Discussion Paper No. 16-058

Competitive Balance and Assortative Matching in the German Bundesliga

Roman Sittl and Arne Jonas Warnke

Zentrum für Europäische
Wirtschaftsforschung GmbH

Centre for European
Economic Research

Discussion Paper No. 16-058

Competitive Balance and Assortative Matching in the German Bundesliga

Roman Sittl and Arne Jonas Warnke

Competitive Balance and Assortative Matching in the German Bundesliga*

Roman Sittl† and Arne Jonas Warnke‡

August - 2016

Abstract

In this paper we consider trends in the distribution of player talent across association football clubs over time. Player talent is the most important prerequisite for team success in professional sports leagues and changes in players' assortativeness in regard to the clubs they play for may arguably be an important factor for changes in competitive balance. We offer a new approach for measuring player talent and its distribution - the partial correlation of each player with the goal margin. We use this measure to analyze the degree of competitive balance over time. This approach enables us to examine how player mobility drives competitive balance over time. Empirical results are based on 19 seasons of the first two divisions of the German Bundesliga as well as domestic cup games. Our results show a decrease in competitive balance over time; better teams tend to attract increasingly better players. We show that this is driven by an increasingly unequal inter-divisional distribution of teams, coaches and players, as well as increasing assortativeness in the 1st Bundesliga. We further demonstrate that player transfers between Bundesliga teams results in assortative matching between players and teams. These domestic transfers do not, however, explain the reduction in competitive balance over time. Furthermore, we show that UEFA Champions League payments may have contributed to the reduction in competitive balance over the last two decades.

JEL Classification: Z2; J44; J63; L51; L83

Keywords: competitive balance, uncertainty of outcome, player mobility, playing talent, football, association football, soccer, sports economics, Bundesliga, UEFA champions league

---

*Special thanks go to Martin Kiefel, Bernd Fitzenberger, Bernd Frick, Jan Höcker, Martin Hud, François Laisney, Michael Lechner, Tim Pawlowski, Andreas Peichl, Vera Schmitz, Thomas Walter and seminar participants at ZEW Mannheim and Universität St. Gallen, 7th ESEA Conference on Sports Economics in Zurich (2015), 20th Conference of the German Association of Sport Economics and Sport Management (2016) and International Conference Sport Economics & Sport Management (SESM, 2016). This paper was previously circulated as "Competitive Balance in the German Bundesliga: A Fixed Effects Approach".

†University of Mannheim. E-mail: rsittl@mail.uni-mannheim.de

‡ZEW Centre for European Economic Research Mannheim. E-mail: warnke@zew.de.

1 Introduction and Literature

Trends in competitive balance, or the lack of predictability of competitions, is widely discussed amongst fans, officials and academics interested in association football (e.g. The Economist, 2016).[1] Competitive balance refers to the distribution of playing talent across clubs and the resulting uncertainty about match or championship outcomes. New broadcasting deals, such as that in the English Premier League, further intensify this debate, raising awareness of diverging financial power and inequality across and within leagues in Europe. The ongoing domination of the German Bundesliga by Bayern München, for example, often dampens the fans' of other Bundesliga clubs enthusiasm about the limited success of their teams. Fans of small market teams often complain about 'buying up policies' of large market teams. Such policies inhibit the equal distribution of player talent and consequently diminish competitive balance. To take one example, Robert Lewandowski was transferred from Borussia Dortmund, a contender for winning the league, to the most successful team, Bayern München. Likewise, Borussia Dortmund was able to attract promising player talent from less successful Bundesliga clubs, as in the case of Marco Reus in 2012 (Borussia Mönchengladbach to Borussia Dortmund).

Whilst this pattern is certainly evident on an anecdotal level, this study shall empirically analyze whether any trends exist in terms of the assortative matching of players to teams.[2] By looking at the degree of assortative matching for each season, we examine trends in competitive balance within the last two decades in the German Bundesliga. This study contributes to the existing literature by offering a novel approach to measuring performance in football and a new method of investigating trends in competitive balance, focusing on changes in the distribution of player talent across clubs. Looking at single match data, we draw on up-to-the-minute lineup data as an indicator of the performance of players, teams and coaches. Through estimation of our player, team and coach measures, we are able to decompose success in football (measured by the goal margin achieved) into long-term and medium-term institutional effects (team strength and ability to attract better coaches) and actual player talent (a more short- and medium-term measure of performance). Utilizing the tendency of players and coaches to switch frequently between teams, we examine whether better players are evermore at better clubs, or whether long- and short-term success increasingly go hand in hand.

The paper is organized as follows. In Section 2 we discuss theoretical and empirical findings on competitive balance and outline features of the German Bundesliga during the last two decades and Section 3 introduces our data set and empirical framework. Section 4 provides regression results and our subsequent interpretation regarding competitive balance. Section 5 provides some conclusions. We demonstrate the robustness of the results

[1] In the paper we use the term *football* for association football or soccer.

[2] The concept of assortative matching is based on marriage market models. This term is used to describe mating between partners and spouses in terms of education, income etc. In the literature of, for example, job mobility, assortative matching refers to matching of high-wage workers to high-wage firms and low-wage workers and low-wage firms. In this paper, assortative matching/assortativeness relates to matching of better players (workers) to better teams (firms) and vice versa.

in the Appendix.

2 Background

2.1 Literature Review

The empirical literature analyzing competitive balance varies in its measurement of competitive balance as it can be interpreted in various ways. For example, it can refer to the number of different teams winning a title or how points are distributed across clubs at the end of a season. However, in the theoretical literature it is commonly agreed that the distribution of talent defines competitive balance. Therefore, we define competition in a league as balanced if there is an equal and stable distribution of talent across teams. This connection between player talent and competitive balance was first stated and theoretically analyzed by Rottenberg [1956] who pinned down the peculiarities of the sports industry and investigated the effects of the reserve clause (limiting player mobility) in American baseball. As described by Cairns et al. [1986], there are specific demand-side externalities to this industry:

For a single club its own playing success will also be significant. Hence a given team may have incentives to continue increasing its playing strength vis-à-vis its competitors, generating attendances for itself without taking account of any external costs of reduced attendances elsewhere, due to lessened uncertainty of outcome.

This peculiarity of sports economics is also described in Neale [1964] by the *Louis-Schmeling Paradox* refering to the two famous boxers. While firms in 'normal' markets seek for monopoly in order to maximize profit and diminish competition, there would be no profits at all in sports if there were no surviving competitors. Louis needs Schmeling (and vice versa) in order to create an entertaining competition.

The important question in the literature is whether teams internalize these demand-side externalities and whether *rich clubs [...] outbid the poor for talent, taking all the competent players for themselves and leaving only the incompetent for the other teams* Rottenberg [1956]. Rottenberg, however, finds that there is no need for a reserve clause or other restriction on player mobility to ensure competitive balance. This result is known as the *invariance principle*, which is primarily derived from the assumption that clubs are profit maximizers and that they internalize these externalities. Sloane [1971] has questioned whether this assumption can be applied to European football, deriving a model in which teams are thought to be utility maximizers subject to a budget constraint. In this setting, there is no equilibrating force towards competitive balance. Top players are attracted to big market teams in order to maximize the probability of winning. In this setting, a balanced competition is not necessarily reached endogenously, see Koning [2009] for an overview. This setting gives justification for imposing restriction rules on competition, as analyzed, for example, by Szymanski und Késenne [2004] for gate revenue sharing. This short review shows that a not too equal distribution of playing talent is a vital element of sports industries. These theoretical models give ambiguous predictions about whether competitive balance is an equilibrium or not. Therefore, we offer a novel approach to look empirically at trends in competitive balance, measured by the changing distribution of playing talent across clubs, for two decades of the German Bundesliga.

Empirical research on trends in competitive balance generally returns ambiguous results concerning changes in Germany. It is not clear whether competitive balance has actually decreased or remained stable throughout the history of the Bundesliga. Goossens [2005], Feddersen [2006], Feddersen und Maennig [2005] , Koning [2009] and Haan et al. [2007] detect no significant changes in competitive balance, whereas Pawlowski et al. [2010], Partosch [2014], Groot [2008] and Michie und Oughton [2004] have found evidence for decreasing competitive balance. Similar results are found for other European leagues. Generally, results vary depending on domestic leagues, time periods and on the application of different measures of competitive balance. In the case of decreasing competitive balance, changes can be attributed to regulatory developments, as in the case for gate revenue sharing, investigated by Robinson und Simmons [2014]. Other factors determining competitive balance include the Bosman Ruling, as investigated by Binder und Findlay [2011], or the Champions League, see e.g. Pawlowski et al. [2010]. The majority of these studies primarily apply descriptive methods based on final rankings, analyzing competitive balance based on aggregated seasonal outcomes and assessing trends by tracking competitive balance measures over time, such as the Herfindahl-Hirschman Index or the standard deviation of winning percentage. To our best knowledge, no study has yet directly analysed the distribution of playing talent across clubs.

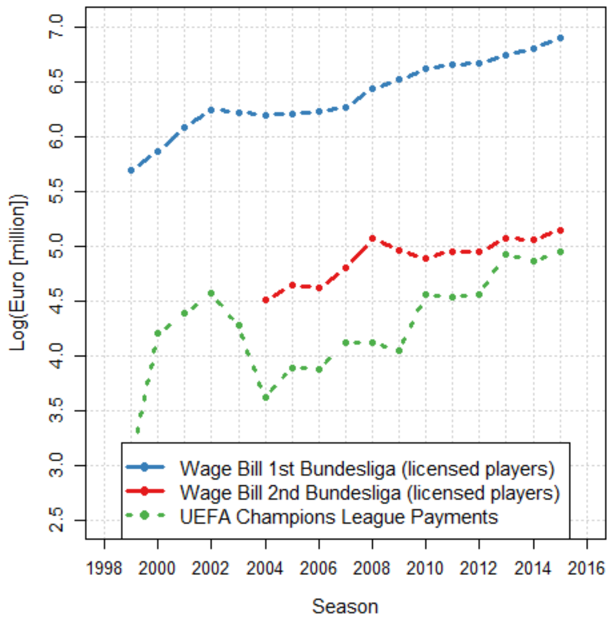
The direct channel of transfers and its effect on competitive balance has rarely been analyzed in sports. Maxcy et al. [2007] analyzes Baseball player transfers after changing the MLB's system of revenue sharing to a more egalitarian system. Maxcy et al. [2007] finds that this change in 1997 resulted in increased divesting in talent of low revenue producing clubs. For football, Robinson und Simmons [2014] examine player mobility before and after the abolishment of gate revenue sharing in England. They find increased probability of better quality players to move to bigger teams afterwards (inter- and intra-divisional). But rather than looking directly at player distribution, these studies investigate changes in player movement after certain league policy changes.

Summing up, it is generally acknowledged that player talent is the most important factor determining (long-term) success of football teams, as seen, for example, in the high correlation between average team wage bill and performance, compare Hall et al. [2002]. Theoretically, Rottenberg [1956] and Késenne [2000] assume the distribution of player talent to be a crucial determinant of competitive balance: 'Competitive balance in a sports league [...] depends primarily on the distribution of player talent among teams'. Given the importance of the debate and the rich literature on this topic (e.g. Szymanski [2001] or Flores et al. [2010]), it is surprising that there are only a few studies which actually consider disaggregated player data. Most studies simply rely on information about end-of-season league position to look at trends in competitive balance. We use a new measure of player performance, similar to the Plus-Minus statistic used in ice-hockey. By focusing on the team's net scoring, compare for example Macdonald et al. [2012], this individual performance measure has been successfully applied to estimate a player's impact on a match in other sports than football.[3] Our performance estimates then enable us to identify changes in the assortativeness of players to teams, thus enabling these trends to be connecting with competitive balance.

2.2 Bundesliga in 1998-2016

The Bundesliga is one of the "Big Five" leagues in Europe which dominate continental club football competitions. Findings based on the German league are therefore highly relevant for other sports leagues in Europe and further afield. Providing a background for the empirical analysis, this passage briefly summarizes the main structural changes in German professional football in the course of the last 19 seasons, giving an overview of the economic and sporting development in the Bundesliga.

Figure 1: Revenue and Expenditure Streams



Source: DFL [2006–2015] and UEFA [2004–2015], Partosch [2014]. No data is available for 1997/98, for 2015/16 and for the 2nd Bundesliga before 2003/04.

