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Ignoring Millions of Euros: Transfer Fees and Sunk Costs in Professional Football*

Julian Hackinger†

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Abstract

According to neoclassical economics, sunk costs should be ignored in the decision-making process. Although experimental evidence tells us that subjects often fail to do so, field evidence for this behaviour remains scarce. Most empirical articles use data from draft systems in professional sports and analyse whether a player's draft order affects his time on the pitch. In contrast to the draft system, European football teams frequently spend large amounts of money on transfer fees. The discrepancy between fee-bound and free transfers arouses suspicion to encounter the sunk-cost fallacy among football managers. Using data from Germany, I investigate whether this is indeed the case, i.e. that player utilisation is affected by initially paid transfer fees. I hereby contribute to the literature in three ways. To the best of my knowledge, I am the first to examine the sunk-cost fallacy in European sports and professional football. Second, I am able to control for confounding factors previous studies have expressed concern about. Third, I conduct the analysis on the level of individual matches, thereby obtaining a sample size many times larger than that of comparable studies. Unlike the majority of previous articles that studied the sunk-cost fallacy in the context of professional sports, I am unable to find evidence supporting this behavioural bias on a seasonal level. A more detailed analysis on the match level reveals a sunk-cost effect which, however, is economically negligible and decreases with a player's tenure. The results therefore corroborate a rational behaviour among professional sports team managers.

Keywords: Sunk-cost fallacy; Football; Soccer; Transfer market; Behavioural Sports Economics.

JEL Classification: D01, D23, J40, L20, Z22.
PsycINFO Classification: 3660.

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†Email: julian.hackinger@tum.de. Postal address: Technical University of Munich, Chair of Economics, Arcisstr. 21, 80333 Munich, Germany. Phone: +49 89 289 25707. ORCID: 0000-0002-6011-892X.

1 Introduction

According to neoclassical economics, decisions should be based exclusively on an action's marginal costs and benefits. Being irreversible, sunk costs should not be taken into account when evaluating available alternatives. However, personal experience teaches us that we often behave differently if we have already invested time, money or effort in a project. Since the first studies on the sunk-cost fallacy (Arkes and Blumer, 1985; Thaler, 1980) this behaviour has been studied in many economic and psychological experiments. Yet it is often argued that experimental results lack generalizability and only consider hypothetical or low-stakes decisions. Despite these weaknesses, evidence of the sunk-cost fallacy outside the laboratory is rather scarce (Keefer, 2017).[1] Highly sensitive data is necessary to detect the sunk-cost fallacy for both corporate and individual behaviour. Of course, this data is difficult to obtain. With abundant data in the context of professional sports, economists have discovered a unique opportunity to analyse the sunk-cost fallacy and other phenomena (Kahn, 2000). However, studies so far have exclusively examined the sunk-cost fallacy (or escalation of commitment[2]) in professional sports leagues' draft systems[3], where a rookie's salary is determined by his draft order. The articles examine whether a player's draft order and his corresponding salary affect his subsequent utilisation by the club to which he was drafted.

Importantly, in most leagues that apply a draft system, a large proportion of the salary costs are paid out biweekly or monthly during the season (e.g. Keefer, 2015). At the same time, the coach can continuously observe a player's performance and decide whether to employ him. It can therefore be argued that the labour costs are not experienced as sunk. Apart from that, parts of the salary are paid in the form of merit-based bonuses. This turns a fraction of a player's salary into marginal rather than sunk costs.

Unlike the draft system, teams in European football leagues have three different options to acquire their players. First, teams can train young players to a professional level.

[1] Augenblick (2015) and Ho et al. (2018) are exceptions for empirical and non-sports related studies.

[2] The terminology "escalation of commitment" more generally refers to the phenomenon that decision makers exaggerate investments following previous commitment. The sunk-cost fallacy is associated with commitment following previous expenditures of economic resources (Camerer and Weber, 1999, p. 60).

[3] In a draft, teams alternately select rookies from a pool of young talented players.

Second, they can sign players whose contracts expire or who are currently without an employer and therefore free of charge. Third, teams can compensate competing teams to sign one of their players with an ongoing contract. In the latter case, transfer fees are paid. With Neymar da Silva Santos Júnior's move from Futbol Club Barcelona to Paris Saint-Germain Football Club for 222 million Euros, these fees have risen to incredible levels. Although Neymar's transfer and its fee is unique to date, it typifies the overall trend in the market. By June 2018, the five most expensive transfers in history took place between 2016 and 2018. As Figure 1 demonstrates, this development is also apparent in the German Bundesliga, with the average transfer fee having more than doubled from 2012 to 2016. Due to the strong contrast between free and fee-bound transfers, such a system is expected to be susceptible to the sunk-cost fallacy.[4] I therefore hypothesise that there is a sunk-cost effect in professional football, where players are mostly exchanged on a transfer market. For that reason, I investigate whether player utilisation in German professional football is affected by initially paid fees. More specifically, I analyse the highest league in Germany, the Bundesliga.

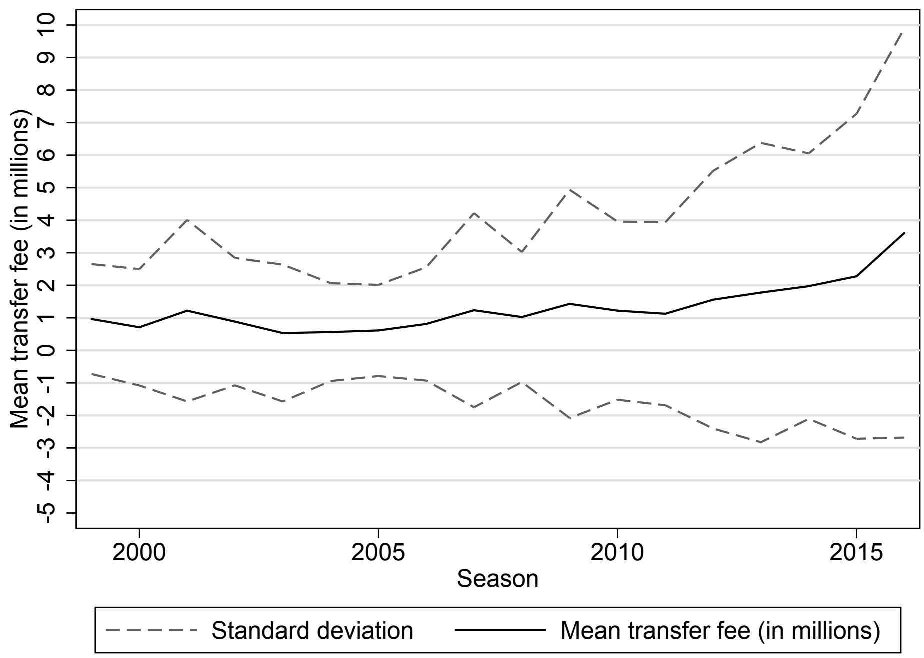


Figure 1: Mean transfer fee in the German Bundesliga from 1999/2000 until 2016/2017.

[4]The context is comparable to the market for yearlings described by Camerer and Weber (1999, p. 81), in which young unraced horses are bought for relatively large amounts of money, but dropped if they perform poorly in their debut.

I am hereby able to contribute to the literature in multiple ways. To my knowledge, this is the first study that examines the sunk-cost fallacy in European sports in general and professional football in particular. So far, existing studies in the sports environment have used data from American football, basketball, and baseball in the United States and Australian football in Australia. The European setting allows a study of the sunk-cost fallacy in another labour market with different rules. There is neither a draft system nor a salary cap in European professional football. Instead, players are traded for money. Supply and demand determine transfer fees and salaries. The football labour market is therefore more similar to common labour markets than its US counterpart. Moreover, I control for two variables that are often argued to confound the results, which have not yet been accounted for. First, by including Google hits of players, I control for fan appeal. Second, coaches might be more likely to consider transfer fees in their line-up decision with players who were acquired during the coach's own spell (Pedace and Smith, 2013; Staw, 1976). I do not find evidence for an effect of either of these. Finally, in addition to the seasonal level, I conduct the analysis on the level of individual matches, obtaining a sample size many times larger than that of comparable studies.

In contrast to the majority of previous articles (Camerer and Weber, 1999; Keefer, 2015, 2017; Staw and Hoang, 1995) that studied the sunk-cost fallacy in the context of professional sports, I am not able to find evidence supporting this behavioural bias on a seasonal level. An analogous analysis on the match level reveals a sunk-cost effect. However, the corresponding coefficient is negligible when compared to those of measures of performance and decreases with a player's tenure. Hence, the overall results corroborate rational professional sports team management. This is in line with the findings of Borland et al. (2011) and Leeds et al. (2015). Playing time in the German Bundesliga is primarily determined by previous and predicted performance. Coaches and managers therefore seem to be able to ignore the huge transfer fees they paid in the first place.

I proceed as follows: Section 2 summarises the relevant literature. I then describe the data in Section 3 and the empirical approach in Section 4. Section 5 presents and discusses the results. Section 6 concludes.

2 Literature

One of the earliest studies on evidence of sunk-cost effects is a set of experiments by Arkes and Blumer (1985). In a field experiment, the authors randomly provided discounts to some purchasers of a subscription to a theatre series. Subsequently, they recorded how many plays the subjects attended. As the discounts were assigned randomly, preferences over the plays and hence the number of plays attended should, on average, not differ between treatment groups. However, the group that paid the normal price attended significantly more plays than subjects who received a discount. Arkes and Blumer (1985) therefore conclude that, in this example, subjects took sunk costs into account, which provides evidence of the sunk-cost fallacy.

Following a series of other experiments on the sunk-cost effect and the phenomenon of escalation of commitment (see Friedman et al., 2007 and McAfee et al., 2010 for surveys), one of the first and most prominent field studies on the sunk-cost fallacy is Staw and Hoang (1995). The authors use the National Basketball Association (NBA) draft between 1980 and 1986 to test whether a player's time on the pitch and survival in the NBA depend on the financial commitment incurred by the draft order of a player. In a draft, experts first rank college players (rookies) by talent. Starting with the lowest ranked team of the past season, each team then alternately selects one young prospect from the pool of rookies. The order of the draft determines the rookie's salary. The higher a rookie's position in the draft, the sooner he will be selected, and the higher is his salary. Since these salary costs, as well as the opportunity costs of having neglected the option to choose another player, are determined at the start of a given season, they can be considered sunk. Consequently, the managerial decision on who to send onto the pitch should only be based on player productivity. Yet Staw and Hoang (1995) find significant effects of draft order on players' playing time and survival in the NBA. An earlier draft and the correlated higher salary granted the player more time on the pitch and a longer career in the NBA after controlling for productivity and other factors.

Camerer and Weber (1999) attempted to challenge the results of Staw and Hoang (1995) by re-examining a sample of NBA players in the 1986 to 1991 drafts. They tested the presence of sunk-cost effects, but accounted for several other alternative rational explanations. For this purpose, Camerer and Weber (1999) used a different set of control variables (e.g. disaggregated measures of performance) and added the quality of back-up players, pre-draft player rankings by an outside expert, and control for players being traded. After the inclusion of these additional variables, they apply a two-stage regression model, intending to extract the informational content that the draft order has on performance. Nevertheless, Camerer and Weber (1999) find persisting evidence of a sunk-cost effect, albeit to a slightly smaller extent.

