany in season t; log transformation is applied to this variable.	SPIO (2021)
D_t^*	Seasonal dummy: it is the indicator variable for each year that equals 1 for that year and 0 otherwise.	-
DIV_{it}	League dummy: it is the indicator variable that equals 1 if club i plays in the 2. Bundesliga in season t and 0 otherwise.	-
GD_{it}	Goal difference: it is the number of goals scored minus the number of goals conceded by club i in season t, divided by 100.	Bundesliga table and standings
GDP_t^*	Gross domestic product per capita: it is the measure of value added through the production of goods and services per person in season t (in West Germany before 1992 and reunified Germany afterwards). The GDP deflator is applied to convert the nominal value to the real value; log transformation is applied to this variable.	OECD (2021a); GDP deflator
$UEFA_t$	UEFA coefficient: it is the season club coefficient that is based on the performance of German clubs in the UEFA Champions League and UEFA Europa League in season t, divided by 10.	UEFA coefficient
PT_{it}	Points: it is the number of points earned by club i in season t, divided by 100.	Bundesliga table and standings
RK_{it}	Ranking: it is the position club i ended up in season t in either the Bundesliga or 2. Bundesliga, divided by 100.	Bundesliga table and standings
U_t^*	Reunification dummy: it is the indicator variable that equals 1 after the German reunification in 1990 and 0 otherwise.	-
UN_t^*	Unemployment rate: it is the percentage of the labour force that was without work, currently available for work, and seeking work in year t; log transformation is applied to this variable	OECD (2021b)

*Variable refers to the first calendar year of season t.

E Code and data

The '*Thesis.zip*' contains the code and data sets that are used to obtain the results and figures in this thesis. The code is written in Stata version 16.1 and can be used for replication after changing the current path of each data set to the correct path in the do-files. Table 17 presents a short description of each file.

Table 17: File descriptions.

File	Description
Thesis-Replication.do	Replicates the analyses in Van Ours (2021) and performs additional regressions and econometric tests.
Attendance-Panel-Data.dta	Data set with the club-specific and season/year-specific variables for the first and second stage regressions for the Netherlands.
Attendance-International-Data.dta	Data set with the variables for the international analysis for the Netherlands.
Thesis-Extension.do	Performs the analyses for Germany as presented in this thesis.
Germany-Panel-Data.dta	Data set with the club-specific and season/year-specific variables for the first and second stage regressions for Germany.
Germany-International-Data.dta	Data set with the variables for the international analysis for Germany.

Note: The Driscoll-Kraay standard errors are produced using the -xtscc- command; The Wooldridge test is performed using the -xtserial- command.