Economic Development

At first sight the period between 1998 and 2016 can be economically characterized as a boom period for the German Bundesliga. A more detailed look at the development of different revenue and expenditure streams of all clubs in the Bundesliga, however, using reports on the economic situation of the Bundesliga (published annually by the DFL [2006–2015]) and information gathered by Feddersen [2006] and Partosch [2014],

[3] While writing this paper, we became aware of another paper using a similar model to look at player performance in football: Sæbø und Hvattum [2015] concurrently show the usefulness of this measure for football analysis using transfer fees as outcome. However, this study neither looks at the team dimension nor refers to competitive balance.

reveals that the period considered in our study can in fact be separated into two to three different periods. Financial data is available for the seasons from 1998/99 to 2014/15.

Figure 1 plots the logarithm total wage bill for licensed player by division for each season plus UEFA Champions League revenues to top teams. For the 1st Bundesliga, personnel expenditures follow a corresponding progress throughout the period. There was a large increase in playing staff expenditures in the early period (1998-2002). This is caused by a huge increase in TV-right revenues. The Kirch media group was the major contributor to this development, investing massively in Bundesliga TV rights at the turn of the millennium.[4] The turning point was caused by the Kirch insolvency in 2002 and the following 5-6 seasons are characterized by an adjustment process in the aftermath of this. From 2008 onwards, all revenue and expenditure categories in the 1st Bundesliga grew constantly throughout these seasons. A very similar distinction in periods can be observed for Champions League revenues of German clubs (see Figure 1), strongly connected to their international sporting success, as will be discussed below. The development in the 2nd Bundesliga, for which no data is available before 2004, is more influenced by the relegation of certain well-endowed teams, the peak in 2008 is for example due to the presence of teams such as Bor. Mönchengladbach, 1899 Hoffenheim or FC Köln. The difference in personnel expenditures between the 1st and 2nd Bundesliga has considerably grown over time, it more than doubled from 402 million Euro in 2004 to 826 million Euro in 2015.

Regulatory and Sporting Development

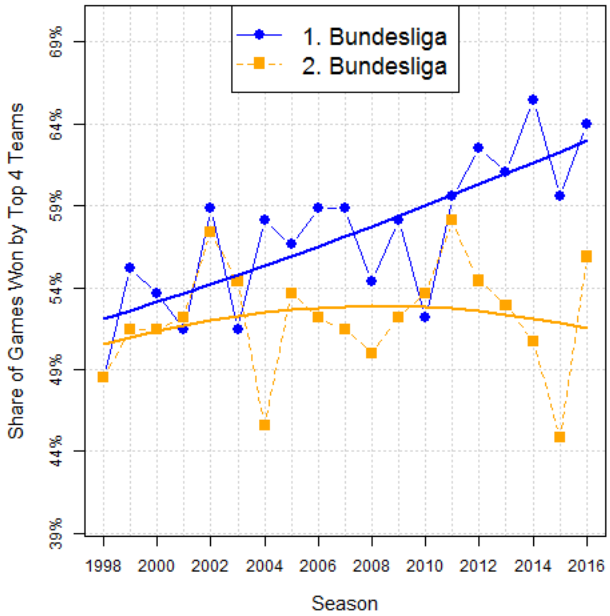
Besides a change in the format of relegation, no major regulatory changes took place between 1997-2016. Prior to 2008/09, three teams were promoted or relegated between the first two divisions of the German Bundesliga at the end of each season. Since 2008, when the relegation playoff was introduced, the team finishing 16th in the first league plays the team placed third in the second league.[5] Since 2009, only two play-offs have been won by the lower division team. In total, only eight teams have stayed in the 1st Bundesliga during the entire sample period.

The championship outcome in the 1st Bundesliga is mainly dominated by FC Bayern München, who won the Bundesliga 12 times during the observed 19-year period. The remaining 7 championship titles are distributed as follows: three times Borussia Dortmund and once Werder Bremen, VfB Stuttgart, VfL Wolfsburg and FC Kaiserslautern. Some teams were able to compete with FC Bayern München during more than one season. These teams, however, such as Werder Bremen since 2010/11 or Borussia Dortmund between 2004/05 and 2009/10, failed to regularly qualify for international championships. No other team than Bayern München showed a consistently excellent level of performance, winning a record four consecutive championship titles between 2012/13 and 2015/16.

[4] Compare Frick und Prinz [2006] who give an overview of the development of the financial situation in the Bundesliga up to 2003.

[5] During the entire Bundesliga period, there was already a relegation play-off in place between 1982 and 1991.

Figure 2: Share of Games won per Season by Top Four Teams (By End-of-Season League Position)



Note: The lines represent non-parametric kernel density regression curves.

This dominance is also reflected in Figure 2 which shows a standard measure of competitive balance; the average share of games won by the four best teams according to the end-of-season league table for the first two divisions.[6] For the 1st Bundesliga this measure shows a more or less continuous increase in the dominance of the top teams or, accordingly, a decrease in competitive balance over time. In contrast, no trend is observed for the 2nd Bundesliga.

3 Data and Empirical Framework

Match day reports taken from the online web page of the German *Kicker Sportmagazin* provide the data base. It contains detailed match day data for 11,626 matches played in the first two divisions of the German Bundesliga between 1997/1998 and 2015/2016.[7] Table 1 summarizes the characteristics of this data set. Furthermore, we add all DFB-Pokal (German Cup) games between teams which play in a given season in one of the first two divisions. This allows us to observe in-season matches between teams from the two different divisions and increases the precision of our results. To assure comparability between Bundesliga and cup matches, we use the results achieved in cup matches after 90 minutes, ignoring extra time or penalty shootout.[8]

[6] This graph looks very similar for other measures, e.g. the standard deviation of points.

[7] There are 5,813 games in each divisions. Two games (one in each division) are missing because those games were judged by the DFB sports court after the game. These are St. Pauli vs Schalke 04 in the first division in 2010/11 and FC Rot-Weiß Erfurt vs SpVgg Unterhaching, 2004/05 in the second division.

[8] Including German Cup games does not alter our results. The number of draws after 90 minutes is quite similar between Bundesliga matches (26.3%) and German Cup matches (26.7%) and statistically they are not distinguishable from each other (according to a t-test, p-value: 0.84). The front runner wins almost 55% of cup matches after 90 minutes between two teams from different divisions and in only 20% of the

Table 1 shows the sample sizes of the whole sample and the subset of players and coaches we use in most analyses. In general we include only players who have played in at least 50 games in the two divisions, and consider coaches who have Bundesliga tenure of at least 18 games. Estimation of player or coach performance is very imprecise for individuals with only few observations. We show in the Appendix that the sample restriction does not change our results.

The number of matches and teams is not reduced in the restricted sample.[9] Further information is available in the Appendix.

Table 1: Descriptives of the Population and the Main Sample (Players >= 50 Games and Coaches > 17 Games)

	Total	1st Bundesliga	2nd Bundesliga	German Cup
# Matches	12,133	5,813	5,813	507
# Teams	73	36	65	72
# Players	5,072	2,795	3,736	3,224
# Players (>=50 Games)	2,140	1,645	1,601	1,469
# Coaches	364	170	285	222
# Coaches (>17 Games)	215	127	171	181

Note: We include only German Cup games between two teams which both play in either of the top two divisions of the Bundesliga in a given season. The row "Players (>=50 Games)" should be read as follows (similar for coaches with more than 17 games): There are 2,140 players who appear in at least 50 matches in the both divisons or the cup, 1,645 out of them play at least one of those 50+ games in the 1st Bundesliga.

As already stated, we first introduce a new performance measure for player, team and coach performance which we then use to investigate changes in competitive balance over time. This performance measure is the partial correlation of each player (and team and coach) with the goal margin, derived from a simple linear regression of goals scored minus goals conceded (taking into account the exact minutes when goals were scored or how the lineup changed through substitutions or dissmissals) on players, team and coaches, plus a few control variables.

Though rarely used in the empirical literature, goal margin is a particularly suitable measure to reflect inequality in player talent. Firstly, player productivity, in terms of the goal margin outcome, can be directly and frequently observed on an almost weekly basis, without the need to aggregate a huge number of statistics (and is aplicable also for the youth sector where detailed statistics are not available). Secondly, it captures the defensive and attacking quality of teams. Both components are probably more or less equally important, particularly for competitiveness in the long run. Thirdly, the goal margin is important for achieving success in sports such as national championship or cup titles since winning or losing can be directly derived from the goal margin. Finally, besides capturing

cases does the underdog win, although 62% of those matches are played at the home stadium of the second-division team (the home distribution between the divisions is skewed due to certain rules that lower-tier teams are allowed to play at home in early rounds of the cup).

[9]Although there are many players who play in fewer than 50 games in total, they do not have a large influence on the results since the distribution of total games played is very right-skewed. Players appearing in more than 50 games in total account for 86% of all player-game observations and for 88% of all minutes played.

variation from match to match, we can also include within-game changes in the lineup by looking at the exact minutes of goals scored.

To measure separate individual performance, we run a simple linear regression, sometimes referred to as a hierarchical fixed effect model, which captures the goal margin on player, team and coach fixed effects and further controls:

$$\text{Goal\_Margin}_{it} = \gamma_i + \lambda_{J(i,t)} + \varphi_{G(i,t)} + \lambda^{\text{O}}_{J(i,t)} + x_{it}\beta + \varepsilon_{it} \tag{1}$$

Further information about the goal margin is given in the next paragraph. This empirical framework considers all matches from the viewpoint of each player who starts or is substituted for a team in a given match. The goal margin of player i on match day t is assumed to be linear function of a player fixed effect γ_i, a team fixed effect λ_j - where $J(i,t) = j$ if player i plays for team j on match day t-, a coach fixed effect φ_k -where $G(i,t) = k$ if coach k manages player i on match day t -, opponent fixed effects λ^{O}_j, time varying characteristics x_{it} and a noise term ε_{it}. x_{it} includes possible league and season effects (such as rule changes etc.) and a dummy if the player plays for the home team. We interact the season indicators with league information as well as with the home advantage indicator to allow home advantage, for example, to vary non-linearly over time. Furthermore, we include the age of players of i at match day t (and age squared) and control for the number of times players from both teams are sent off during a match (either no dismissals, one dismissal or two and more dismissals for a team in a match).[10] Our sample size is 287,685 which means that we observe on average 23.7 players each game, where each players is observed in at least 50 games during the whole period.[11]

The goal margin represents the difference between goals scored and goals conceded for team J_i of player i for the time he is on the pitch. We look at in-game changes by tracking minutes of substitutions and replacements, dismissals and of course, the timing of goals scored. The goal margin generally equals the final score for players who appear in the lineup and are not replaced during a match. Players therefore have a different impact on a game depending on the total number of minutes played. Equation (1) is estimated via weighted least squares dummy variable regression.[12] Observations are weighted by the fraction of minutes played in each match. Accordingly, players replaced in minute x are weighted by $x/91$, players brought in minute x are weighted by $(91-x)/91$ and players starting and finishing a match are weighted by 1.

The following example, Bayern München vs. FC Augsburg (32nd match day, 2014/15), illustrates our approach. Bayern München lost on home ground 0:1, with Augsburg's Bobadilla scoring in the 71st minute. Table 2 depicts information for three selected players of this match in our final data set. Philipp Lahm was chosen to be in the starting line up by his coach Guardiola, but he was replaced in the 14th minute. Since the score

[10] Results are robust to not including age and age squared.

[11] The maximum is 28 since 22 players are in the starting lineup and up to 3 players in each team may be replaced during match. Teams tend to use all 6 possible substitutions in the majority of games (in slightly more than two-thirds of all matches).

[12] Results are very similar if we estimate Equation (1) via ridge regression, see Appendix A.2.2.

up to this point was 0:0, Philip Lahm's contribution in this match is a goal margin of 0 and he is weighted by the fraction 0.15 in this match. Meanwhile, his team-mate Robert Lewandowski played on the pitch until the 74th minute and was therefore on the pitch when Augsburg scored their winning goal. Hence, he is observed with a goal difference of -1 and he is weighted by the fraction 0.81 in this match. Additionally, since Bayern München received a red card in this match, we control for the number of players on the pitch, as well as for the number of players for the opposing team. To take one example from FC Augsburg, Abdual Rahman Baba played through all the minutes and is therefore weighted by 1 and attributed a goal difference of 1. Since his team received no red card, the number of players on the pitch for FC Augsburg is 11, while their opposing team, Bayern München, only had 10 players on the pitch.