Based on these findings for the NBA and the characteristics of the European football transfer market as described in Section 1, I formulate the main hypothesis of this paper:

Hypothesis 1 *Professional football managers in the Bundesliga exhibit the sunk-cost fallacy by considering paid transfer fees in addition to predicted performance when fielding players.*

In their article, Camerer and Weber (1999) elaborate on rational explanations for occurrences of sunk-cost effects. First, uncertainty about the costs and benefits of an action promote the escalation of the very action. With regard to football players, this is less of a concern. The transfer fee paid by the team to acquire the player is known to the team executives and modern technologies allow the precise measurement of performance. This also precludes a self-serving bias in judging costs and benefits (Camerer and Weber, 1999, p. 61). Second, the interests of a team coach and those of the team, its owners and its fans could be non-aligned. Transfers in German professional football are usually a joint decision taken by the coach and the entire management, including scouts as well as athletic and finance directors. Furthermore, it is unlikely that team coaches pursue a different goal to that of long-term stakeholders. It can be assumed that both strive to maximise playing success (Garcia-del Barrio and Szymanski, 2009).

Finally, Camerer and Weber (1999) suspect that teams might try to recoup the sunk costs by investing further playing time for a given player. While the authors argue that this is not an issue in the NBA, it might indeed be one in both Bundesliga and NBA. Since players in professional football are frequently traded, teams in principle have the opportunity to recoup a fraction or even more of the initially paid transfer fee. To this end, players must perform well to attract potential buyers and to generate a higher transfer price. Additional time on the pitch for a player that is planned for sale might increase the perceived ability of a given player. Therefore, if coaches arrive at the decision to sell a player but still think he is undervalued, they might decide to grant him more playing time. However, ex ante, it is unclear whether a player can perform well enough to increase his market value. Hence, fielding him is risky. Note that these considerations apply to all players. Thus, irrespective of whether or not a player is up for sale, managers should only invest additional playing time in the player if they think it can increase his value. Consequently, even managers who seek to recoup transfer fees should ignore initially paid transfer fees and only focus on a player's potential. Yet this explanation still leaves the possibility of erroneously identifying a sunk-cost effect. Given that additional playing time promotes player performance, it can be worthwhile for managers to field players they expect to improve, even if this is not justified by the currently predicted performance.[5] Accordingly, I investigate the following hypotheses:

Hypothesis 2a *More playing time leads to a higher performance of a player.*

Hypothesis 2b *Managers invest in players by granting them more playing time.*

Apart from Staw and Hoang (1995) and Camerer and Weber (1999), there are four other studies that investigate the sunk-cost effects of draft order on playing time. Borland et al. (2011) examine draft order effects in the Australian Football League (AFL). Using the amount of games played as dependent variable and accounting for the information contained in a player's draft order, they find no evidence of a sunk-cost effect. Instead, Borland et al. (2011) find that coaches grant more playing time to promising talents, expecting the additional experience to improve their performance, and thus supporting Hypothesis 2b.

Consistent results are provided by Leeds et al. (2015) for the NBA. Although the initial results indicate that the draft order has an effect on playing time, a regression

[5] As NBA players can also be exchanged for draft positions or other players, the same issue might arise there as well.

discontinuity design eliminates this effect. In order to control for unobserved variables, Leeds et al. (2015) exploit the discontinuity between the first and the second draft round. Moreover, the authors control for injuries and suspensions by limiting the dependent variable to the net potential playing time. While I am also able to control for injuries and suspension spells, my data does not allow a regression discontinuity design.

Similarly, Keefer (2017) uses the discontinuity between the first and the second round in the National Football League (NFL) draft to control for unobserved variables, applying a fuzzy regression discontinuity design. In contrast to Leeds et al. (2015), the author finds that players drafted in the first round receive a wage premium. The additional earnings result in more playing time. Keefer (2015) substantiates these results.

In addition to these studies, further scholars considered draft order effects in studies with a different focus. Groothuis and Hill (2004) find evidence that being drafted earlier is associated with a longer career. Similarly, results obtained by Coates and Oguntimein (2010) suggest that draft order has an effect on playing time and career length. Interestingly, research by Pedace and Smith (2013) supports the idea that managers overly invest in players recruited by themselves. They find that successors are more likely to divest poorly performing players.

3 Data

For the analysis, I use data from the highest professional football league in Germany, the Bundesliga, and primarily obtain data from two websites, `www.transfermarkt.de` and `www.kicker.de`. I use DataGorri (Hackinger, 2018) for the data collection, a tool that automates the collection of tabular data such as performance tables and rankings. Transfermarkt is a popular German-based football information website where community members track transfer fees and successfully discuss market values (Herm et al., 2014; Peeters, 2018). The transfer fees that are paid constitute my measure of sunk costs. The market value is an estimation of a player's value to a team.

Additionally, the website provides match-level and season-level data on measures of performance (number of goals, assists, cards, appointments to the roster, minutes played and matches, substitutions as well as the team's average amount of points won when a given player has played[6]) and characteristics of players (age, nationality, footedness, height, position, tenure). In existing studies on the sunk-cost fallacy, all observations are of young rookies. In contrast, players of all ages can be sold and purchased on the European football transfer market. Therefore, I control for the effect age has on playing time. Analogous to Leeds et al. (2015) and Keefer (2017), I account for native players playing less or more often than foreign ones by including a dummy for German citizenship.

Transfermarkt also features information on coaches. During his spell, a coach is often involved in transfer decisions. The corresponding transfer fees might carry more weight in his line-up decisions (Keefer, 2015; Pedace and Smith, 2013; Staw, 1976). Moreover, I conjecture that a potential significant sunk-cost effect might vary with respect to a coach's experience. Therefore, I collect and add corresponding variables and, where appropriate, interaction terms to the estimations.

I also use Transfermarkt to record whether a player is on loan. Besides final player transfers, European football teams have the opportunity to lend and borrow players, usually for 6 months to two seasons. This means that while players on loan remain under contract with the lending team, they are an inherent part of the borrowing team's roster and are not allowed to play for the lending team. These players are often expected to have a high potential, which managers may want to test prior to a final transfer. Also, more competitive teams often lend young talented players to lower ranked teams to provide these players with more playing time and opportunities to develop and prove themselves. Otherwise, a loan can be an emergency replacement for an injured or suspended player that is only needed until the absent player returns. Generally, teams can borrow players to increase overall team size and/or quality in the short term. Just like final transfers,

[6]In modern European football, teams earn zero points for a defeat, one point for a draw, and three points for a win.

teams can lend a player entirely for free or for a loan fee[7] (which I treat as a transfer fee).[8] In the sample, five percent of the observations are for players on loan.

Transfermarkt also registers spells of injuries and suspensions of players. I use these to calculate the maximum amount of time a player could potentially spend on the pitch. Since reliable data on injury and suspension spells is only available from the 2007/2008 season onwards, I restrict the sample to the 2007/2008 to 2016/2017 seasons. I still resort to values from earlier seasons for lagged variables other than those related to injuries and suspensions.

Finally, apart from rankings, Transfermarkt provides information as to whether teams played international competitions like the UEFA Champions League (CL) or the UEFA Europa League (EL) during given seasons. Participation implies a more intense playing schedule and is likely to affect individual players' playing time in the national league. Coaches might want to give certain players a break, which can result in more or less playing time on the individual player level. For that reason, I include dummy variables for teams that played international matches. In addition, I repeat the analysis only with teams that did not play internationally.

At the sports newspaper Kicker, a team of expert journalists evaluates players' performances after every Bundesliga match. They assign grades on a scale from one to six, with one being the best score. I use the grades per match and the average grades per season as an aggregated measure of performance.

Both Staw and Hoang (1995) and Camerer and Weber (1999) argue that fan appeal could be a critical confounding factor when analysing the effect of sunk costs on playing time. Usually, popular players are more valuable to teams as they generate higher jersey sales and attract more spectators to the stadium. Hence, regardless of their performance, it could make economic sense to grant more playing time to more expensive players. I am not aware of any study that uses sports data in the context of the sunk-cost fallacy that could control for fan appeal. To account for popularity, I collect the number

[7] Although many teams have to pay a fee for players on loan, the contract is referred to as a loan and not a rental contract.

[8] As a special case with loans, the salary costs are often split between the lending and the borrowing team.

of Google hits per season for each player by searching for "(player name) (team name) (fussball[9])".[10] To record only the Google hits for a given season t, I restrict the Google hits using Google Tools to between the start (July 1 of year t) and the end (June 30 of year $t + 1$) of that season.[11] Thus, for a player X who played in the German Bundesliga from the 2008/2009 until the 2012/2013 season, I obtain a specific number of Google hits for each of the five seasons.

Table 1 summarises the statistics on players. Each observation hereby represents one player in the case of personal characteristics (e.g. nationality). In other cases it represents one transfer, one match, or one season per player. Hence, each player usually comprises more than one observation. The average player in the sample is about 24 years old. Interestingly, players initially appear to be valued higher on average by the Transfermarkt community (3.51 million) than what teams actually paid as transfer fees (1.72 million). Across the sample that starts with observations in 2007, a time where the Internet was not yet as common as it is now, players have an average of about one thousand Google hits per season. Playing time for the average player is a little less than half a season. As Figure 2a demonstrates, a large fraction of players does not play at all. However, these observations mostly relate to talented young players from youth teams who were appointed to a team's roster as back-ups but were not given a chance to prove themselves. If a player does not play a minimum amount of minutes (usually thirty minutes per match), he is not graded by Kicker. Without a measure of performance, these players drop out of the corresponding estimations. I resort to other measures for robustness checks (points per minute and a disaggregated measure of performance). Figure 2b shows the distribution of playing time per season for graded players only.

[9] "Fussball" is the German word for football and was included in the search request to restrict the query to results related to football.

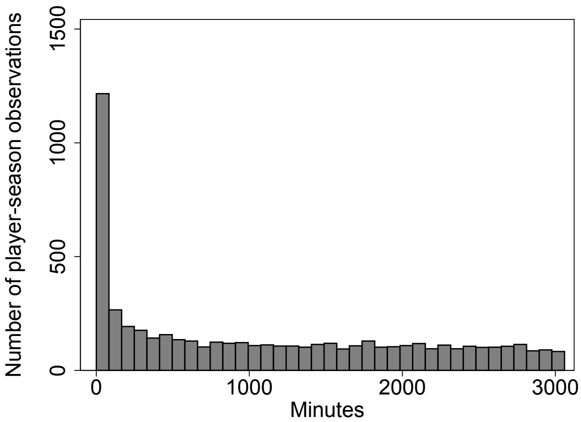
[10] The results of players who moved from one Bundesliga club to another in a given season were added together to obtain one single figure per player and season.

[11] The Python code to download that data can be obtained from the author on request.

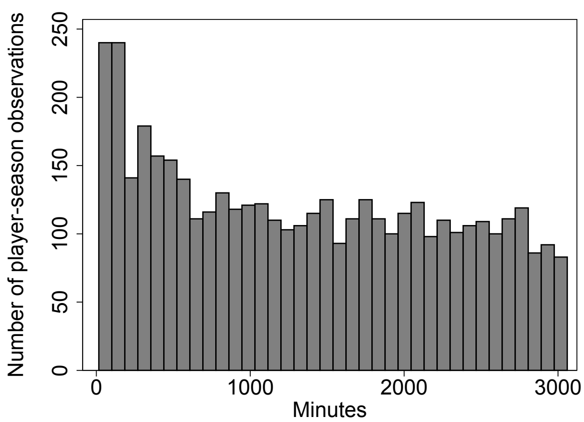
Table 1: Summary statistics.

	Mean	Std. Dev.	Min	Max	Obs.
Grade	3.74	0.54	2.00	6.00	4,352
Matches	15.53	11.51	0.00	34.00	5,390
Minutes	1,112.30	978.40	0.00	3,060.00	5,390
Fraction of minutes played	0.45	0.37	0.00	1.00	5,390
Substitutions (in)	3.14	3.89	0.00	27.00	5,390
Substitutions (out)	3.15	4.03	0.00	29.00	5,390
Goals	1.59	3.18	0.00	31.00	5,390
Assists	1.41	2.38	0.00	22.00	5,390
Points per match	1.16	0.73	0.00	3.00	5,390
Yellow cards	2.03	2.41	0.00	14.00	5,390
Red cards	0.05	0.22	0.00	2.00	5,390
Market value (in millions)	3.51	5.78	0.00	75.00	5,390
Loan	0.05	0.21	0.00	1.00	5,390
Google hits (in thousand)	0.93	2.68	0.00	48.60	5,390
Age	24.40	4.39	16.00	44.00	5,390
Minutes per match	38.23	41.50	0.00	90.00	158,180
Goals per match	0.10	0.34	0.00	5.00	84,498
Assists per match	0.09	0.32	0.00	4.00	84,498
Yellow cards per match	0.13	0.34	0.00	1.00	84,498
Red cards per match	0.00	0.06	0.00	1.00	84,498
Match grade	3.59	0.96	1.00	6.00	70,908
Transfer fee (in millions)	1.72	4.04	0.00	43.00	1,945
Height	1.83	0.06	1.65	2.01	1,868
Right foot	0.59	0.49	0.00	1.00	1,995
Left foot	0.20	0.40	0.00	1.00	1,995
Both feet	0.14	0.34	0.00	1.00	1,995
German (1=German)	0.45	0.50	0.00	1.00	1,995
Home score	1.63	1.35	0.00	9.00	3,060
Away score	1.25	1.19	0.00	8.00	3,060

Note: Each player or each season/match/transfer of each player counts as one observation.



(a) All players.



(b) Players evaluated by Kicker.

Figure 2: Histograms of playing time per season per player.

4 Empirical method

In line with existing studies on the sunk-cost fallacy in professional sports, I regress a measure of the player's time on the pitch on the sunk cost his current team has incurred. The latter corresponds to the transfer fee paid to acquire the player in the first place. With respect to control variables, I attempt to stay as close to the studies on the sunk-cost effect in US sports leagues as the different setting allows, while adding additional variables where needed. So far, studies have only investigated the sunk-cost effect on the seasonal level. However, the performance in previous matches is more likely to matter for the line-up decisions than entire previous seasons. As Transfermarkt and Kicker also provide match-level data, I investigate the sunk-cost effect on both a seasonal and match level.

4.1 Seasonal level

Regarding the dependent variable in the season-level analysis, I follow the approaches of Staw and Hoang (1995) and Camerer and Weber (1999), and Leeds et al. (2015). The two former apply Ordinary Least Squares (OLS) to regress the playing time per season on the sunk costs and control for performance as well as injuries that reduce the minutes players potentially could play. Leeds et al. (2015) take a different approach, incorporating injuries and suspensions into the dependent variable. In the same way, I use the ratio of actually played minutes out of a player's total potential. In order to calculate the potential playing time, I take the maximum playing time per season of 34 matches (17 matches for transfers in the winter transfer window) and subtract matches the player missed due to injury or suspension (disciplinary sanctions due to five yellow cards, yellow-red cards, red cards, or team-internal suspensions), and missed matches due to individual days off or appointments to the national team. The sample contains both players who have played all and those who have played none of their potential matches.

Due to the characteristics of the transfer market, transfers can be categorised into free and fee-bound transfers. For that reason, I include two variables for transfer fees.

To analyse the extensive margin, I introduce a dummy as to whether a transfer incurred a fee or not. If yes, the transfer fee paid constitutes the intensive margin.

Similar to Staw and Hoang (1995), I use Kicker grades as an aggregated measure of performance to control for player quality. Further, I control for market values at the beginning of each season. These are exogenous on the first match day and explain variance that cannot be explained by the Kicker grades. They are continuously updated and can serve as additional proxies for player potential. Missing market values usually result from the respective players being unknown and of very low value.[12] For that reason, I set the missing market values to zero.

Just like Camerer and Weber (1999), I include the performance of back-up players (grades, points per match, or disaggregated measures) as a control variable. The quality of all of the other players in the team who could potentially replace the player in focus also impacts his playing time. For this, I categorise all players as either goalkeeper, defender, midfield, or attack and calculate the average performance (e.g. grades) of the other players who play in the same position. This automatically eliminates all observations of goalkeepers who played every match in one season, as no back-up performance for substitutes exists. In these situations, I cannot be sure whether the goalkeepers played all the matches due to their ability or due to a lack of alternatives. Additionally, I also use the positional variable in order to control for effects related to a player's position.

Furthermore, the overall strength of a team might play a role. Its effect on playing time could go in either direction. On the one hand, better performing teams have higher earnings (DFL Deutsche Fußball Liga GmbH, 2017) and would therefore be able to hire more players for the subsequent season. Larger rosters could result in less playing time per player. Alternatively, successful teams could use the larger budget to replace players with better and more expensive ones. If the number of players in a team thereby remains constant, the performance of previous seasons should not alter the average player's time on the field. On the other hand, one could expect teams that performed poorly to buy additional players or higher quality replacements if their budget allows. To control for

[12]Starting from 2005, one can find meaningful market values for almost all players in the German Bundesliga on Transfermarkt.

such effects, I include the previous season's final rank per team (as in Keefer, 2017) and the total number of players in a team. Finally, I control for season and team effects.

In the first estimation, I use OLS to regress playing times on the pitch on transfer fees, including lagged performances as well as player and team controls.

$$\begin{aligned} Minutes_{i,t} = \beta_0 &+ \beta_1 Grade_{i,t-1} + \beta_2 BackupGrade_{i,t-1} + \\ &+ \beta_3 FeeBound_{i,t} + \beta_4 TransferFee_{i,t} + \\ &+ \beta_5 Loan_{i,t} + \beta_6 MarketValue_{i,t} + \\ &+ \beta_7 Injured_{i,t} + \beta_8 Suspended_{i,t} + \\ &+ \beta_9 MatchesOtherTeam_{i,t} + \beta_{10} Winter_{i,t} + \\ &+ \beta_{11} Age_{i,t} + \beta_{12} AgeSquared_{i,t} + \beta_{13} German_i + \beta_{14} Google_{i,t-1} + \\ &+ \beta_{15} \#PlayersTeam_{i,t} + \beta_{16} CL_{i,t} + \beta_{17} EL_{i,t} + \beta_{18} Rank_{i,t-1} + \\ &+ \textstyle\sum_{j=19}^{21} \beta_j Position_{j,i} + \sum_{k=22}^{52} \beta_k Team_{k,i,t} + \sum_{l=53}^{61} \beta_l Season_{l,t} \end{aligned} \tag{1}$$

The second estimation employs playing time as a fraction of total potential playing time. The dependent variable is therefore bound between 0 and 1. As Figure 3 shows, many players play none or all of their potential minutes. Given their past performance, an OLS estimation would predict that some of them play less than zero minutes or more than their potential maximum. Yet I only observe a fraction of minutes played of zero to a hundred percent. For that reason, I chose a Tobit model as the main identification method.

As first suggested by Camerer and Weber (1999), I precede the main estimation with a linear regression predicting current performance using lagged performances, transfer fees, and controls. This disentangles the information a transfer fee contains regarding performance and its effect on playing time. Hence, the final empirical strategy is a two-stage model with a linear regression predicting the performance of a player (his Kicker grade, average points per match, or goals, assists, and cards) and a Tobit regression with the fraction of minutes played out of the potential playing time as the dependent variable. I follow the example of Staw and Hoang (1995) and Camerer and Weber (1999) and estimate the model for each season a player was under contract with the same team.

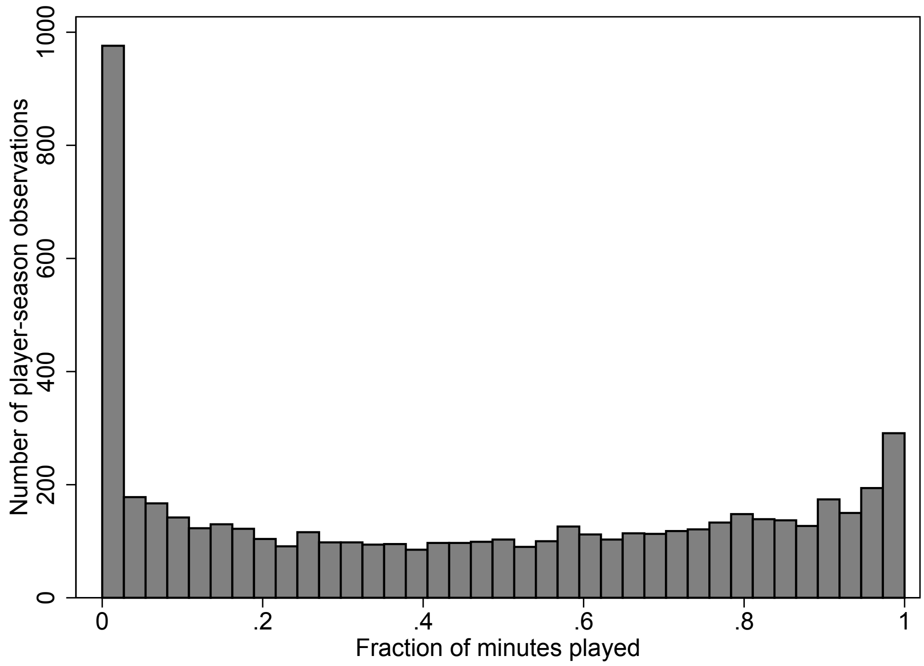


Figure 3: Histogram of the fractions of playing time out of the total potential playing time per season per player.

Since I use lagged grades, I lose the observations from the first season for players who moved up from non-graded (non-domestic or lower level) leagues. The estimation for the first season is only based on 65 observations with no significant coefficients and I report only seasons two to five. However, in general, I can resort to Kicker grades prior to the 2007/2008 season.

The model can be written as

$$FractionMinutes_i^* = \widehat{Performance}_i \beta + X_i \gamma + u_i \tag{2}$$

$$\widehat{Performance}_i = \sum_{j=1}^{4} Performance_{t-j,i} \Pi_j + X_i \Phi + v_i, \tag{3}$$

where the fraction of minutes played is the unobserved latent variable. The observed dependent variable is equal to

$$FractionMinutes_{1i} = \begin{cases} 0, & \text{if } FractionMinutes_i^* < 0 \\ FractionMinutes_i^*, & \text{if } 0 \leq FractionMinutes_i^* \leq 1 \\ 1, & \text{if } FractionMinutes_i^* > 1. \end{cases} \tag{4}$$

X represents the matrix of regressors, β, γ, Π_1 through Π_4, Φ the parameters to be estimated and u_i and v_i the random error terms. The main equation to be estimated using a Tobit model (Equation (2)) is

$$\begin{aligned} FractionMinutes_{i,t} = {} & \beta_0 + \beta_1 \widehat{Performance}_{i,t} + \beta_2 BackupPerformance_{i,t-1} + \\ & + \beta_3 FeeBound_{i,t} + \beta_4 TransferFee_{i,t} + \\ & + \beta_5 Loan_{i,t} + \beta_6 MarketValue_{i,t} + \\ & + \beta_7 Age_{i,t} + \beta_8 AgeSquared_{i,t} + \\ & + \beta_9 German_i + \beta_{10} Google_{i,t-1} + \\ & + \beta_{11} CL_{i,t} + \beta_{12} EL_{i,t} + \beta_{13} Rank_{i,t-1} + \\ & + \textstyle\sum_{j=14}^{16} \beta_j Position_{j,i} + \sum_{k=17}^{48} \beta_k Team_{k,i,t} + \\ & + \textstyle\sum_{l=49}^{57} \beta_l Season_{l,t}. \end{aligned} \tag{5}$$

In the first specification of the Tobit estimation, I use Kicker grades as measure of performance. Further, I resort to the average points per match as an aggregated measure of performance and goals, assists, and penalty cards as a disaggregated measure of performance.