Table 2: Example: Bayern Munich vs. FC Augsburg (09/05/2015)

Goal Difference	0	-1	1
Player	P. Lahm	R. Lewandowski	A. Baba
Team	Bayern München	Bayern München	FC Augsburg
Coach	Guardiola	Guardiola	Weinzierl
Home Ground	1	1	0
Minute Out	14	74	91
Minute Fraction	0.15	0.81	1
Age	31	26	20
Number of Players on Pitch, Team	10	10	11
Number of Players on Pitch, Opponent	11	11	10

Returning to our empirical framework, the player component γ_i is interpreted as the average impact of a player on the goal margin, involving a combination of different skills, such as work rate and a talent factor. With regard to competitive balance, γ_i represents a short-run factor for explaining performance inequality. In contrast, λ_j reflects long-run team heterogeneity. λ_j influences team performance as an average institutional goal premium (or expectation), capturing, for example, the effectiveness of official boards in constructing a competitively viable team, the quality of training facilities and other resources, such as physical therapists among others. Additionally, φ_k reflects the average effectiveness/ability of each coach, controlled for the amount of player talent and resources available. In line with the interpretation of the other parameters, the coach effect captures performance heterogeneity in the medium run. Time varying characteristics include season dummies, opponent fixed effects and a home dummy. Opponent fixed effects $\lambda^{O}_{J(i,t)}$ control for the opponent team j faces on match day t and the home dummy represents a goal premium evoked by the home advantage. Fan support or a greater tendency to play more aggressively and offensively on home ground provide evidence for the home advantage in soccer, which is not assumed to be part of competitive balance. Furthermore, the impact of a single player is not fixed and may change over the life-course. We therefore add age and age squared to capture career-related performance changes. Equation (1) does not take into account that the outcome is the same for all players of one team in a given match. We run another specification on the match level to account for possible effects of fellow players, among others, which gives similar results and is described in the

Appendix.

Hierarchical fixed effects models have become popular in different fields in economics in recent years. Bertrand und Schoar [2003] for example looked at the effects of managers on firm performance while Chetty et al. [2014] use such an approach to study long-term effects of teacher quality on students. Card et al. [2013] decompose changes in variation of individual wages in West-Germany with respect to variation of person and establishment effects. Hentschel et al. [2014] transfer this model to football by analyzing the impact of coaches on team success between 1993/1994 and 2013/2014 (without considering player talent). Applying a very parsimonious approach, they include team fixed effects, coach effects and half season effects in order to explain the average number of points gained by a coach during a half season. Exploiting the fact that coaches move frequently between teams, they are able to disentangle coach and team fixed effects. Whilst the findings are interesting in their own right, facilitating the identification of under- and over-performing coaches, they also provide evidence that coaches or executives generally play a considerable role, affecting organizational performance.

The available data set turns out to be particularly suitable for this indicator of performance. The important feature of this data set is the availability of a high share of players and coaches moving between teams – a prerequisite for the precise estimation of their separate impact on sporting success [Abowd und Kramarz, 1999]. The system of relegation and promotion in football also contributes to a high fluctuation of players, coaches and teams between seasons. Amongst all players in our sample, an average of 50% remain in the same team from one season to another, 15% move to another team in our sample and 35% drop out of the sample (e.g. retire or move abroad). Table 7 shows that more than 70% of all players with at least 50 games play for at least two different teams. The same is true for 58% of all coaches (with at least 17 games). For our main sample of players who appear in at least 50 Bundesliga games, 59% are retained, 19% move and 22% drop out. Regarding teams, only eight teams managed to stay in the 1st Bundesliga all 19 seasons, while 28 different teams were relegated to the second division at least once in the course of the 19 seasons. As relegation is connected with great losses in revenues, the likelihood of a team being relegated is closely related to changes in the distribution of talent across teams.

4 Empirical Results

4.1 Player and Team Performance

Before considering trends in competitive balance (in Section 4.2), we will provide an overview of the results from estimating Equation (1). We focus here on the results derived from the sample of players who appear in at least 50 games. Further analyses and robustness checks to other specifications are available in the Appendix.

Results are generally in line with expectations and with existing literature. Unsurprisingly, home advantage is associated with a large and statistically significant advantage with respect to the goal margin. This applies across all seasons, comparable to having one top player (98th-percentile of the player performance distribution) on the pitch rather than one median player.[13] The magnitude of the home advantage is comparable between both divisions of the Bundesliga, but it is larger in the German Cup. It decreases strongly over time, the reduction being by more than 40% over the sample period (see Table 3. Age follows an inverse U-shaped pattern with player performance with an insignificant positive coefficient for the linear age term and a strong and highly significant negative coefficient for age squared. The estimated decline in performance with age is considerable; a player at the age of 30 has on average a lower performance of 0.8 standard deviations of player fixed effects. Dismissals (yellow/red and red cards) are strongly associated with the goal margin (for either the own or the opponent team).

Player, team and coach performance measures are all important predictors of the goal margin. This is shown by simple F-statistics of joint significance, which gives a p-value of nearly zero for players, teams and coaches, respectively. A variance decomposition (available upon request) shows that team heterogeneity is the most important performance dimension, followed by coach differences and finally player heterogeneity.[14] Given that there are eleven players on the pitch, but only one coach for each team, this variation in the performance measures seems plausible. It highlights the importance of medium to long-term institutional factors for success in football. The variance decomposition shows also that the residual variation makes up slightly more than 80% of the total variation. Again, this is not surprising given the difficulties of predicting football matches and the discrete nature of our outcome.

Analyzing the estimated effects in more detail, Table 4 presents percentile differences of team, player and coach effects and their corresponding difference in the goal premium. For example, a player at the 5th percentile in the player effects distribution, whilst replacing a player at the 95th percentile yields, on average, ceteribus paribus, a goal premium of 1.03. Particularly in view of the fact that superstars such as Robben, Gündogan or Thomas Müller are representing the top percentiles of player distribution, the difference identified in performance and ability is deemed reasonable. These players indeed have the ability to turn a match around, with high influence on the goal margin outcome due to their single contribution.[15] Figure 12 shows the distribution of player performance for players who appear only in the 1st Bundesliga (25%), those who always play in the 2nd Bundesliga in the sample period (23%), and those who play for teams in both divisions (52%). The distributions look reasonable with a clear hierarchy but considerable overlap between players in different divisions. The density estimation is based on the 2,138 individual players who play in at least 50 games during our sample period. The density

[13]For statistical tests, we carry out multi-way clustering by teams and players as described in Cameron und Miller [2015] for non-nested hierarchical data.

[14]As a proxy for this analysis one can look at the standard deviation of teams (sd(λ) $\approx$ 0.522), which is approximately two-thirds larger than the standard deviation of the player performance distribution (sd(γ) $\approx$ 0.307) with coaches being in between (sd(φ) $\approx$ 0.376).

[15]Nonetheless, there are some surprising results for players who have played in relatively few games.

Table 3: Estimation Results, Sample 50+

Player, Team and Coach Parameters	
Number of player effects	2140
Number of team effects	73
Number of coach effects	214
Summary of parameter estimates	
Std. dev. of player fixed effects	0.307
Std. dev. of team fixed effects	0.522
Std. dev. of opponent fixed effects	0.510
Std. dev. of coach fixed effects	0.376
Other parameters and statistics	
Mean Home advantage in 1998-2000	0.804
Mean Home advantage in 2014-2016	0.468
1 dismissal own team	-0.681
2+ dismissals own team	-0.917
1 dismissal opponent	0.671
2+ dismissals opponent	0.920
Age (standardized)	0.104
Age squared (standardized)	-0.201
RMSE	1.6893
Adjusted R-squared	0.198
Std. dev. of goal margin	1.49
Sample size	287,685

Note: Results from Equation (1). The number of parameter and their standard deviation include reference groups.

estimation is slightly skewed to the left, this is a reflection of the fact that better players play, on average, in more games. We find a similar convincing hierarchy for the sum of team and coach effects (see Figure 4).

Player performance measures are closely related to professional grades attributed by the *Kicker* sports magazine. Amongst other things, these grades have been used in Buraimo et al. [2015] to analyze moral hazard aspects with respect to contract length of Bundesliga players. If we run the same Equation (1) for grades rather than for the goal margin, we find a correlation of $\rho \approx -0.79$ between our performance measure and the coefficients derived from the regression with grades as outcome (in Germany lower grades are better), see Appendix.

Looking at percentile differences for coach effects, we also see a strong dispersion in coach abilities. The difference between the 95th and 5th percentile in the coach distributions constitutes a goal margin of approximately 1.26. Again, comparing these results with common perception of coach ability supports the plausibility of our results. For instance, top coaches such as Jürgen Klopp or Thomas Tuchel are found in the top percentiles of our coach effects distribution (along coaches such as Martin Schmidt who currently manages Mainz 05 or Edmund Becker who promoted Karlsruher SC to the 1st Bundesliga). Our results also confirm the importance and great contribution of managers to organizational success, as illustrated by Hentschel et al. [2014]. We find strong rank correlation between our estimated coach effects and their coefficients for coaches which are estimated without taking players into account.

Table 4: Percentile Difference of Team/Player/Coach Fixed Effects in the *50+Sample*

	Corresponding Goal Margin Impact		
Percentile Difference	Team FE	Player FE	Coach FE
95th - 5th	1.53	1.03	1.25
90th - 10th	1.25	0.80	0.92
75th - 25th	0.70	0.42	0.44
75th - 50th	0.32	0.23	0.20
50th - 25th	0.38	0.19	0.24
# Parameter Estimates	73	2140	214

Note: Results from Equation (1). Reference groups are included.

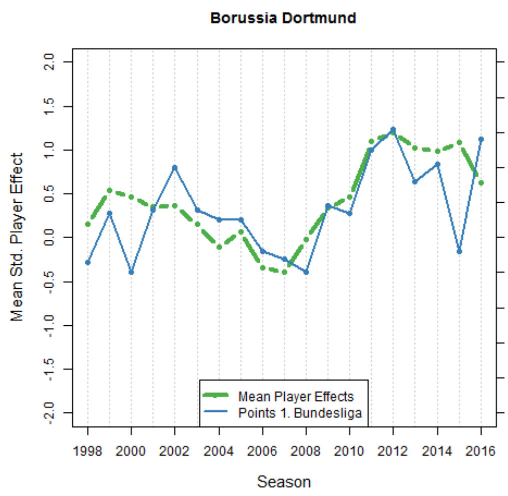
We observe strong trends in average performance over time, which is a well-known issue for various rating measures (e.g. in chess *Elo*-ratings which have been adapted to football). We cannot determine the extent to which this phenomenon is caused by for example true performance gains over time or reflects statistical artifacts. In the following, we therefore standardize team, player and coach fixed effects by season by subtracting the respective season-specific mean effect and dividing by the respective standard deviation (of players or coaches within a season). Standardizing does not alter the interpretation of our results because the covariance of standardized variables is simply the correlation.[16]

[16]Results regarding player talent are very similar. The Pearson correlation between players (non-

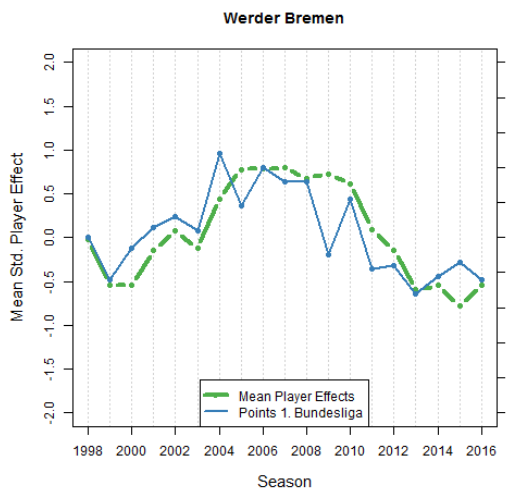
Where we illustrate aggregated individual performance measures (such as in Figure 4), we simply average season-specific standardized fixed-effects.