4.2 Match level

On the aggregate seasonal level, many confounds cancel each other out (e.g. each team is both the home team and the away team in the two meetings per season). Other factors have to be taken into account on a match level. One might employ a different line-up and substitution strategy against directly competing teams than teams at the other end of the ranking. Additionally, I conjecture that the match day might matter. At the beginning of each season, coaches could test several players. On the other hand, injuries or an intense competition at the end of a season could alter playing time on later match days. Therefore, I drop the variable indicating the team's final rank in the previous season and add the teams' difference in rank at kickoff, the match day as well as corresponding squared terms to the set of control variables of Models 1 and 5. A player's tenure with his current team measured in matches is also added. Furthermore, I account for players who are instructed by the same coach who hired them.

I also eliminate the variables that account for the number of matches a player was injured, suspended, or played with another team from Model 1. In these cases, the player plays zero minutes and it is not up to the coach to decide how many minutes he fields this player. Instead, I only estimate the match level model for players who are available.

5 Results

5.1 Seasonal level

5.1.1 Main analysis

The OLS regression at a seasonal level (Table 2) demonstrates that managers in the German Bundesliga do not appear to be very susceptible to the sunk-cost fallacy. Only the variable of the intensive margin of transfer fees in the second season is significant. Yet the coefficient is negative, contrary to a sunk-cost effect. Otherwise, as hypothesised, past performances of the player himself and those of his teammates on the same position predict playing time well. Alongside measures that control for players being unavailable due to injury, suspension, or appearances for the national team, or a transfer in the winter transfer period, the assessment of the Transfermarkt community at the beginning of the season is significant in all of the four seasons that were covered. In contrast, the popularity of a player, as measured in Google hits, has no additional influence on a player's time on the pitch. Notably, according to the OLS estimates, German players play significantly more minutes in two of the four seasons.

Table 2: Ordinary Least Squares regression.

	Minutes played			
	Season 2	Season 3	Season 4	Season 5
Grade_{t-1}	-455.4***	-586.6***	-490.6**	-583.1***
	(66.42)	(84.68)	(137.4)	(134.4)
Back-up grade_{t-1}	529.1***	307.0**	701.6***	365.3
	(112.5)	(97.90)	(169.5)	(278.3)
Fee-bound transfer	83.06	-4.832	-35.56	72.56
	(43.77)	(81.46)	(93.65)	(139.3)
Transfer fee (in millions)	-27.04*	-12.10	-0.948	6.841
	(11.58)	(11.61)	(10.78)	(8.732)
Loan	-19.57			
	(130.3)			
Market value (in millions)	57.21**	33.01**	34.49**	26.22**
	(18.26)	(9.913)	(10.92)	(9.081)
Injured matches	-54.43***	-54.98***	-69.55***	-79.14***
	(3.499)	(5.158)	(4.262)	(5.965)
Suspended matches	179.8***	139.6	44.27	42.95
	(30.61)	(74.95)	(31.00)	(53.00)
Matches with other team	-73.61***	-128.8***	-149.2***	-222.1***
	(7.785)	(20.63)	(19.69)	(37.55)
Winter transfer	-1046.6***	-1007.0***	-1160.5***	-1209.3***
	(53.05)	(102.0)	(144.0)	(184.6)
Age	45.33	-67.93	-52.41	-142.3
	(56.27)	(102.0)	(157.0)	(139.6)
Age squared	-0.886	0.934	1.080	2.540
	(1.114)	(2.018)	(2.964)	(2.553)
German (1=German)	129.1*	35.59	229.3*	180.7
	(46.68)	(81.63)	(101.9)	(101.0)
Google hits_{t-1} (in thousands)	30.45	-26.65	19.69	-45.22
	(21.35)	(18.10)	(35.73)	(44.62)
Number of players in team	11.18	-17.22	1.295	15.80
	(6.037)	(12.04)	(17.68)	(15.18)
Champions League	-99.82	-8.251	-262.8	-67.81
	(193.8)	(155.1)	(205.2)	(242.5)
Europa League	18.58	129.3	-104.8	-28.84
	(116.4)	(118.5)	(144.1)	(119.5)
Rank_{t-1}	-8.180	9.406	-50.01*	1.847
	(12.86)	(12.52)	(21.31)	(24.51)
Constant	-403.8	4640.8**	1890.7	3959.7
	(761.8)	(1635.4)	(2771.0)	(2460.7)
Position Effects	Yes	Yes	Yes	Yes
Team Effects	Yes	Yes	Yes	Yes
Season Effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.513	0.449	0.531	0.517
Observations	869	590	356	242

Standard errors clustered on the team level in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In the first stage of the IV Tobit model (Table 3) it is clear that the performance in the previous season is the best predictor of current performance. The grade from two years before a given season has some explanatory power for a current season. The grade from three years before does not matter anymore. Since players are evolving, this is not very surprising. Remarkably, the transfer fee does not predict future performance very well. Having moved to a team for a transfer fee is associated with a slightly better grade. However, this effect is only significant in the second season. Thus, it cannot be argued that transfer fees serve as a long-term indicator of performance. Instead, the continuously updated measure of market value is correlated with a better performance in three of the four seasons. Again, German players on average receive better grades in their second season. However, since the effect is not present in either of the other seasons, Kicker evaluations do not seem to exhibit a discriminatory bias.

The second-stage Tobit regression (Table 4) confirms the results from the OLS regression. Line-up decisions are primarily driven by predicted performance. Apart from the fourth season, both variables that relate to transfer fees are insignificant. In fact, a higher transfer fee is even associated with less playing time. Although other variables become significant in some seasons, only predicted performance constantly explains players' time on the pitch. In short, I cannot find that football coaches in Germany consider transfer fees when selecting players for the next match on a seasonal level.

Admittedly, it is possible that I am unable to find an effect because the sample size is too small. I therefore estimate effect sizes that I can preclude according to the data in a statistical power analysis. Since there is no straightforward method to conduct a power analysis following a two-stage Tobit estimation, I approximate a threshold for each of the four estimations in Table 4 by using a power analysis for multivariate logistic regression designs with a continuous predictor variable (the transfer fee). I start by calculating the statistical power given the actual data. Subsequently, I increase the effect size (in the positive direction) in increments until I obtain a statistical power of 80 percent. By doing so, I can reject effect sizes greater than .012 in Season 2, .013 in Season 3, .016 in Season 4, and .017 in Season 5 with a probability of 80 percent. Assuming the effect

Table 3: First-stage linear regression predicting grades.

	Grade			
	Season 2	Season 3	Season 4	Season 5
Grade_{t-1}	0.209***	0.299***	0.277**	0.331*
	(0.0572)	(0.0420)	(0.0843)	(0.132)
Grade_{t-2}		0.148**	0.152**	0.0727
		(0.0553)	(0.0494)	(0.108)
Grade_{t-3}			0.0390	0.121
			(0.0715)	(0.1000)
Grade_{t-4}				-0.0553
				(0.0518)
Back-up grade_{t-1}	-0.0818	0.0305	-0.160	0.0427
	(0.0838)	(0.0773)	(0.103)	(0.165)
Fee-bound transfer	-0.0712*	0.0101	0.0205	0.0825
	(0.0305)	(0.0534)	(0.0587)	(0.131)
Transfer fee (in millions)	0.0118	0.000694	-0.00423	-0.0167**
	(0.00898)	(0.00694)	(0.00584)	(0.00519)
Loan	-0.0542			
	(0.0721)			
Market value (in millions)	-0.0265*	-0.0119*	-0.00653	-0.0136*
	(0.0122)	(0.00582)	(0.00503)	(0.00539)
Age	0.0266	0.111*	0.0439	-0.216
	(0.0598)	(0.0474)	(0.0788)	(0.136)
Age squared	-0.000552	-0.00223*	-0.000782	0.00368
	(0.00113)	(0.000916)	(0.00141)	(0.00240)
German (1=German)	-0.127***	-0.0542	-0.00286	-0.111
	(0.0262)	(0.0319)	(0.0403)	(0.0756)
Google hits_{t-1} (in thousands)	-0.0123	-0.00726	-0.00485	0.0523*
	(0.0114)	(0.0217)	(0.0148)	(0.0251)
Champions League	-0.0732	0.0360	-0.316	0.174
	(0.0982)	(0.158)	(0.163)	(0.0902)
Europa League	-0.174**	-0.0967	-0.241*	-0.0622
	(0.0569)	(0.0741)	(0.0973)	(0.113)
Rank_{t-1}	-0.0124	-0.00990	-0.0122	-0.00741
	(0.00790)	(0.00937)	(0.0121)	(0.0136)
Constant	3.258***	0.0548	1.513	5.141*
	(0.913)	(0.726)	(1.342)	(2.332)
Position Effects	Yes	Yes	Yes	Yes
Team Effects	Yes	Yes	Yes	Yes
Season Effects	Yes	Yes	Yes	Yes
Observations	767	449	234	130

Standard errors clustered on the team level in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Second-stage Tobit regression.

	Fraction of potential minutes played			
	Season 2	Season 3	Season 4	Season 5
Predicted grade	-1.072***	-0.648***	-0.793***	-0.769*
	(0.245)	(0.141)	(0.189)	(0.314)
Back-up grade$_{t-1}$	0.0741	0.138*	0.174	0.0397
	(0.0885)	(0.0652)	(0.0959)	(0.162)
Fee-bound transfer	-0.0257	0.00890	0.0244	0.0641
	(0.0461)	(0.0302)	(0.0513)	(0.114)
Transfer fee (in millions)	0.00515	-0.00126	-0.0123***	-0.00710
	(0.00876)	(0.00426)	(0.00271)	(0.00830)
Loan	-0.0617			
	(0.0768)			
Market value (in millions)	-0.00628	0.00279	0.00662	-0.00545
	(0.0127)	(0.00477)	(0.00474)	(0.00874)
Age	0.0406	0.0235	0.133*	-0.0534
	(0.0626)	(0.0401)	(0.0619)	(0.132)
Age squared	-0.000769	-0.000637	-0.00253*	0.000834
	(0.00118)	(0.000805)	(0.00115)	(0.00220)
German (1=German)	-0.0994*	-0.0407	0.0214	-0.0273
	(0.0435)	(0.0244)	(0.0391)	(0.0813)
Google hits$_{t-1}$ (in thousands)	-0.00538	0.00202	0.00725	0.0311
	(0.0126)	(0.0129)	(0.0155)	(0.0360)
Champions League	-0.138	0.0735	-0.253*	0.102
	(0.0959)	(0.0881)	(0.128)	(0.133)
Europa League	-0.194**	-0.0120	-0.201**	-0.114
	(0.0633)	(0.0421)	(0.0751)	(0.0782)
Rank$_{t-1}$	-0.0140*	-0.00126	-0.0262*	-0.00411
	(0.00697)	(0.00570)	(0.0113)	(0.0118)
Constant	3.924***	1.804*	0.218	3.657
	(1.130)	(0.708)	(0.984)	(2.997)
Position Effects	Yes	Yes	Yes	Yes
Team Effects	Yes	Yes	Yes	Yes
Season Effects	Yes	Yes	Yes	Yes
Observations	767	449	234	130

Standard errors clustered on the team level in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Except for Season 5 ($p = .105$), all Wald tests of exogeneity of the instrumented variable (predicted grade) are significant.

size in Season 2 is .012 and ignoring the insignificant and negative effect of the extensive margin of transfer fees, an increase of one million Euro in the transfer fee would only result in a 1.2 percentage point increase in the fraction of played minutes. Given that the sample mean of transfer fees for players in their second season is 2.58 million, the average player plays 3 percentage points more than a player hired for free, or on average 58 instead of 55 percent of the potential minutes. On average, this equals 66 minutes more over a complete season, and therefore not even an entire match.

Furthermore, comparing the effect and sample sizes in this study and others demonstrates that the sunk-cost effect is at most relatively small in professional football. For example, Staw and Hoang (1995) and Camerer and Weber (1999) find a significant sunk-cost effect, but analyse substantially fewer observations in the first three seasons. For instance, while I use 767 observations in Season 2, Staw and Hoang (1995) use 241 and Camerer and Weber (1999) only use 202 observations.[13]

Finally, I test the hypothesis that teams might use playing time as an investment to promote players. Indeed, average transfer fees increase with age as long as players are 25 years old or younger and decrease thereafter (see Figure 4). This suggests that players are still improving in the first half of their career. This development could be strengthened by providing young players with more playing time. It might be worthwhile fielding them regardless of their past performances. Therefore, I first analyse whether playing time can be considered an investment in young prospects by including an interaction term of past playing time and age when predicting grades. The results suggest that it benefits players of all ages to spend time on the pitch, supporting Hypothesis 2a (Table A.1). Having played a larger fraction of one's potential minutes in season $t - 1$ is significantly associated with better grades in season t. The additional interaction terms of the young player dummy (younger than 22, 24, 26, and 28) and a player's past season playing time are insignificant. However, the changing sign from Specification (1) to (2) seems to be suggestive evidence that playing time is particularly effective to improve the performance

[13] Borland et al. (2011) have slightly more observations (e.g. 985 observations in Season 2), but also conclude that the sunk-cost effect found in their data disappears when taking into account the information contained in a player's draft order as well as incentives to award playing time to talented players.

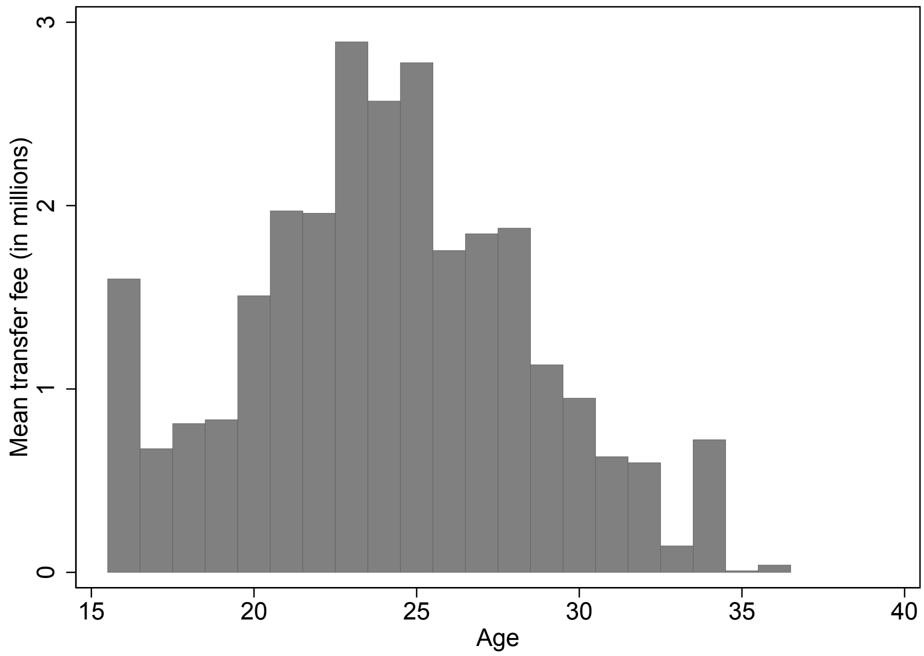


Figure 4: Mean transfer fee and player age in the German Bundesliga from 1999/2000 until 2016/2017.

in the subsequent year for players younger than 22 (Figure 5). Moreover, I divide the sample into young and old players to see whether there are any significant differences in coefficients when estimating Model 5. The corresponding two-stage Tobit estimation results provide suggestive evidence that teams use playing time as an investment in more junior players (Tables A.2 through A.7 for players younger than 22, 24, 26, and 28 years and older than 23 and 25 years, respectively). While the predicted grade significantly explains the playing time of older players, past performance seems to be less relevant for players younger than 22 (Figure 6). Put differently, whereas old players are replaced if they perform poorly, young prospects are given a second chance. Given the suggestive evidence that playing time can substantially improve the performance of younger players, this strategy would be a rational response.

5.1.2 Robustness checks

Bundesliga teams that enter European competitions may exhibit a different behaviour regarding their line-up decision. I expect them to give important players a rest during league matches to enable them to reach their top performance in international matches.

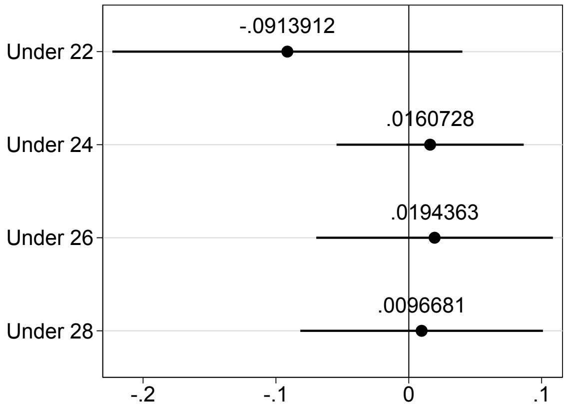


Figure 5: Point estimates for the effect of additional playing time on the grade of the following season for players younger than 22, 24, 26, and 28.

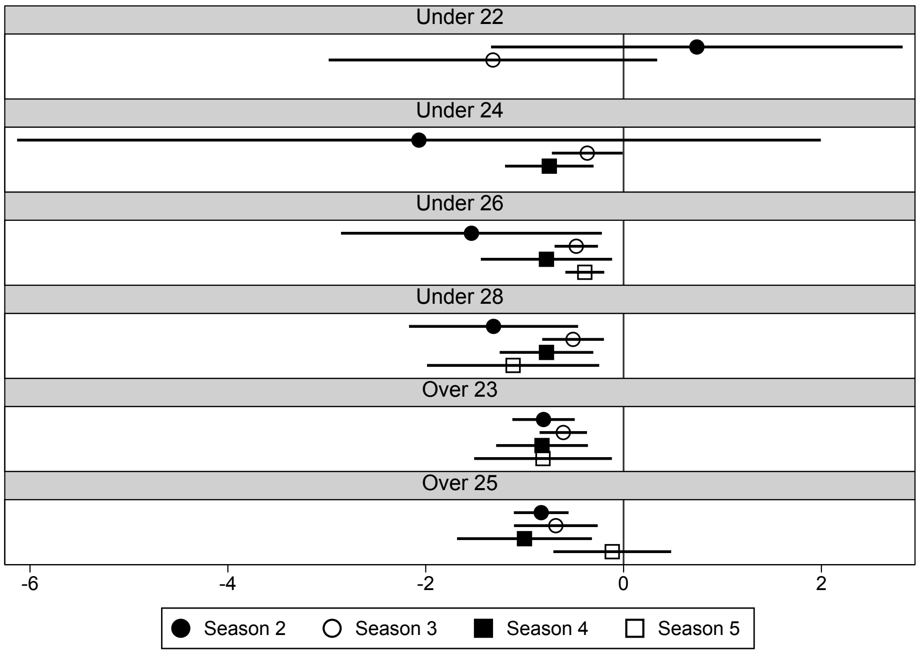


Figure 6: Effect sizes and standard errors of predicted grade on playing time for players younger than 22, 24, 26, and 28, and older than 23, and 25.

The latter are often more important in terms of financial aspects and prestige. If the aforementioned players came with higher transfer fees, but were often rested from league games for the European matches, it would bias a potential sunk-cost effect downwards. I run the IV Tobit model from above, excluding teams that participate in international cups. Table 5 shows the corresponding results of the second stage. It does not indicate a positive effect of transfer fees on playing time.

Table 5: Second-stage Tobit regression for teams that did not play international cups in the respective seasons.

	Fraction of potential minutes played			
	Season 2	Season 3	Season 4	Season 5
Predicted grade	-1.398**	-0.738***	-0.623*	-9.154
	(0.521)	(0.180)	(0.259)	(21.98)
Back-up grade$_{t-1}$	0.0274	0.131	0.257	-2.997
	(0.158)	(0.103)	(0.187)	(7.719)
Fee-bound transfer	-0.0281	0.0322	-0.0152	4.065
	(0.0702)	(0.0358)	(0.0778)	(10.31)
Transfer fee (in millions)	0.000111	0.0118	-0.00405	-0.495
	(0.0246)	(0.0133)	(0.00810)	(1.271)
Loan	-0.164			
	(0.136)			
Market value (in millions)	-0.00290	0.00539	0.0187	-0.621
	(0.0422)	(0.0218)	(0.0110)	(1.529)
Age	0.0578	-0.0228	0.109	-3.640
	(0.111)	(0.0729)	(0.0622)	(10.01)
Age squared	-0.00114	0.000153	-0.00179	0.0588
	(0.00211)	(0.00139)	(0.00113)	(0.162)
German (1=German)	-0.0957	-0.0336	0.108	-1.120
	(0.0539)	(0.0448)	(0.0799)	(3.071)
Google hits$_{t-1}$ (in thousands)	-0.0112	0.0351	-0.0819	1.110
	(0.0353)	(0.0348)	(0.0765)	(1.907)
Rank$_{t-1}$	-0.0153	0.00854	-0.0273	0.258
	(0.0148)	(0.0113)	(0.0174)	(0.797)
Constant	5.175***	2.068	-0.856	88.32
	(1.391)	(1.170)	(2.363)	(229.8)
Position Effects	Yes	Yes	Yes	Yes
Team Effects	Yes	Yes	Yes	Yes
Season Effects	Yes	Yes	Yes	Yes
Observations	448	224	101	54

Standard errors clustered on the team level in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Wald tests of exogeneity of the instrumented variable (predicted grade) are significant for Season 2 (p = .035) and 3 (p = .011), but not for Season 4 (p = .353) and 5 ($p = .675$).

The grades from Kicker are sports journalists' assessments. These could be biased, taking into account transfer fees. Consider two otherwise identical and equally well performing players with different transfer fees. If the Kicker journalists rated a player who has been bought for a high fee (unjustly) better than his counterfactual, this would bias the estimate for transfer fees downwards. For that reason, I resort to alternative measures of performance that cannot fall prey to the sunk-cost fallacy. An alternative single measure of performance is the average points per match won by a team when a given player was fielded. Tables 6 and 7 report the IV Tobit results using points per match instead of Kicker grades as a proxy for performance. Controlling for performance with this purely observational measure produces the same insignificant effect of transfer fees on playing time. Again, a higher transfer fee is even associated with less playing time in season four.