Figure 3: Mean Player Effects

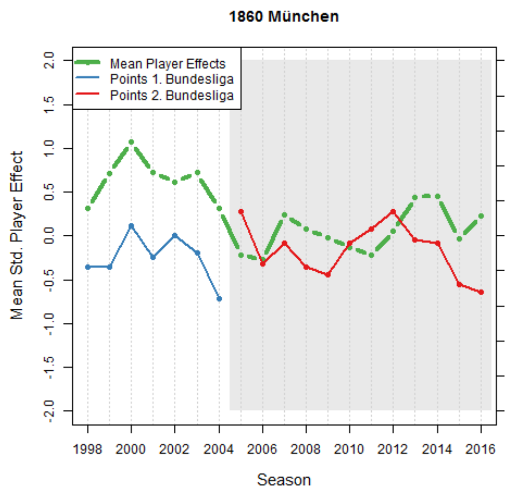
(a) Borussia Dortmund



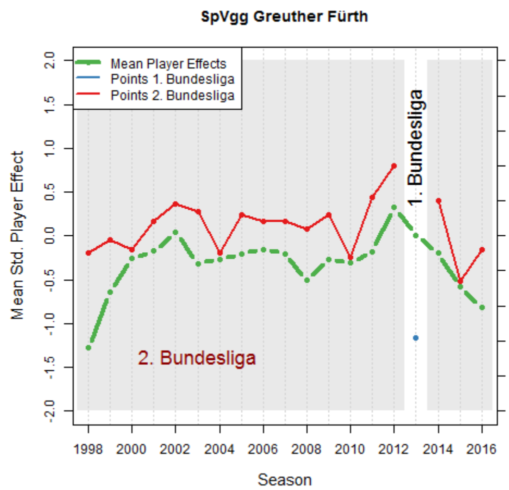
(b) Werder Bremen



(c) 1860 München



(d) SpVgg Greuther Fürth



In regard to estimated player productivity, Figure 3 reveals (unsurprisingly) that the mean player fixed effects and average points have a corresponding development for different teams. A first glance at trends in player performance over time amongst clubs which are observed in the entire sample period, gives an initial indication of declining competitive balance.

Amongst the teams who have made gains in terms of player talent are Bayern München, Bor. Mönchengladbach, FC Schalke 04 and, perhaps surprinsingly, Eintracht Frankfurt. Teams such as 1. FC Kaiserslautern, 1860 München, 1. FC Nürnberg, Hertha BSC and Werder Bremen, for example, have lost out in this area.

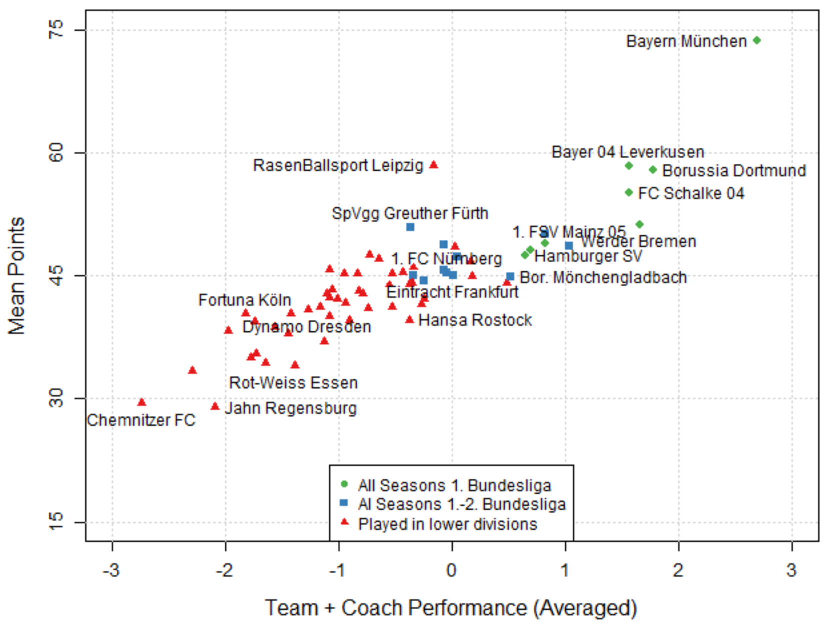
Looking at Werder Bremen (Figure 3(b)), we can see a strong connection between

standardized) fixed-effects and the mean of the player fixed effects standardized by season is $\rho = 0.86$ and the Spearman's rank correlation coefficient is $\rho = 0.84$.

both measures of performance. In 2003/04 Werder Bremen won the Bundesliga championship and in the following seasons were able to regularly qualify for the Champions League, resulting in steadily rising mean player effects. Failing to regularly qualify for international competitions since 2008/2009, however, Werder Bremen has experienced a sharp decline in final league positions, as well as in average player talent. The drop in mean player performance of Werder Bremen before the season 2008/09 and in 2010/11 is one of the largest in the whole sample. In summer 2010, Werder Bremen lost Mesut Özil (to Real Madrid) while Naldo (who won the German cup with Wolfsburg in 2014/15) was severely injured such that he missed the whole following season. Both Özil and Naldo are well ranked players. A similar development can be seen for Borussia Dortmund (Figure 3(a)). In this case, however, we can see that the financially challenging seasons between 2004 and 2009 had a rather modest influence on average player talent. In contrast, Borussia Dortmund's recent success in the Bundesliga is characterized by a huge increase in player productivity. Robert Lewandowski, Mario Götze and Shinji Kagawa were, for example, amongst the best ten players in the season 2011/12. Figures 3(c) and 3(d) show different trends in player talent for 1860 München and SpVgg Greuther Fürth, two clubs who played in both divisions during the sample period. While 1860 München shows a more or less long-term decline in player talent, we see a inverted U-shaped series for SpVgg Greuther Fürth which succeded to be promoted to the Bundesliga in 2012/13 but was relegated after only one season.

Regarding team effects, Figure 4 depicts the relation between the estimated (conditional) team effects added to their corresponding mean coach effects and the (unconditional) average points gained by each team. We find a strong positive relation between the two measures of team performance ($\rho \approx 0.89$).

Figure 4: Team + Mean Coach FE and Mean Points by Match



All together, these results confirm the plausibility of our estimated effects as well as the validity of splitting team productivity into a team (long-term), coach (medium term) and player (short term) component. It also reveals a high dispersion of, for example, player effects, indeed implying high inequality within the Bundesliga. The next section addresses this issue by looking at the correlation of player and team effects over time.

4.2 Assortative Matching of Players to Clubs

Returning now to competitive balance, we identify decreasing competitive balance on the basis of rising assortativeness of players in regard to the teams they play for. We understand increased assortative matching to imply that teams with high long run productivity increasingly attracted players with high individual productivity, while players with low productivity are increasingly signed by teams with lower long run productivity. We have already seen in the previous section that teams such as Bayern München or Schalke 04 have managed to attract better player talent, but does this indicate rising assortative matching in general?

To answer this question, we focus on the pattern of player movement by looking at the correlation between our team and player effects for each season. This correlation indicates the degree of imbalance for each season, providing insight into whether better players increasingly migrate to teams which exhibit long-term success. This in turn provides direct insight into the allocation of talent as a measure of competitive balance.

We look at each club's squad in a season and analyze the correlation between club and player fixed effects. The squad consists of all players who participate in at least one game for a given team during a season (weighted by the number of minutes played to take into account individuals' playing time). If players switch clubs in the winter break, they may therefore appear twice in the sample. Club effects are defined as the sum of team and coach fixed effects.[17]

$$Cor_x = Cor\Big(\overline{\gamma}_{j,T}\,, \overline{\lambda_j} + \overline{\varphi}_{j,T}\Big) \tag{2}$$

Where $\overline{\gamma}_{j,T}$ are standardized (by season) fixed effects of all players of team j in season T, $\overline{\lambda_j}$ are standardized team fixed-effects of team j and $\overline{\varphi}_{j,T}$ are standardized and seasonal-averaged coach-fixed effects of team j in season T.[18] All parameters are estimated via Equation (1) and player fixed-effects are weighted by minutes played in matches in the Bundesliga (1st or 2nd division, German Cup games are not considered here).

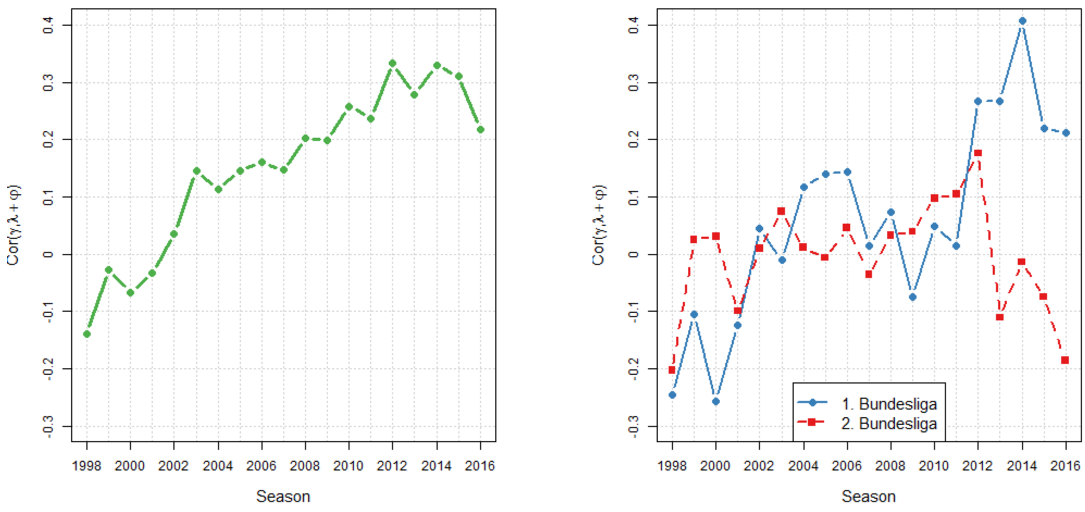
Figure 5(a) plots the correlation coefficient for the main sample, Sample 50+. There is a clear rising linear trend revealing increased assortative matching throughout the period. Better players increasingly tend to play for superior teams and the opposite is true for

[17] An average coach fixed effect is calculated for each season and for each team in order to incorporate possible coach switches during a season. Results are very similar if we do not consider coaches at all and just look at the correlation for players and teams.

[18] Results are almost identical if we look at $Cov(\gamma_{j,T},) = \frac{1}{N-1}\sum\big((\overline{\gamma}_{j,T})(\overline{\lambda_j} + \overline{\varphi}_{j,T})\big)$ as in Card et al. [2013].

Figure 5: Assortative Matching

(a) Both Leagues (b) By League



weaker teams.[19] This increase was most marked between 2000 and 2003. This was followed by a more or less linear increase until 2012. Assortative matching seems to have stagnated on a high level since 2012.[20] This is in line with the results of simple measures such as the share of games won by the top four teams (see Figure 2). This result is also confirmed by the other specifications and for different sub-samples, as seen for example in Figure 9 and Figure 10 in the Appendix.

Next, we investigate the reasons for the reduction in aggregated competitive balance over time. To answer the question whether this development is driven by between or within divisional transfers, we apply a simple statistical decomposition. We decompose the pooled correlation of players to clubs using the *Law of total variance* which also applies to covariances (for simplicity, we look here at covariance terms):

$$
\begin{aligned}
&cov(\overline{\gamma}_{j,T},\lambda_j+\overline{\varphi}_{j,T}) = \qquad (3)\\
&\quad = \underbrace{E\left[cov(\overline{\gamma}_{j,T},\overline{\lambda_j}+\overline{\varphi}_{j,T}\,|Z)\right]}_{\text{Changes within 1st and 2nd Bundesliga}} + \underbrace{cov\left[E(\overline{\gamma}_{j,T}\,|Z)\,,E(\overline{\lambda_j}+\overline{\varphi}_{j,T}\,|Z)\right]}_{\text{Changes between 1st and 2nd Bundesliga}}
\end{aligned}
$$

where Z is a binary variable indicating the division.

The first term in Equation (3) measures distributional changes of playing talent within both divisions. This terms allows us to analyze whether the decrease in competitive balance is for example mostly driven by increased inequality in playing talent in the 1st Bundesliga. Figure 5(b) shows indeed that assortative matching has increased in the 1st Bundesliga but not in the 2nd Bundesliga. For the former, we witness a strong increase in

[19]To some limited extent, better players in high-performing teams could also increasingly play more minutes.

[20]We place little importance to the drop in competitive balance to the season 2015/16 as there is greater uncertainty in the first and last seasons in our sample. This is because we observe fewer players in these seasons who play in a total of at least 50 games, due to the left- and right censoring of our sample. For this reason, we do not emphasize the negative correlation in the beginning of the sample period which is not apparent in the results for the Ridge regression which penalizes large coefficients, see Appendix A.2.2.