As an additional robustness check, I follow the lead of Camerer and Weber (1999) and replace the aggregated measures (Kicker grades and points per match) with disaggregated measures (goals, assists, yellow, yellow-red, and red cards). I estimate Model 5 for a restricted sample of outfield players (Table 8). The disaggregated measures include the number of goals, which is certainly not a good predictor for the playing time of goalkeepers. While none of the coefficients of the individual disaggregated measures are significant, they are jointly significant. The estimates of the extensive and intensive margin of transfer fees are all insignificant, similar to the ones obtained in Table 4 and 7. An analogous analysis for goalkeepers and defenders with goals conceded instead of goals shot does not indicate any significant coefficients either (Table B.8).[14]

5.2 Match level

The OLS and IV Tobit estimates of the match-level analysis substantiate the results obtained at the seasonal level (Tables 9 and 10). In the aggregate, players' transfer fees do not seem to matter for how many minutes they play. The coefficients on the extensive and intensive margin are insignificant in both estimations.

[14] Goalkeepers only account for a very small sample size (e.g. 93 observations in Season 2) and neither the performance measures nor the transfer fee variables are significant.

Table 6: First-stage linear regression predicting points per match.

	Points per match			
	Season 2	Season 3	Season 4	Season 5
Points per match$_{t-1}$	0.221**	0.249**	0.298***	-0.121**
	(0.0773)	(0.0833)	(0.0644)	(0.0454)
Points per match$_{t-2}$		0.114*	0.0185	-0.0235
		(0.0539)	(0.0575)	(0.0472)
Points per match$_{t-3}$			0.0849	-0.0700
			(0.0608)	(0.0957)
Points per match$_{t-4}$				-0.00724
				(0.0299)
Back-up points per match$_{t-1}$	-0.106	-0.0112	-0.0849	-0.129
	(0.0687)	(0.0897)	(0.126)	(0.153)
Fee-bound transfer	0.118**	0.0162	0.0249	-0.0849
	(0.0418)	(0.0491)	(0.0860)	(0.119)
Transfer fee (in millions)	-0.0158***	-0.00648	0.00524	-0.000450
	(0.00474)	(0.00666)	(0.00840)	(0.00512)
Loan	0.0664			
	(0.0704)			
Market value (in millions)	0.0305***	0.0174*	0.0124	0.0157**
	(0.00652)	(0.00756)	(0.00694)	(0.00529)
Age	0.0306	0.120	0.0142	0.298
	(0.0484)	(0.112)	(0.128)	(0.171)
Age squared	-0.000450	-0.00227	-0.000479	-0.00441
	(0.000923)	(0.00217)	(0.00237)	(0.00297)
German (1=German)	0.0745*	0.0826	0.0477	0.124
	(0.0355)	(0.0460)	(0.0705)	(0.0731)
Google hits$_{t-1}$ (in thousands)	0.0197*	-0.0203	-0.0253***	-0.0380
	(0.00877)	(0.0353)	(0.00537)	(0.0217)
Champions League	0.195	0.279	0.539**	-0.184
	(0.117)	(0.193)	(0.173)	(0.203)
Europa League	0.219*	0.190	0.431**	0.257*
	(0.0865)	(0.104)	(0.165)	(0.102)
Rank$_{t-1}$	0.0200	0.0315	0.0361*	-0.00387
	(0.0116)	(0.0166)	(0.0162)	(0.0198)
Constant	0.267	0.206	1.070	-2.972
	(0.586)	(1.372)	(1.642)	(2.630)
Position Effects	Yes	Yes	Yes	Yes
Team Effects	Yes	Yes	Yes	Yes
Season Effects	Yes	Yes	Yes	Yes
Observations	989	560	282	163

Standard errors clustered on the team level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Second-stage Tobit regression of the fraction of minutes played on predicted points per match.

	Fraction of potential minutes played			
	Season 2	Season 3	Season 4	Season 5
Predicted points per match	0.736**	0.717***	0.616**	-1.246
	(0.226)	(0.214)	(0.213)	(1.095)
Back-up points per match$_{t-1}$	-0.0799	-0.0299	-0.139	-0.154
	(0.0476)	(0.0722)	(0.0725)	(0.225)
Fee-bound transfer	0.0125	0.0178	0.0165	-0.0795
	(0.0419)	(0.0433)	(0.0498)	(0.171)
Transfer fee (in millions)	-0.00923	-0.00337	-0.0110**	0.00124
	(0.00617)	(0.00470)	(0.00388)	(0.00950)
Loan	-0.00565			
	(0.0834)			
Market value (in millions)	0.0220*	0.0144*	0.0192***	0.0400*
	(0.0100)	(0.00595)	(0.00400)	(0.0172)
Age	0.00491	-0.0599	0.0712	0.507
	(0.0307)	(0.0640)	(0.0531)	(0.431)
Age squared	-0.0000576	0.00115	-0.00120	-0.00769
	(0.000595)	(0.00122)	(0.000974)	(0.00685)
German (1=German)	-0.0264	-0.0252	0.0623	0.287**
	(0.0298)	(0.0446)	(0.0440)	(0.108)
Google hits$_{t-1}$ (in thousands)	-0.00223	0.00113	0.0122	-0.0924*
	(0.0154)	(0.0262)	(0.0118)	(0.0449)
Champions League	-0.202	-0.112	-0.464*	-0.436
	(0.106)	(0.131)	(0.188)	(0.275)
Europa League	-0.179*	-0.0822	-0.303	0.206
	(0.0805)	(0.0901)	(0.161)	(0.354)
Rank$_{t-1}$	-0.0121	-0.00626	-0.0399**	-0.00443
	(0.00864)	(0.00984)	(0.0133)	(0.0219)
Constant	-0.565	-0.463	-1.628	-6.108
	(0.497)	(0.915)	(1.061)	(5.559)
Position Effects	Yes	Yes	Yes	Yes
Team Effects	Yes	Yes	Yes	Yes
Season Effects	Yes	Yes	Yes	Yes
Observations	989	560	282	163

Standard errors clustered on the team level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Except for Season 5 ($p = .193$), all Wald tests of exogeneity of the instrumented variable (predicted points per match) are significant.

Table 8: Second-stage Tobit regression of the fraction of minutes played on predicted disaggregated measures for outfield players.

	Fraction of potential minutes played			
	Season 2	Season 3	Season 4	Season 5
Predicted goals	0.00442	-0.00443	0.0213	-0.00929
	(0.0679)	(0.0879)	(0.0174)	(0.0543)
Predicted assists	0.0240	0.0641	0.0580	0.0418
	(0.0490)	(0.0507)	(0.0412)	(0.0542)
Predicted yellow cards	0.217	0.0274	0.0425	-0.000389
	(0.365)	(0.216)	(0.0341)	(0.137)
Predicted yellow-red cards	-1.905	-0.549	0.243	0.672
	(4.598)	(1.916)	(0.834)	(0.869)
Predicted red cards	-0.294	3.242	-0.0397	-0.387
	(3.659)	(10.61)	(0.553)	(1.832)
Back-up goals$_{t-1}$	-0.0130	0.0108	-0.0286	-0.0896*
	(0.0389)	(0.0288)	(0.0207)	(0.0438)
Back-up assists$_{t-1}$	0.0130	0.0119	0.0593	0.114
	(0.0481)	(0.131)	(0.0345)	(0.172)
Back-up yellow cards$_{t-1}$	-0.0654	-0.136	-0.0832**	-0.0178
	(0.0555)	(0.400)	(0.0312)	(0.0459)
Back-up yellow-red cards$_{t-1}$	0.259	-0.878	-0.403	0.825
	(0.631)	(2.577)	(0.419)	(1.612)
Back-up red cards$_{t-1}$	0.0117	0.758	0.202	0.798
	(0.409)	(3.234)	(0.194)	(1.010)
Fee-bound transfer	0.00194	0.00232	0.0299	0.00665
	(0.0809)	(0.125)	(0.0495)	(0.0735)
Transfer fee (in millions)	0.000714	-0.0163	-0.00718*	0.00672
	(0.0141)	(0.0370)	(0.00335)	(0.00677)
Loan	-0.102			
	(0.431)			
Market value (in millions)	0.00249	0.0220	0.00704	0.00644
	(0.0289)	(0.0592)	(0.00805)	(0.00928)
Age	-0.0407	-0.0142	0.0597	-0.0357
	(0.266)	(0.0937)	(0.0591)	(0.473)
Age squared	0.000817	0.000375	-0.00105	0.00102
	(0.00518)	(0.00189)	(0.000988)	(0.00880)
German (1=German)	-0.0735	0.0593	0.0587	0.118
	(0.257)	(0.229)	(0.0574)	(0.162)
Google hits$_{t-1}$ (in thousands)	-0.00870	-0.0477	-0.00573	-0.0303
	(0.0598)	(0.143)	(0.00478)	(0.0398)
Champions League	-0.0577	-0.0149	0.0196	0.0362
	(0.179)	(0.222)	(0.0935)	(0.267)
Europa League	-0.0405	-0.168	0.0248	0.117
	(0.156)	(0.435)	(0.0922)	(0.179)
Rank$_{t-1}$	0.00146	0.0138	-0.00785	0.00393
	(0.0235)	(0.0733)	(0.00899)	(0.0214)
Constant	1.062	0.553	-0.856	0.209
	(4.919)	(1.537)	(0.978)	(7.703)
Position Effects	Yes	Yes	Yes	Yes
Team Effects	Yes	Yes	Yes	Yes
Season Effects	Yes	Yes	Yes	Yes
Observations	896	501	245	136

Standard errors clustered on the team level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Except for Season 4 (p = .083), all Wald tests of exogeneity of the instrumented variable (predicted goals, assists, and cards) are significant.

Table 9: Ordinary Least Squares regression of minutes played per match.

	Minutes played	
Match grade$_{t-1}$ if graded	-5.128***	(0.491)
Match grade$_{t-2}$ if graded	-2.269***	(0.189)
Match grade$_{t-3}$ if graded	-1.348***	(0.0991)
Match grade$_{t-4}$ if graded	-1.069***	(0.158)
Match grade$_{t-5}$ if graded	-1.032***	(0.134)
Match graded$_{t-1}$	44.74***	(2.934)
Match graded$_{t-2}$	18.79***	(0.923)
Match graded$_{t-3}$	10.65***	(0.522)
Match graded$_{t-4}$	9.756***	(0.639)
Match graded$_{t-5}$	10.59***	(0.779)
Match played$_{t-1}$	8.691***	(0.539)
Match played$_{t-2}$	3.128***	(0.576)
Match played$_{t-3}$	1.815***	(0.382)
Match played$_{t-4}$	-0.0744	(0.481)
Match played$_{t-5}$	0.301	(0.441)
Match backup grade$_{t-1}$ if graded	1.094**	(0.307)
Fee-bound transfer	0.692	(0.686)
Transfer fee (in millions)	0.0503	(0.0464)
Loan	-0.222	(1.175)
Market value (in millions)	0.476**	(0.167)
Age	1.622***	(0.435)
Age squared	-0.0281**	(0.00861)
German (1=German)	0.612	(0.399)
Google hits previous season (in thousands)	-0.122	(0.173)
Hiring coach	0.00770	(0.364)
Tenure in team	0.0347**	(0.00984)
Tenure in team squared	-0.0000740	(0.0000375)
Number of players in team	0.0628	(0.0357)
Champions League	0.0187	(0.635)
Europa League	0.00192	(0.436)
Rank difference	0.0895***	(0.0132)
Rank difference squared	0.00207	(0.00160)
Match day	0.162***	(0.0404)
Match day squared	-0.00350**	(0.000989)
Constant	-26.51***	(5.424)
Position Effects	Yes	
Team Effects	Yes	
Season Effects	Yes	
Adjusted R^2	0.524	
Observations	78490	

Standard errors clustered on the team level in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: IV Tobit regression of minutes played per match.