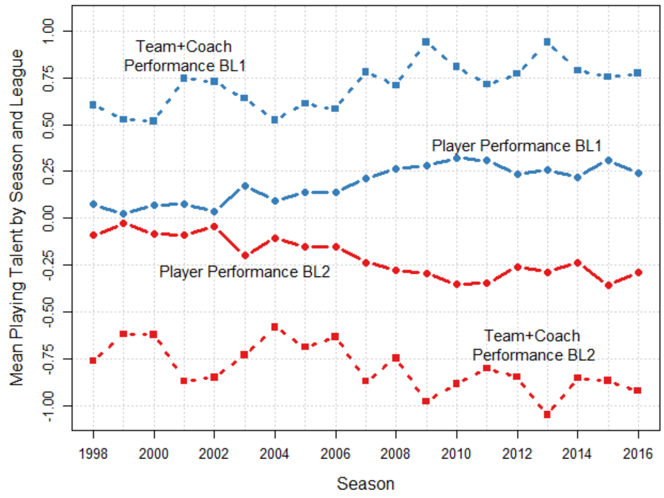
the assortativeness of player talent until 2004, followed by slight declines until 2009 and a subsequent strong increase. This pattern is not observed for the 2nd Bundesliga where the distribution of player talent remained more or less stable over time (perhaps except for a drop in assortative matching in recent years).[21] In particular, we see increased assortativeness amongst the 19 most established teams which we observe for all seasons in the sample. There is no trend, however, for the next 19 teams in the sample which we observe for between 7 and 18 seasons (or for all other teams). Bayern München is the record champion and the team with the highest fixed-effect (and highest average players fixed-effect) in the sample. This team is an important driver of this trend because it is also one of the teams with the largest increase in player talent. The increase in assortative matching is not, however, only due to Bayern München (see Appendix).

The second term in Equation (3) looks at assortative matching between the two top divisions. Here we investigate whether the 2nd Bundesliga loses ground to the top division. Since inter-divisional financial inequality has widened substantially (see e.g. Frick und Prinz, 2006 or Figure 1), we expect increasing heterogeneity of player talent over time between the first and second division. Furthermore, financial inequality has also increased within the 1st Bundesliga due to UEFA Champions League payments and advertisement deals. Figure 6 shows the trends in player performance and in the sum of team and coach performance by division over time. There is a clear trend in both performance measures. Player talent between the 1st Bundesliga and the 2nd Bundesliga has become increasingly unequally distributed over time with better players progressively appearing in the 1st Bundesliga. There are several explanations for this. Firstly, the 1st Bundesliga progressively managed to retain better players whilst the opposite is true of the 2nd Bundesliga. Secondly, weaker players increasingly tend to move down to the second division. Thirdly, better players tend to play more often (or more minutes) over time in the 1st Bundesliga but not in the 2nd Bundesliga. We see a similar trend of increasing polarization between both divisions for the additive measure of team and coach performance. Coach performance in particular has become stronger in the 1st Bundesliga but poorer in the 2nd Bundesliga over time. Looking at the only 1st Bundesliga season of SpVgg Greuther Fürth (see Figure 3), for example, our model would had predicted a positive goal margin of +14 if Fürth had remained in the 2nd Bundesliga, an absolute difference of 35 in goal margin compared to the prediction for the 1st Bundesliga. To summarize, it is clear that the first Bundesliga has become stronger over time, whilst the 2nd Bundesliga has lost ground.

Next, we link changes in competitive balance (approximated by changes in assortative matching) to financial information. Unfortunately, only limited information is available about the financial situation of German football clubs since they are not required to publish detailed accounts (see Frick und Prinz, 2006). Therefore, we have to rely on

[21] Results for the 2nd Bundesliga are less precise compared to those for the top division. This is because there are more teams in the second league which we are able to observe only for a few seasons (compare Table 9). Having said this, if analyses are restricted to teams which we observe for at least 5 to 10 seasons, results appear fairly similar.

Figure 6: Trends in Performance Measures by League



Note: Results from Equation (3).

aggregated data published by the UEFA and the German Football League (DFL).

Figure 1 shows total revenues from media contracts, match-day earnings, merchandising, advertising, transfers and other sources by league. This information is gathered from DFL Bundesliga reports available to us since 2006 (DFL, 2006–2015, unfortunately DFL could not provide data for the 2nd Bundesliga before 2004). The graph shows clearly that absolute revenues between 1st and 2nd Bundesliga have diverged. These differences in revenues are most probably the main driver of increased differences in playing talent between both divisions.

Several studies have highlighted the role of increasing payments to teams participating in the UEFA Champions League [Pawlowski et al., 2010, Binder und Findlay, 2011] in the reduction in competitive balance in Europe's major leagues. We link inflation-adjusted revenues from the UEFA Champions League (see Figure 1) to our measure of competitive balance (for the 1st Bundesliga only) and to a linear time trend. This is illustrated in Table 5. We use a lagged value of the UEFA Champions League payments to preclude possible reversed causality issues and take the logarithm of the annual payments made to Bundesliga clubs. The results indicate that UEFA Champions League may play a role for inhibiting competitive balance. Alongside a general trend towards increasing assortative matching (or a reduction in competitive balance), we find that competitive balance decreases in seasons after large UEFA Champions League payments have been made to Bundesliga clubs.

4.3 Drivers of Increassed Asortativeness

In this section, we look specifically at transfer and drivers of reduced competitive balance. As outlined in Section 3, more than 70% of all players (with more than 50 games in total) appear at least at two clubs (see Table 7), a necessary precondition for our analyses. Transfers often gain a considerable media attention, especially between Bundesliga teams: Mario Götze's move from Borussia Dortmund to Bayern München in 2013 was covered

Table 5: UEFA Champions League Payments to Bundesliga Clubs and Subsequent Competitive Balance

Outcome: Competitive Balance [$Cor(\overline{\gamma}_{j,T}, \overline{\lambda_j} + \overline{\varphi}_{j,T})$]			
	Estimate	Std. Error	t value
Log(Lagged UEFA CL Payments)	0.097$*$	0.060	1.61
Linear Time Trend	0.017$**$	0.0062	2.80
Intercept	$-0.536**$	0.2094	-2.56
n	18		
R^2	0.63		

*Note: Heteroscedasticity robust standard error; p-values **: p*< 0.01*; *:* $0.05 > p >= 0.01$.

by news channels as an "Earthquake in the Bundesliga" [Kulish, April 24, 2013]. Transfers between teams in our sample have increased slightly over time (today about 16% to 18% of all players in our sample played in the previous season for another team in our sample) and it is not a priori clear whether transfers are the main driver of decreased competitive balance. Bayern München, for example, won recent championships with several top players such as David Alaba, Philipp Lahm, Thomas Müller, Bastian Schweinsteiger who played already for their youth team. Bevor we look at the drivers of decreased competitive balance, we investigate whether our measure of player performance is predictive for movements to better teams.

Regarding transfers, common wisdom says that (only) one good season will bring you to a (much) better team but it should also be the case that the long-term performance matters for where you end up. We investigate this question looking at transfers only. To investigate career building and professional decline, we look at the change in average team effects between the destination and the origin team ($\lambda_{k,t} - \lambda_{j,t-1}$). As before, we use player fixed-effects γ_i as proxy for long-term performance. To measure short-term success, we look at the average residual $\overline{\varepsilon_{iT_i}}$ of individual i in the season T_i preceding the transfer. Both explanatory variables are standardized by subtracting the mean and dividing by the standard deviation to make effect sizes comparable. The results are shown in Table 6.[22] We see that both player fixed-effects and performance deviation from the long-term average in the season before a move are predictive for the difference in team strength due to the transfer. This highlights that player fixed-effects take into consideration (unknown) performance measures which are also relevant for scouts. Furthermore, scouts seem to take into consideration also performance during an often relatively short time period for a transfer.

In the following, we investigate whether player transfers between Bundesliga teams drive the reduction in competitive balance. We distinguish between three groups of players, those staying in the team, moving between teams in our sample and unknown moves. The first group are *Stayers*. *Stayers* are defined as players who have already played for the relevant club in the previous season. These players constitute almost 50% of our sam-

[22] Results are robust to including individuals who do not switch teams.

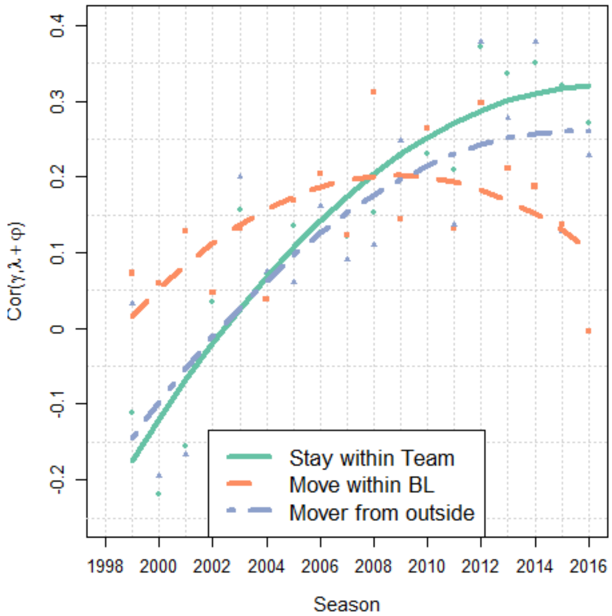
Table 6: Transfer Prediction

Outcome: Change in Team Fixed Effects ($\lambda_{k,t} - \lambda_{j,t-1}$)			
	Estimate	Std. Error	t value
Player Effect (Standardized)	0.0203$*$	0.0085	2.39
Average Residual in Season before Transfer (Std.)	0.0653$**$	0.0079	8.29
Intercept	-0.0058	0.0087	-0.66
n	2544		
R^2	0.0299		

*Note: Cluster-robust standard error (by player); p-values **: p< 0.01; *: 0.05 > p >= 0.01.*

ple. The second group consists of players who move between Bundesliga teams. In other words, players who play two consecutive seasons in either the 1st and 2nd Bundesliga but not for the same team (ca. 15%). *Movers* represent transfers such as that of Mesut Özil, who was sold by Schalke 04 to Werder Bremen in 2008, as well as loans such as that of Toni Kroos, who was loaned by Bayern München to Bayer Leverkusen in 2009 and 2010. A third group includes players for whom we do not know whether they previously played for the same clubs, but in a different division (e.g. youth team), or for another team not included in our sample, for a team in a lower division, or a team based abroad, for example (35%). Mesut Özil for example, is classified as *unknown* in 2010, as he moved to Real Madrid in the summer break. We match players with the teams to which they move or where they stay in the subsequent season and calculate Equation (1) separately for all three groups.

Figure 7: Assortativeness of Player and Club Fixed Effects by Player Groups



Note: Smoothing by cubic polynomial.

Figure 7 shows the correlation analysis for these three groups. The mover sample illustrates positive assortative matching to clubs for all seasons. This trend is fairly stable over time. This indicates that player transfers between Bundesliga teams reduces competitive balance by allocating better players to better teams. However, it is not only transfers which have caused the reduction in competitive balance over time. Bayern München, for example, is notorious for buying player talent from temporarily competing teams such as Bayer Leverkusen in the early 2000's (e.g. Michael Ballack or Lucio), Werder Bremen (e.g. Miroslav Klose or Claudio Pizarro) or, most recently, Borussia Dortmund (e.g. Mario Götze or Robert Lewandowski).

In contrast, the other two groups show a strong increase in assortativeness over time, up until approximately 2012. Reduction in competitive balance is therefore attributed to two other mechanisms. Firstly, the increased availability of up-and-coming young players to play in the top divisions of the Bundesliga has reduced competitive balance. These young players are trained in clubs' own youth academies, which have been mandatory since 2002/03, or are attracted to clubs at a young age. The transfer of players from abroad may also play a significant role here. Secondly, competitive balance may be reduced by the retention of certain players, e.g. top stars such as Bernd Leno, Thomas Müller or Marco Reus who could have left the Bundesliga in the mid 2000s, when German teams were performing badly in international competitions.