	Second stage Minutes per match	First stage Predicted grade
Predicted grade	-85.80***	
	(9.154)	
Fee-bound transfer	1.156	0.00362
	(2.732)	(0.0163)
Transfer fee (in millions)	0.130	-0.00340
	(0.202)	(0.00176)
Back-up match grade$_{t-1}$	-3.394***	-0.0320***
	(0.737)	(0.00477)
Loan	-4.022	-0.0451
	(5.516)	(0.0530)
Market value (in millions)	0.181	-0.00498***
	(0.306)	(0.00130)
Age	7.736*	0.0264
	(3.707)	(0.0214)
Age squared	-0.157*	-0.000609
	(0.0713)	(0.000407)
German (1=German)	-2.314	-0.0474**
	(2.349)	(0.0145)
Google hits previous season (in thousands)	-0.119	0.00324
	(0.849)	(0.00375)
Hiring coach	-1.198	-0.0333**
	(1.360)	(0.0121)
Tenure in team	0.0654	-0.000463
	(0.0378)	(0.000277)
Tenure in team squared	-0.000143	0.000000740
	(0.000135)	(0.000000858)
Number of players in team	0.957*	0.00558*
	(0.375)	(0.00241)
Champions League	-2.677	0.0251
	(4.809)	(0.0311)
Europa League	-7.600**	-0.0503**
	(2.588)	(0.0194)
Rank difference	0.647***	0.00416***
	(0.0799)	(0.000628)
Rank difference squared	-0.000475	-0.0000599
	(0.00797)	(0.0000333)
Match day	0.442**	-0.000529
	(0.149)	(0.00109)
Match day squared	-0.0123**	-0.00000834
	(0.00387)	(0.0000283)
Constant	179.3**	3.788***
	(58.23)	(0.310)
Position Effects	Yes	Yes
Team Effects	Yes	Yes
Season Effects	Yes	Yes
Grades of previous 20 match days	No	Yes
Observations	68067	

Standard errors clustered on the team level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The Wald test of exogeneity of the instrumented variable (predicted match grade) is significant.

A major advantage of using match level data is that it allows the inclusion of observations earlier than the second season. A sunk-cost effect might be more pronounced just after a player has been hired as the costs are then temporally closer. Therefore, I add an interaction term of transfer fees and the tenure of a player measured in match days. This makes the intensive variable of the transfer fee significant, yet negligible (Table 11). There is indeed a small sunk-cost effect that decreases over time. Starting with match day 21 (the first 20 matches are excluded due to the lagged variables), the average player with a transfer fee of 1.72 million Euro *ceteris paribus* plays one and a half minutes more. Compared to the effect of a predicted increase in performance measured in grades of almost an entire match (86.95 minutes), the sunk-cost effect is minuscule.[15] In the aggregate regressions for the players' first to fifth seasons, this sunk-cost effect disappears (Table 12; Table C.11 uses Google hits for the current season in Season 1 as the lagged variable is missing for many players in the first season).

In addition, coaches could only acknowledge transfer fees in their line-up decisions if the transfer fee is high relative to those of the other players in the roster. Therefore, I compute the transfer fee relative to the total transfer fees for the current roster. This specification cannot detect a significant sunk-cost effect either (Table C.12).

Coaches might also differ in the extent to which they commit the sunk-cost fallacy. While Haita-Falah (2017) does not find a significant relationship between cognitive ability and the tendency to honour sunk costs, there seems to be a correlation with age (Strough et al., 2008). Hence, I test whether more experienced, older coaches are less prone to acknowledge sunk costs. I find that the interaction effects of the transfer fee coefficients and the coaches' age are not significant (Table C.13).

Finally, I analyse whether a sunk-cost effect is only apparent for players who play under the same coach they debuted with. As described by Camerer and Weber (1999), it can be argued that new coaches may be able to ignore sunk costs incurred by predecessors (McCarthy et al., 1993; Schoorman, 1988; Staw et al., 1997). By contrast, Olivola (2018) provides evidence that the sunk-cost effect is an interpersonal phenomenon. Comparing

[15] Table C.10 shows that decreasing the lag to five matches does not qualitatively change the result.

Table 11: IV Tobit regression of minutes played per match, interacting the transfer fee variables with the player's tenure in the team.

	Second stage Minutes per match	First stage Predicted grade
Predicted grade	-86.95***	
	(8.681)	
Fee-bound transfer	4.766	0.0241
	(4.783)	(0.0281)
Transfer fee (in millions)	1.000***	0.00173
	(0.273)	(0.00196)
Fee-bound transfer × Tenure in team	-0.0404	-0.000226
	(0.0416)	(0.000286)
Transfer fee (in millions) × Tenure in team	-0.00777**	-0.0000463*
	(0.00263)	(0.0000209)
Back-up match grade$_{t-1}$	-3.396***	-0.0319***
	(0.735)	(0.00468)
Loan	-3.627	-0.0423
	(5.539)	(0.0531)
Market value (in millions)	0.0421	-0.00570***
	(0.336)	(0.00121)
Age	6.935	0.0217
	(3.787)	(0.0211)
Age squared	-0.142	-0.000518
	(0.0731)	(0.000403)
German (1=German)	-2.520	-0.0481***
	(2.332)	(0.0141)
Google hits previous season (in thousands)	0.363	0.00614
	(0.871)	(0.00486)
Hiring coach	-1.172	-0.0329**
	(1.353)	(0.0123)
Tenure in team	0.128**	-0.0000963
	(0.0420)	(0.000343)
Tenure in team squared	-0.000215	0.000000283
	(0.000127)	(0.000000810)
Number of players in team	0.972**	0.00564*
	(0.372)	(0.00237)
Champions League	-2.584	0.0255
	(4.883)	(0.0311)
Europa League	-7.886**	-0.0516**
	(2.582)	(0.0195)
Rank difference	0.654***	0.00417***
	(0.0780)	(0.000625)
Rank difference squared	0.0000253	-0.0000565
	(0.00818)	(0.0000338)
Match day	0.440**	-0.000539
	(0.150)	(0.00108)
Match day squared	-0.0124**	-0.00000845
	(0.00389)	(0.0000280)
Constant	189.6***	3.820***
	(55.20)	(0.299)
Position Effects	Yes	Yes
Team Effects	Yes	Yes
Season Effects	Yes	Yes
Grades of previous 20 match days	No	Yes
Observations	68067	

Standard errors clustered on the team level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Tenure in team is measured in matches. The Wald test of exogeneity of the instrumented variable (predicted match grade) is significant.

Table 12: Second-stage Tobit regression of minutes played per match on a seasonal level, interacting the transfer fee variables with the player's tenure in the team.

	Minutes per match				
	Season 1	Season 2	Season 3	Season 4	Season 5
Predicted grade	-187.6***	-97.09***	-88.07***	-82.34***	-94.25***
	(40.10)	(12.23)	(12.66)	(11.20)	(16.43)
Back-up match grade$_{t-1}$	6.776*	-0.797	-3.324*	-4.127*	-9.844**
	(3.147)	(1.060)	(1.340)	(1.889)	(3.080)
Fee-bound transfer	28.00	-5.092	-8.395	-3.861	44.11*
	(33.65)	(7.769)	(12.75)	(29.12)	(17.32)
Transfer fee (in millions)	0.555	2.336*	-1.138	8.896	11.51**
	(8.016)	(0.940)	(1.543)	(4.856)	(4.379)
Fee-bound transfer × Tenure in team	-0.120	0.143	0.178	0.0436	-0.304*
	(0.703)	(0.138)	(0.156)	(0.268)	(0.144)
Transfer fee (in millions) × Tenure in team	-0.0759	-0.0340	0.00831	-0.0694	-0.0707*
	(0.105)	(0.0175)	(0.0203)	(0.0390)	(0.0295)
Loan	-182.3**	-4.768			
	(56.64)	(6.230)			
Market value (in millions)	-9.373	-0.0779	-0.0629	0.813	-0.784
	(5.871)	(0.746)	(0.541)	(0.789)	(0.422)
Age	37.84	0.876	6.430	17.83*	-12.60
	(43.78)	(5.555)	(5.968)	(7.912)	(7.703)
Age squared	-0.651	-0.0198	-0.130	-0.331*	0.173
	(0.968)	(0.104)	(0.118)	(0.153)	(0.134)
German (1=German)	-6.383	-6.396*	-1.676	0.669	-1.151
	(19.37)	(2.835)	(3.518)	(3.699)	(4.945)
Google hits previous season (in thousands)	51.13**	0.127	1.424	-2.826	3.882
	(17.81)	(1.081)	(2.345)	(1.870)	(2.129)
Hiring coach	13.98	-0.616	-5.020	-2.107	18.09***
	(17.09)	(2.288)	(4.671)	(6.477)	(4.966)
Tenure in team	0.881	0.292	-0.0756	0.421	0.0966
	(2.993)	(0.612)	(0.587)	(0.595)	(0.492)
Tenure in team squared	-0.00718	-0.00178	-0.000418	-0.00183	0.00113
	(0.0338)	(0.00665)	(0.00426)	(0.00287)	(0.00229)
Number of players in team	4.311	0.734	0.998	2.108	0.0928
	(3.826)	(0.580)	(0.574)	(1.317)	(0.641)
Champions League	9.240	0.999	-4.526	-10.29	-5.726
	(17.87)	(8.167)	(9.265)	(7.963)	(9.484)
Europa League	-16.90	-8.143	-2.158	-13.64	-24.77***
	(24.07)	(5.008)	(3.283)	(7.910)	(6.353)
Rank difference	1.505***	0.731***	0.284*	0.949***	0.370
	(0.381)	(0.133)	(0.129)	(0.218)	(0.316)
Rank difference squared	0.00989	0.00766	-0.00408	-0.00383	-0.00177
	(0.0261)	(0.0157)	(0.0141)	(0.0211)	(0.0257)
Match day	-0.902	-0.0211	0.512	0.725	0.596
	(3.026)	(0.408)	(0.397)	(0.527)	(0.819)
Match day squared	0.0316	-0.000369	-0.0123	-0.0180	-0.0237
	(0.0362)	(0.0104)	(0.0129)	(0.0126)	(0.0208)
Constant	-166.8	327.8***	166.4*	-30.78	552.6***
	(529.4)	(89.24)	(84.80)	(105.2)	(145.0)
Position Effects	Yes	Yes	Yes	Yes	Yes
Team Effects	Yes	Yes	Yes	Yes	Yes
Season Effects	Yes	Yes	Yes	Yes	Yes
Observations	2923	23954	15092	9614	6746

Standard errors clustered on the team level in parentheses
Grade instrumented with grades of previous 20 (5 in the first season) match days.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Tenure in team is measured in matches. All Wald tests of exogeneity of the instrumented variable (predicted match grade) are significant.

Columns (1) and (2) in Table 13, I find no clear evidence for either an interpersonal or an intra-personal sunk-cost effect. However, the switching signs of the coefficients of the variables related to the transfer fee should arouse suspicion and motivate further research.