5 Conclusion

We offer a new approach to measuring player performance which enables us to investigate the role of player mobility for competitive balance. This approach allows us directly to test theoretical predictions regarding transfers of player talent as described by Cairns et al. [1986]: *Hence a given team may have incentives to continue increasing its playing strength vis-à-vis its competitors, generating attendances for itself without taking account of any external costs of reduced attendances elsewhere, due to lessened uncertainty of outcome.* Player performance is measured by the partial correlation of each player with his goal margin, taking into account substitutions, dismissals and other important contributors to team success such as home advantage. Using data relating to 19 seasons of the top two divisions of the German Bundesliga plus domestic cup matches, we investigate changing trends in the distribution of player talent across clubs. Player talent is arguably the most important prerequisite for success in sports and its distribution is therefore a critical measure of the degree of competitive balance. By linking the distribution of player talent to competitive balance, we overcome problems faced by the previous literature which relied mostly on aggregated end-of-season league position and could often not detect significant changes over time.

Our results indicate that there is a clear trend towards a more unequal distribution of player talent across teams in the German Bundesliga top divisions between 1998 and 2016. We interpret this as a reduction in competitive balance. Drivers of this decline in competitive balance are, on the one hand, rising inter-divisional inequality of teams, coaches and players between the two German top football divisions. On the other hand, we see increasing assortative matching of players to teams within the top division of the German football league system (1st Bundesliga). This does not hold for the 2nd Bundesliga where financial endowments such as media payments grew much more slowly compared to those in the 1st Bundesliga, where strong increases in revenue have been seen over the last two decades.

We show that there is a circular trend, whereby more successful teams tend to attract better players. We point out that UEFA Champions League payments might play a distinct role in allowing certain clubs to attract better player talent. Furthermore, we show that the reduction in competitive balance is not driven by the direct movement of players between Bundesliga clubs. It is rather the increased hiring of talented players at a younger age from abroad, which explain the reduction in competitive balance. Furthermore, the retention of players by certain teams also increasingly drives these trends.

We confirm the results found by Groot [2008] or Pawlowski et al. [2010] who also provide evidence for decreased competitive balance in the 1st Bundesliga in recent years, and add information about the 2nd Bundesliga which has been neglected in the previous literature. In line with our results, Pawlowski et al. [2010] also finds that increasing Champions League payments is one remarkable driver of this development, not only in Germany but also in other European Leagues. However, our results differ from the findings of earlier studies (see Section 2.1) which did not detect any changes in competitive balance for the beginning of our sample period. It is difficult to say why these studies come to inconclusive results since each study uses a different (aggregated) method with varying sample periods. Using individual level player data, we are able to provide clear evidence for gradually declining competitive balance. Hereby, we reveal important theoretical causes: how competitive balance is determined by player mobility.

Nevertheless, we are unable to assess whether more competitive balance is desirable. Increased assortative matching may be socially optimal since more successful teams have usually a larger fan base. Indeed, economics theory is also unable to provide an answer to this question. On the one hand, the 1st Bundesliga has the highest average stadium attendance amongst football leagues worldwide, and attendance figures have risen considerably within the last two decades. This may indicate that the degree of competitive balance is currently not harmful to levels of fan interest (and empirical studies have so far not found a link between measures of competitive balance and stadium attendance). On the other hand, Bayern München has just won a record fourth consecutive championship with total points at the end of the season unseen only a few years ago. Based on our results, one could argue that the football market seems to work efficiently by allowing increasingly better equipped teams to attract better players. Regulations such as salary caps, gate sharing or restrictions on the transfer of young players could potentially help to increase competitive balance by if this is considered beneficial. Further research should investigate more thoroughly the long-term impact of competitive balance on fan interest and should provide recommendations where necessary.

References

John M Abowd und Francis Kramarz. The analysis of labor markets using matched employer-employee data. *Handbook of Labor Economics*, 3:2629–2710, 1999.

Marianne Bertrand und Antoinette Schoar. Managing with style: The effect of managers on firm policies. *The Quarterly Journal of Economics*, 118(4):1169–1208, 2003.

John J Binder und Murray Findlay. The effects of the bosman ruling on national and club teams in europe. *Journal of Sports Economics*, 13(2):107–129, 2011.

Babatunde Buraimo, Bernd Frick, Michael Hickfang, und Rob Simmons. The economics of long-term contracts in the footballers' labour market. *Scottish Journal of Political Economy*, 62(1):8–24, 2015.

John Cairns, Nicholas Jennett, und Peter J Sloane. The economics of professional team sports: a survey of theory and evidence. *Journal of Economic Studies*, 13(1):3–80, 1986.

A Colin Cameron und Douglas L Miller. A practitioners guide to cluster-robust inference. *Journal of Human Resources*, 50(2):317–372, 2015.

David Card, Jörg Heining, und Patrick Kline. Workplace heterogeneity and the rise of west german wage inequality. *The Quarterly Journal of Economics*, 128(3):967–1015, 2013.

Raj Chetty, John N Friedman, und Jonah E Rockoff. Measuring the impacts of teachers i: Evaluating bias in teacher value-added estimates. *American Economic Review*, 104(9): 2593–2632, 2014.

DFL. Die wirtschaftliche Situation im Lizenzfussball. *Bundesliga Report*, 2006–2015.

Arne Feddersen. *Economic consequences of the UEFA Champions League for national championships: The case of Germany*. Number 01/2006. Hamburg contemporary economic discussions, 2006.

Arne Feddersen und Wolfgang Maennig. *Trends in competitive balance: Is there evidence for growing imbalance in professional sport leagues?*. Number 01/2005. Hamburg contemporary economic discussions, 2005.

Ramón Flores, David Forrest, und Juan de Dios Tena. Impact on competitive balance from allowing foreign players in a sports league: Evidence from european soccer. *Kyklos*, 63(4):546–557, 2010.

Bernd Frick und Joachim Prinz. Crisis? what crisis? football in germany. *Journal of Sports Economics*, 7(1):60–75, 2006.

Jerome Friedman, Trevor Hastie, und Robert Tibshirani. *The elements of statistical learning*, volume 1. Springer series in statistics Springer, Berlin, 2001.

Jerome Friedman, Trevor Hastie, und Robert Tibshirani. Regularization paths for generalized linear models via coordinate descent. *Journal of Statistical Software*, 33(1): 1–22, 2010.

K Goossens. Competitive balance in european football: Comparison by adapting measures: National measure of seasonal imbalance and top 3. Technical report, University of Antwerp, Faculty of Applied Economics, 2005.

Lucas Franciscus Michael Groot. *Economics, uncertainty and European football: Trends in competitive balance*. Edward Elgar Publishing, 2008.

Marco Haan, Ruud H Koning, und Arjen Van Witteloostuijn. Competitive balance in national european soccer competitions. *Statistical thinking in sports*, pages 63–76, 2007.

Stephen Hall, Stefan Szymanski, und Andrew S Zimbalist. Testing causality between team performance and payroll the cases of major league baseball and english soccer. *Journal of Sports Economics*, 3(2):149–168, 2002.

Sandra Hentschel, Gerd Muehlheusser, und Dirk Sliwka. The contribution of managers to organizational success: Evidence from german soccer. 2014.

Stefan Késenne. Revenue sharing and competitive balance in professional team sports. *Journal of Sports Economics*, 1(1):56–65, 2000.

Martin Kiefel und Arne Jonas Warnke. A comparison of bayesian and frequentist association football forecasting models using individual-level player data. *Mimeo*, 2015.

Ruud H. Koning. Sport and measurement of competition. *De Economist*, 157(2):229–249, 2009.

Nicholas Kulish. Bayern munich eyes midfielder götze. *New York Times*, April 24, 2013.

Brian Macdonald et al. Adjusted plus-minus for nhl players using ridge regression with goals, shots, fenwick, and corsi. *Journal of Quantitative Analysis in Sports*, 8(3):1–24, 2012.

Joel G Maxcy et al. Progressive revenue sharing in mlb: The effect on player transfers. *International Association of Sports Economists Working Paper Series, Paper No. 07*, 28, 2007.

Jonathan Michie und Christine Oughton. *Competitive balance in football: trends and effects*. The sportsnexus, 2004.

Walter C Neale. The peculiar economics of professional sports: A contribution to the theory of the firm in sporting competition and in market competition. *The Quarterly Journal of Economics*, pages 1–14, 1964.

Christoph Partosch. Der einfluss der champions league auf die wettbewerbsposition einzelner vereine und die competitive balance der bundesliga. Technical report, Diskussionspapier des Instituts für Organisationsökonomik, 2014.

Tim Pawlowski, Christoph Breuer, und Arnd Hovemann. Top clubs performance and the competitive situation in european domestic football competitions. *Journal of sports economics*, 11(2):186–202, 2010.

Terry Robinson und Robert Simmons. Gate-sharing and talent distribution in the english football league. *International Journal of the Economics of Business*, 21(3):413–429, 2014.

Simon Rottenberg. The baseball players' labor market. *The Journal of Political Economy*, pages 242–258, 1956.

Olav Drivenes Sæbø und Lars Magnus Hvattum. Evaluating the efficiency of the association football transfer market using regression based player ratings. *Norsk Informatikkonferanse (NIK)*, 2015.

Peter J. Sloane. The economics of professional football: the football club as a utility maximizer. *Scottish Journal of Political Economy*, 18(2):121–146, 1971.

Stefan Szymanski. Income inequality, competitive balance and the attractiveness of team sports: Some evidence and a natural experiment from english soccer. *Economic Journal*, pages F69–F84, 2001.

Stefan Szymanski und Stefan Késenne. Competitive balance and gate revenue sharing in team sports. *The Journal of Industrial Economics*, 52(1):165–177, 2004.

The Economist. How to reform the champions league. (April 27th), 2016.

UEFA. Financial report. *UEFA Financial Report*, 2004–2015.

A Appendix

A.1 Data Preparation

Data has been separately prepared in R and Stata. Table 7 shows the descriptive statistics for three different datasets.

As mentioned before, the hierarchical fixed effects model requires strong separability of team, player and coach effects in order to disentangle goal margin variation attributable to team, player and coach specific performance. Separate identification of individual and team fixed effects is only satisfied if all clubs are connected through player mobility, see Abowd und Kramarz [1999]. Therefore, team effects and player effects cannot be disentangled if respective teams and players are only jointly observed. Mover players aid separation concerning this dimension, while also enabling separation of player and team effects for non-movers. As depicted in Table 7, approximately two-fifth of "*Sample All*" are mover players which is much larger than in other areas such as firm mobility (e.g. Card et al., 2013). Even new teams relegated to the 2nd Bundesliga usually have several players with previous Bundesliga experience in their squad which allows to disentangle player and teams effects as well (see also Table 9). In our main sample of players who appear in at least 50 games in total, more than two-thirds of all players play for at least two teams. By excluding players with less than 50 matches, we admittedly lose 57.8% of all players but only 13,9% of all player x match observations since lineup players are mostly quite experienced (or will be quite experienced at the end of their career). We do not loose any entire match observation.[23] As separate identification is more accessible when only considering mover players - observed at least at two different clubs - we introduce the sub-sample *b) Mover 50+*, used as a robustness check.

Furthermore, a similar match condition for coaches is imposed: Only coaches with at least 18 match observations are considered in all samples. All coaches failing to meet this condition are treated as interim coaches, used as the reference category in our estimation. There is a large number of interim coaches, 105 out of 364 coaches in our sample manage less than 10 games in total. Two promising coaches manage their respective team for all seasons we observe them in our sample (Dirk Schuster at SV Darmstadt 98 and Frank Schmidt at 1. FC Heidenheim). Therefore, we cannot separate team and coach fixed effects in these cases and we treat them as reference coaches. This does not influence our results since we add up team and coach fixed effects for the covariance analyses in Section 4 but it could explain the high team effects of SV Darmstadt 98 and 1. FC Heidenheim which represent to some extent coach ability.

Finals in the German Cup are held in Berlin since 1985. To account for the fact that there is no true home team in finals, we add another home category for those matches and count both teams neither as home nor as away.

[23] A few matches from the viewpoint of Jahn Regensburg are missing.

Table 7: Data Sets

	a) Sample All	c) Sample 50+	d) Mover 50+
# Players	5,072	2,140	1,514
Mover Share	39.4%	70.7%	1
# Teams		73	
# Coaches		364	
# Coaches (>17 matches)	215 (57.9% appear at least for two teams)		
Player x Match Obs.	334,234	287,685	223,452

A.2 Robustness

A.2.1 Analysis on the Match-Level

The outcome of a match is the joint result of all players on the pitch (and depends of course on the performance of the opposing team). In our approach so far (Equation (1)), we have not taken into account fellow players. The error terms of different players who appear together in a given match are correlated. This leads to correlation of the error term across team members and, furthermore, to serial correlation of the error term over time, biasing the covariance matrix of the coefficients.[24] An econometric issue regarding the point estimates might arise if for example the performance of players depent on fellow players, e.g. if a left-winger is used to play together with a certain left-back. Moreover, it is possible that those two players play often together against stronger opponents. This leads to an omitted-variable bias with its familiar problems. To account for this fact, we use a second model on match level where we look simultaneously at all players on the pitch. Here, we allow individual player performance to be correlated with fellow players (and opponents).

In this approach, each player of one team in a given match 'receives' the same goal margin, irrespective of whether he was in the lineup or substituted in later. In the previous analysis, we related to each player the goal margin achieved during his playing time (often a zero for late substitutions). Here we relocate the analysis to the match level (or, to be more precise, to the match-team level).[25] Each player impact is still weighted by the number of minutes he played during a match. Substitutes therefore have (still) less influence than players who are on the pitch during the entire match. We illustrate this approach again by the match between Bayern München and FC Augsburg (see Table 2) and the following two final matches of Bayern München in the season 2014/15.

Using this approach, we have to take into account multicollinearity due to the fact that many players often appear together in a given match. These players are therefore statistically difficult to distinguish. We use a linear ridge regression model which is a popular

[24] We used multiway clustering on a high level (player and team) to take into account these correlations [Cameron und Miller, 2015] when referring to variance estimates.

[25] Different goal margins for players with different playing time in a given match would also be possible by shifting the analysis to a minute-based match analysis.

Table 8: Data Sets

Goal Margin	Home × 2014/15	Team Bayern München	…	Team Sent-Offs	…	Opponent FC Augsburg	Opponent SC Freiburg	Opponent Mainz	Player Neuer	Lahm	Dante	Xabi Alonso	T. Müller	Lewandowski	…
-1	1	1	…	1	…	1	0	0	0.846	0.154	1	0	0.813	0.813	...
-1	0	1	…	0	…	0	1	0	1	0.209	0	0.703	0.297	1	...
2	1	1	…	0	…	0	0	1	1	1	1	0.582	0.505	0.802	...

method in machine learning if the number of observations is not very large compared to the number of coefficients to be estimated [Friedman et al., 2001]. Ridge regression minimizes a penalized residual sum of squares.[26]

$$\underset{\beta}{\operatorname{argmin}}\Big[\sum_{i=1}^{2*N}\big(\text{Goal\_Margin}_i-\beta_0-\sum_{j=1}^{p}x_{ij}\beta_j\big)^2+\lambda\sum_{j=1}^{p}\beta_j^2\Big] \tag{4}$$

Here, we look at match j from the viewpoint of each participating team (the number of observations is therefore $2*N = 24,262$, twice the number N of matches in our sample).[27] x has column rank $p = 2,307$ mostly consisting of player indicators (2140) but also columns for each team (73), opponent (73), sent-offs (4), and home advantage (interacted with season to account for shrinking home advantage over time, 19). For simplicity, we do not include season, league, coaches and further interaction between season or home advantage and league (which were not very relevant in the previous analysis).[28] λ controls the amount of shrinkage and is estimated via 20-fold cross-validation.[29] Again, we restrict the analysis to all players with at least 50 observations because those coefficients would be shrunk toward zero anyway and are less informative.

Results on the match-level mostly confirm the results presented in this paper: Coefficients for player strength derived from the ridge regression (Equation (4)) are positively correlated with average standardized (by season) player fixed-effects ($\rho \approx 0.44$) or unstandardized coefficients ($\rho \approx 0.28$) from Equation (1). Taking fellow players into account, we find again a strong increase in assortative matching between players and teams (Equation (2)) for teams which we observe for at least 10 seasons.[30] We do not find trends in assortative matching among all teams which is not surprising since coefficients for teams with fewer seasons are shrunk towards zero. Although the number of observations for teams is large compared to the number of observations for each player, we find a surprisingly low correlation ($\rho \approx 0.26$) for the coefficients of teams, derived from the ridge regression compared to the coefficients estimated in Equation (1). Results regarding team strength estimated in Equation (4) are, in our view, not entirely convincing. For example,

[26] For calculation we use the *glmnet* package for R [Friedman et al., 2010]. Ridge regression methods have also been proposed by Kiefel und Warnke [2015] and Sæbø und Hvattum [2015].

[27] We lose 4 match-team observations due to insufficient number of players with at least 50 games.

[28] Including these variables does not alter our results. The only exception is coaches which further reduces the statistical power of our analysis and gives very noisy results for many teams and coaches for which we have few observations.

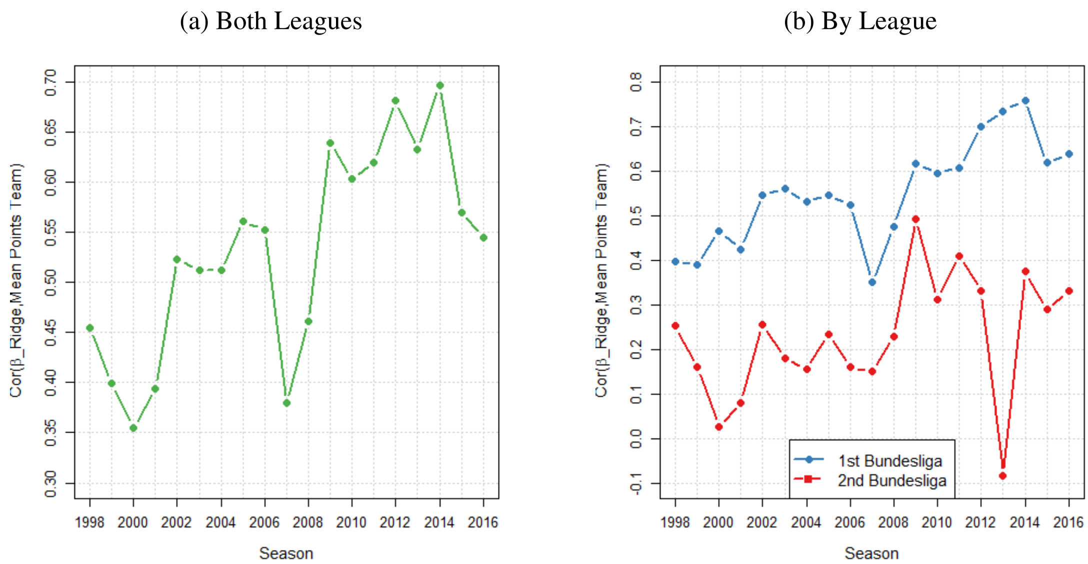
[29] k-fold cross-validation partitions the original sample into k subsamples of equal size. $k-1$ samples are used as training set and one remaining sample is then used for validation. This exercise is repeated k times. As loss function we use the mean squared error criterion. For simplicity, we ignore the here the hierarchical nature of the data.

[30] Surprisingly, the correlation is strongly negative for earlier seasons.

VfR Aalen, SV Wehen Wiesbaden and Wacker Burghausen are included among top five teams (and Bayern München is only ranked 8th). In contrast, coefficients of teams have been convincing in the previous analyses (compare Figure 4). We interpret this finding that the estimated shrinkage parameter λ should probably penalize teams differently to players (e.g. via a hierarchical model). Interestingly, running Equation (4) with or without team indicators does not alter the results for player strength, the correlation between the model described in this paragraph and a parsimonious model without team information and some further interaction (see below) gives a correlation coefficient of $\rho \approx 0.978$.[31] Looking deeper into this topic is beyond the scope of this study but future research should investigate for example a hierarchical ridge regression framework in this context.

Apart from the positive trend described in the previous analysis, we offer further evidence to confirm our results. Similar to Sæbø und Hvattum [2015], we drop team information in Equation (4) and use only player information (plus indicators for the season-specific home advantage and the opponent) and use a very simple measure of team performance: The average points achieved in our sample period.[32] Correlating these player coefficients with the naive measure of team performance, we find a strong increase in assortative matching. This confirms our previous results as shown in Figure 8. The correlation is larger and less volatile for the 1st Bundesliga for which we find a more or less steady increase (with the exception of two seasons 2006/07 and 2007/08). For the case of the 2nd Bundesliga, it seems that assortative matching has also increased from being at around 0.2 until 2008/09 to around 0.3 to 0.4 thereafter (except for the season 2012/13).

Figure 8: Assortative Matching (Ridge Regression on the Match-Level)



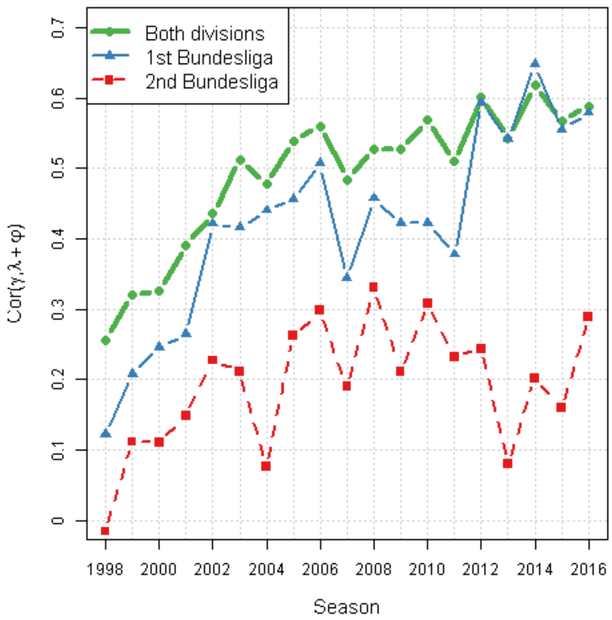
[31] In contrast, dropping team information in Equation (1) alters player coefficients much more.

[32] Unsurprisingly given the large correlation between player coefficients with or without team information (see paragraph above $\rho \approx 0.978$), results look quite similar if we use the model including team indicators and further interaction terms for this analyses.

A.2.2 Ridge Regression Estimate of Equation (1)

We have estimated Equation (1) using ordinary least squares (OLS) to present a simple and widely used (unbiased) estimator. Several recent publications have investigated the distribution of fixed-effects which were estimated via OLS, e.g. Card et al. [2013] or Chetty et al. [2014]. Results presented in this paper are robust to estimating Equation (1) using ridge regression which gives some bias for the coefficients but a lower variance (see Appendix A.2.1 for more details about ridge regression). Figure 9 shows the results for the assortative matching (Equation (2)) when we use ridge regression to estimate Equation (1).[33] As in the previous Section, we use 20-fold cross-validation to calibrate the shrinkage parameter. We base this analysis (as in the case of the OLS) on the sample of players who appear in at least 50 matches and coaches with more than 17 games because the ridge regression becomes computationally intensive for larger samples (and coefficients for players with few games would be shrunk toward zero anyway). Interestingly, we do not find a negative correlation in the beginning of the sample period as in Figure 5 when we use ridge regression. This indicates that the (small) negative correlation in the beginning is due to greater uncertainty in the first (and last) seasons in our sample because players in these seasons tend to play for fewer total (sample) matches. Ridge regression takes this into account by penalizing those coefficients.

Figure 9: Assortativity Matching (Ridge Regression for Equation (1))



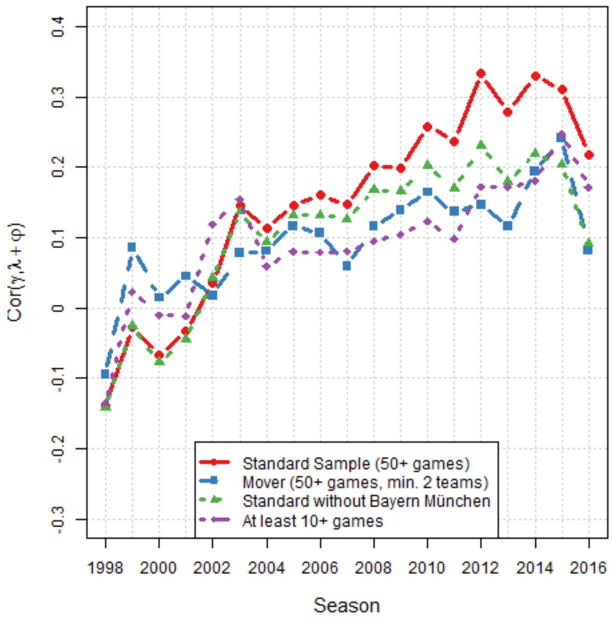
A.2.3 Robustness to Other Samples

The main conclusions are robust to considering a different match condition or only mover players (where separate identification of players and teams is more straightforward and

[33] For the ridge regression approach, we use weights for the correlation (Equation (2)) but not to estimate player, team and coach coefficients (Equation (1)).

precise estimation more accessible) as shown in Figure 10. Sample selection does not drive our results (players with at least 50 observations are of course a selected sample of all players appearing in the 1st or 2nd Bundesliga. To show this, we estimate Equation (1) and Equation (2) separately for the sample of players who appear at least in two teams and those with at least 10 matches. Furthermore, we exclude Bayern München in Equation (2) for the standard sample to assure that results are not driven by one team. Results are weaker for the robustness checks than for the standard sample but an increase in assortative matching is obvious for different samples considered.[34] Furthermore, a match

Figure 10: Assortativity Matching (for Different Samples)



might be already decided at a certain point of time if one team has a large goal margin. Here, teams might bring players who are supposed to get some playing experience, e.g. after injuries, without large incentives to change the actual goal difference. To check whether this changes our results, we ran the analysis based on the sample of lineup and full-time players only. This does not alter the interpretation of our results.

A.2.4 Robustness to Other Outcomes

Our analyses show that playing talent is increasingly unequally distributed across divisions and within the 1st Bundesliga but this does not hold for the 2nd Bundesliga. This pattern is also apparent for the last ten seasons if we look at betting odds for German Cup matches. Unfortunately, betting odds are only available since 2005 but since then there is a clear pattern: If we look at average maximum odd over time for German Cup matches

[34]We expect weaker analyses for different reasons. First, movers for example are not the main driver for increased assortative matching, see for example Section 4.3 and the sample size is here reduced. Second, Bayern München is the team with both the highest team fixed effect and the highest average player performance. Third, although the sample of players playing at least 10 matches is considerably higher than the "50+ sample", performance measures are much less precise in this analysis due to the large random component natural to sports matches (the residual variation makes up slightly more than 80% of the total variation in a variance decomposition for Equation (1)).

between teams of the same league, we see that the average maximum odd has increased statistically significantly for matches between two teams playing in the 1st Bundesliga but no time trend is discernible for matches between two 2nd Bundesliga teams (the number of matches between teams of the 2nd Bundesliga is with 43 compared to 105 considerably lower but a time plot shows in this case a more or less flat line). The average maximum odd has also increased significantly for the 152 matches between 1st Bundesliga and 2nd Bundesliga teams. Looking at football odds, therefore, also indicates decreasing competitive balance between the top two divisions of the German Bundesliga and within the 1st Bundesliga.

A.3 Validity of our measure

Does our measure of the partial correlation of player's appearance on the pitch and the goal margin constitute a valid proxy for performance? We give several arguments why this might be the case. First, in a separate study we show that this approach can be used to give good predictions for future football matches based only on player data (and home advantage).[35] Secondly, our measure is correlated with expert ratings for players' performance – not only with current expert ratings but also with future expert ratings (see Kiefel und Warnke, 2015). The Pearson correlation coefficient between players' performance measured by Equation (2) and by players' average grades during the whole period is $\rho = -.26$ (in Germany lower grades are better). If we adopt a similar approach as in Equation (2) for grades (where we replace goal difference as an outcome with goals), we get a correlation coefficient of $\rho = -.79$. This shows that the partial correlation of each player with the goal margin is closely related with a ratings by experts used in other studies such as Buraimo et al. [2015].

Figure 11: Association Between Player Performance measured by Grades and by Goal Margin

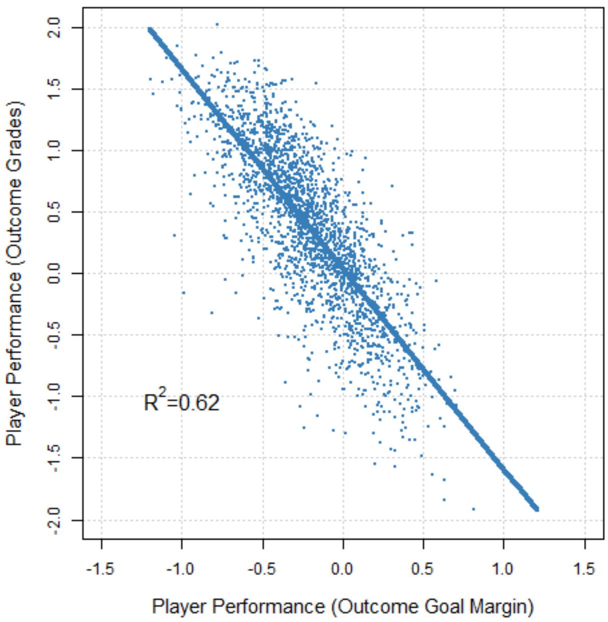
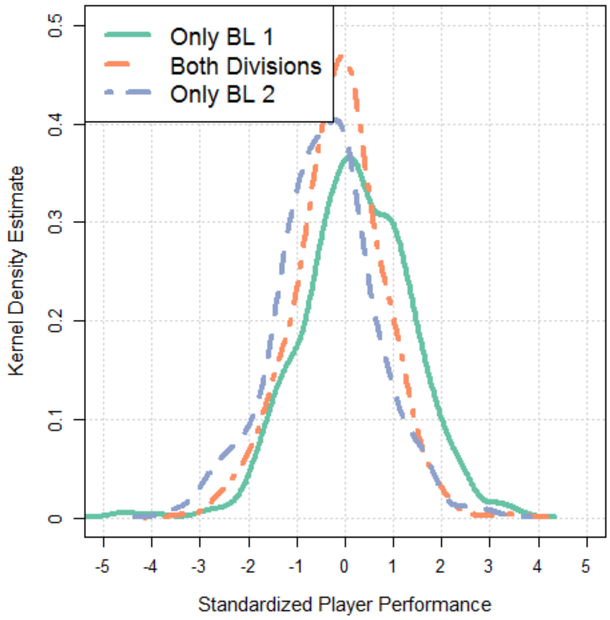


Figure 12 shows the distribution of player performance for players who appear only in the 1st Bundesliga (25%), who always play in the sample period in the 2nd Bundesliga (23%) and those of play for teams in both divisions (52%). The distributions look reasonable with a clear hierarchy but considerable overlap between players of different divisions. The density estimation is based on 2,138 unique appearances in at least 50 games in our sample and it is slightly skewed to the left since better players play more matches on average. We find a similar convincing hierarchy for the sum of team and coach effects (see Figure 4).

[35]This is still work in progress but a current version is available upon request.

Figure 12: Distribution of Player Performance (Player Fixed-Effects for Players with at least 50 games)



Note: Kernel density estimates of individual player performance (for players with at least 50 games) with fixed bandwidth of 0.05. The densities are slightly skewed to left because players with high fixed-effects play more games on average.

Furthermore, we have shown in Section 4.3 that player fixed-effects are important for transfers (besides short-term performance prior to a transfer, see Table 6). A further anecdotal evidence for the validity of our measure can be seen if one looks at the top players who still played in 2015/16 (the last season we observe) in the *50+ Sample*: This lists includes many acclaimed Bayern München players such as Xabi Alonso, Robert Lewandowski, Javi Martinez, Manuel Neuer, Philip Lahm, Frank Ribery or Arjen Robben, Brasilian footballers such as Dante, Luiz Gustavo and Naldo (currently playing for VfL Wolfsburg). But also players like Kagawa or Lukasz Piszczek who won two championships with Borussia Dortmund or Granit Xhaka, who will move to Arsenal London in the next season, and Yann Sommer, the first-team regular goalkeeper for Switzerland, from Borussia Mönchengladbach. We could only find few surprises such as Jan Simunek who plays currently for VfL Bochum and is the only 2nd Bundesliga player within the top 20 players in 2015/16.

Table 9: Teams in the Sample

Team	G	S	P	C	Team	G	S	P	C
Bayern München	722	19 (19)	107	8	Rot Weiss Ahlen	279	8 (0)	76	11
VfB Stuttgart	688	19 (19)	136	17	FC Ingolstadt 04	245	7 (1)	58	8
Werder Bremen	688	19 (19)	111	7	Dynamo Dresden	175	5 (0)	48	5
VfL Wolfsburg	687	19 (19)	141	14	VfL Osnabrück	175	5 (0)	63	5
Borussia Dortmund	685	19 (19)	107	9	Wacker Burghausen	174	5 (0)	36	4
Bayer 04 Leverkusen	684	19 (19)	120	12	Kickers Offenbach	143	4 (0)	37	5
FC Schalke 04	684	19 (19)	121	14	Stuttgarter Kickers	142	4 (0)	30	7
Eintracht Frankfurt	677	19 (14)	141	14	SV Sandhausen	141	4 (0)	35	3
1. FC Kaiserslautern	677	19 (11)	160	13	Waldhof Mannheim	141	4 (0)	38	4
Bor. Mönchengladbach	676	19 (16)	145	15	TuS Koblenz	140	4 (0)	40	4
1860 München	676	19 (7)	132	14	1. FC Saarbrücken	139	4 (0)	38	5
SC Freiburg	675	19 (12)	114	4	Carl Zeiss Jena	109	3 (0)	31	5
VfL Bochum	673	19 (10)	138	11	VfR Aalen	107	3 (0)	23	3
1. FC Köln	672	19 (11)	137	18	SSV Reutlingen 05	106	3 (0)	26	4
Hamburger SV	671	19 (19)	132	14	SSV Ulm 1846	105	3 (1)	23	4
Hertha BSC	670	19 (17)	131	12	Eintracht Trier	105	3 (0)	24	1
1. FC Nürnberg	670	19 (12)	141	14	Fortuna Köln	103	3 (0)	20	3
1. FSV Mainz 05	667	19 (10)	135	10	Tennis Borussia Berlin	73	2 (0)	23	3
SpVgg Greuther Fürth	667	19 (1)	141	9	1. FC Heidenheim	72	2 (0)	14	1
Hannover 96	635	18 (14)	119	14	SV Wehen Wiesbaden	72	2 (0)	26	4
MSV Duisburg	604	17 (5)	151	13	SV Darmstadt 98	71	2 (1)	24	1
Energie Cottbus	596	17 (6)	117	8	KFC Uerdingen 05	71	2 (0)	18	3
Karlsruher SC	593	17 (3)	117	14	RasenBallsport Leipzig	71	2 (0)	15	3
Arminia Bielefeld	567	16 (8)	126	12	Rot-Weiss Essen	71	2 (0)	30	4
FC St. Pauli	519	15 (2)	104	12	VfB Lübeck	71	2 (0)	19	1
Hansa Rostock	496	14 (9)	109	10	Chemnitzer FC	69	2 (0)	13	3
Alemannia Aachen	461	13 (1)	95	10	FC Gütersloh	69	2 (0)	18	3
FC Augsburg	354	10 (5)	76	5	SG Wattenscheid 09	69	2 (0)	11	2
Rot-Weiß Oberhausen	352	10 (0)	64	8	Jahn Regensburg	67	2 (0)	21	4
SC Paderborn 07	348	10 (1)	82	9	SV Meppen	36	1 (0)	11	2
Erzgebirge Aue	348	10 (0)	72	8	FSV Zwickau	35	1 (0)	7	1
1. FC Union Berlin	346	10 (0)	79	7	Sportfreunde Siegen	35	1 (0)	8	3
1899 Hoffenheim	327	9 (8)	65	9	SV Babelsberg 03	35	1 (0)	10	2
SpVgg Unterhaching	314	9 (2)	69	8	VfB Leipzig	35	1 (0)	9	2
Fortuna Düsseldorf	313	9 (1)	75	11	1. FC Schweinfurt 05	34	1 (0)	5	1
FSV Frankfurt	281	8 (0)	74	4	Rot-Weiß Erfurt	34	1 (0)	12	2
Eintracht Braunschweig	280	8 (1)	55	8					

Note: ***G*** *: Total number of games (including domestic cup games);* ***S****: Total number of seasons observed in either the 1st Bundesliga or 2nd Bundesliga in the sample period (in parenthesis only 1st Bundesliga);* ***P****: Total number of unique players with at least 50 games in total who appear in at least one match for the respective team;* ***C****: Total number of unique coaches with at least 18 games in total who managed the respective team.*