5.3 Discussion

Despite its thoroughness, the analysis has certain limitations. First, Google hits are not a perfect proxy for player popularity. It is obvious that they also include coverage on bad performance and misconduct on and off the pitch. This could be detrimental to jersey and ticket sales. Yet, with unknown players in particular, bad news could also have positive effects as they still increase a player's fame (Berger et al., 2010). Given that other data (e.g. on jersey sales) is not available on a detailed level, I am confident to provide a practicable yet convincing solution that might also be applied in future research.

Second, as a further control variable for player potential (in terms of sporting performance and marketing) I include Transfermarkt's market values. By nature, this variable correlates with actual transfer fees. Whereas the market value is an estimate of the value of a player for a team, transfer fees are determined by additional factors such as the remaining duration of a contract and can even be zero for highly valued but contract-less players. At the time of the observed transfers, the correlation of market values and transfer fees is 0.69. As market values are continuously updated, they retain explanatory power in some of the analyses, even after controlling for predicted or past performances. On a seasonal level (not only at the time of a transfer), the correlation between market values and transfer fees is only 0.61. Therefore, I am certain that the variable $MarketValue$ does not confound the results, but rather precludes an omitted variable bias. Moreover, excluding market values from the match-level IV Tobit estimation (Table 10) does not make the transfer fee variables significant.

As discussed in Section 2, existing studies have been able to uncover a sunk-cost effect in US professional sports that feature draft systems (Camerer and Weber, 1999; Keefer, 2015, 2017; Staw and Hoang, 1995). I am unable to empirically identify the reasons for the discrepancy between the behaviour under a draft system compared to a transfer market.

Table 13: Second-stage Tobit regression of minutes played per match by coach-player relationship.

	(1) Under different coach Minutes per match	(2) Under same coach Minutes per match
Predicted grade	-82.04***	-101.8***
	(10.92)	(12.50)
Back-up match grade$_{t-1}$	-3.406***	-3.765***
	(1.008)	(1.021)
Fee-bound transfer	4.067	-3.962
	(2.746)	(4.110)
Transfer fee (in millions)	-0.101	0.701
	(0.191)	(0.600)
Loan	2.167	-6.927
	(8.174)	(7.820)
Market value (in millions)	0.324	-0.465
	(0.298)	(0.566)
Age	7.845	8.709
	(4.305)	(4.888)
Age squared	-0.159	-0.175
	(0.0838)	(0.0939)
German (1=German)	-3.115	-0.453
	(2.966)	(2.682)
Google hits previous season (in thousands)	-0.127	-0.0981
	(0.909)	(1.542)
Tenure in team	0.0500	0.122
	(0.0363)	(0.0862)
Tenure in team squared	-0.000128	-0.0000344
	(0.000119)	(0.000372)
Number of players in team	0.999	0.936
	(0.567)	(0.627)
Champions League	-0.964	2.308
	(5.657)	(5.100)
Europa League	-6.485*	-10.39*
	(3.127)	(4.554)
Rank difference	0.591***	0.730***
	(0.0835)	(0.112)
Rank difference squared	0.00849	-0.0154
	(0.00841)	(0.0152)
Match day	0.444*	0.472
	(0.193)	(0.315)
Match day squared	-0.0124**	-0.0139
	(0.00475)	(0.00860)
Constant	158.3*	247.5**
	(75.45)	(80.23)
Position Effects	Yes	Yes
Team Effects	Yes	Yes
Season Effects	Yes	Yes
Observations	45464	22603

Standard errors clustered on the team level in parentheses
Grade instrumented with grades of previous 20 match days.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The first column is the regression for players who played under a different coach than the one who was in office when the player was acquired. The first column is the regression for players who played under the same coach who was in office when the player was acquired. The Wald tests of exogeneity of the instrumented variable (predicted match grade) are significant.

Yet two accounts come to mind. First, transfer fees and bi-weekly salary payments could exhibit different degrees of salience and might vary with respect to the extent they represent sunk costs. In US sports, salaries are determined ex ante through a player's draft order and are therefore sunk. Bi-weekly or monthly payments could give the impression that these salaries are at the manager's discretion. Transfer fees are paid once, usually before the transferred player moves to the new team. It is conceivable that managers find it less difficult to identify these one-time payments as sunk costs and to ignore them compared to continuous but predetermined transactions. It would be interesting to test this hypothesis in the laboratory.

The second account are structures of the sports labour markets. In the US, several policies are aimed at balancing the league. In the rookie draft, teams pick new talents in reverse order of their past season's ranking. Hence, poorly performing teams are granted the opportunity to hire the players with the biggest prospects. A salary cap also helps to prevent a concentration of the best players among a few teams. Probably the most crucial difference is that US sports leagues are closed while teams in European leagues are subject to promotion and relegation (Andreff, 2011). The rather intense, deregulated market conditions in European professional sports leagues could produce an evolutionary process. Teams only survive at a professional level if they are able to act rationally. Behavioural biases such as the sunk-cost fallacy will push teams down the ranks and, due to relegation, out of the market. If market forces are not present or weaker as in US leagues, it might take longer for irrational behaviour to disappear. Falk and Szech (2013) experimentally document how market interaction can erode moral values. My results suggest that it could also alleviate behavioural biases. Future research should investigate the market conditions under which biases emerge or disappear.

Comparing the findings to results of the sunk-cost effect from the laboratory contributes to research on how professional experience in a given context can promote rational behaviour. Palacios-Huerta and Volij (2008), and Walker and Wooders (2001) show that professional football and tennis players, who have experience with interactions similar to those of mixed-strategy games, play closer to the equilibrium in these games than college students. Similarly, the sunk-cost fallacy could be detected in a number of experiments that primarily took students as subjects (e.g. Friedman et al., 2007). However, students rarely face situations that provide large incentives to overcome the sunk-cost fallacy. In contrast, irrational decisions are quickly penalised in professional sports. Top-level football coaches have to pick line-ups every match day. They are well advised to learn from their own experience and the observation of peers how honouring sunk-costs can reduce their chances of winning or even cost them their job.

6 Conclusion

I am unable to find evidence supporting the sunk-cost fallacy among professional football coaches on a seasonal level. This finding is robust to varying measures of performance (aggregated and disaggregated). It is in contrast to the results of a majority of previous articles that studied this behavioural bias in the context of professional sports (Camerer and Weber, 1999; Keefer, 2015, 2017; Staw and Hoang, 1995). A more detailed analysis on the match level reveals a sunk-cost effect. However, when compared to the effect of predicted performance on playing time, the effect of transfer fees is negligible and decreases with a player's tenure. Furthermore, I do not find that coaches with more experience are less prone to exhibit the sunk-cost fallacy. Finally, coaches do not seem to grant more playing time to players in whose transfer they were involved in. Hence, similarly to Borland et al. (2011) and Leeds et al. (2015), the results support rational behaviour in professional sports team management. Previous and predicted performance are the primary determinants of a player's time on the pitch in the German Bundesliga. Coaches and managers seem to be able to ignore the huge transfer fees they paid beforehand, as soon as players fail to live up to their expectations.

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A Playing time as an investment

Table A.1: Ordinary Least Squares regression of playing time as an investment in players younger than 22, 24, 26, and 28 years.

	Grade			
	(1)	(2)	(3)	(4)
Fraction of minutes played$_{t-1}$	-0.230***	-0.259***	-0.264***	-0.259***
	(0.0334)	(0.0338)	(0.0462)	(0.0544)
U22$_{t-1}$ $\times$ Fraction of minutes played$_{t-1}$	-0.0914			
	(0.0638)			
U24$_{t-1}$ $\times$ Fraction of minutes played$_{t-1}$		0.0161		
		(0.0341)		
U26$_{t-1}$ $\times$ Fraction of minutes played$_{t-1}$			0.0194	
			(0.0432)	
U28$_{t-1}$ $\times$ Fraction of minutes played$_{t-1}$				0.00967
				(0.0442)
Grade$_{t-1}$	0.229***	0.230***	0.230***	0.230***
	(0.0281)	(0.0284)	(0.0285)	(0.0286)
Back-up grade$_{t-1}$	0.0113	0.0133	0.0125	0.0123
	(0.0518)	(0.0516)	(0.0524)	(0.0522)
Fee-bound transfer	0.00414	0.00391	0.00348	0.00413
	(0.0231)	(0.0230)	(0.0235)	(0.0227)
Transfer fee (in millions)	-0.00193	-0.00194	-0.00190	-0.00193
	(0.00277)	(0.00269)	(0.00279)	(0.00272)
Loan	-0.0297	-0.0234	-0.0239	-0.0234
	(0.0735)	(0.0730)	(0.0732)	(0.0732)
Market value (in millions)	-0.0108***	-0.0108***	-0.0109***	-0.0108***
	(0.00226)	(0.00236)	(0.00240)	(0.00241)
Age	-0.00782	0.0270	0.0232	0.0207
	(0.0354)	(0.0280)	(0.0246)	(0.0287)
Age squared	0.00000166	-0.000569	-0.000490	-0.000457
	(0.000633)	(0.000512)	(0.000485)	(0.000578)
German (1=German)	-0.0868***	-0.0869***	-0.0872***	-0.0870***
	(0.0182)	(0.0180)	(0.0182)	(0.0181)
Google hits$_{t-1}$ (in thousands)	-0.00456	-0.00442	-0.00434	-0.00450
	(0.00603)	(0.00612)	(0.00613)	(0.00623)
Champions League	-0.0437	-0.0456	-0.0461	-0.0459
	(0.0656)	(0.0669)	(0.0665)	(0.0667)
Europa League	-0.143**	-0.145**	-0.145***	-0.145**
	(0.0383)	(0.0389)	(0.0388)	(0.0388)
Rank$_{t-1}$	-0.0106	-0.0106	-0.0106	-0.0106
	(0.00534)	(0.00535)	(0.00536)	(0.00536)
Constant	3.120***	2.610***	2.655***	2.700***
	(0.550)	(0.492)	(0.462)	(0.490)
Position Effects	Yes	Yes	Yes	Yes
Team Effects	Yes	Yes	Yes	Yes
Season Effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.360	0.359	0.359	0.359
Observations	2327	2327	2327	2327

Standard errors clustered on the team level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.2: Second-stage Tobit regression for players younger than 22 years.

	Fraction of potential minutes played	
	Season 2	Season 3
Predicted grade	0.741	-1.320
	(1.062)	(0.847)
Back-up grade$_{t-1}$	0.479*	-1.243
	(0.205)	(1.170)
Fee-bound transfer	0.0493	-0.244
	(0.140)	(0.234)
Transfer fee (in millions)	-0.0129	0.0223
	(0.0221)	(0.0390)
Loan	0.119	
	(0.199)	
Market value (in millions)	0.0663*	-0.0383
	(0.0322)	(0.0545)
Age	-2.857	4.750
	(2.379)	(8.167)
Age squared	0.0751	-0.116
	(0.0622)	(0.204)
German (1=German)	0.296	-0.441
	(0.378)	(0.406)
Google hits$_{t-1}$ (in thousands)	-0.0410	0.194
	(0.0467)	(0.190)
Champions League	0.0155	0.382
	(0.264)	(0.848)
Europa League	0.00127	-0.114
	(0.201)	(0.215)
Rank$_{t-1}$	-0.00865	0.0524
	(0.0162)	(0.0643)
Constant	21.81	-40.06
	(17.95)	(77.23)
Position Effects	Yes	Yes
Team Effects	Yes	Yes
Season Effects	Yes	Yes
Observations	166	55

Standard errors clustered on the team level in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: None of the Wald tests of exogeneity of the instrumented variable (predicted grade) are significant ($p = .361$ and $p = .170$).

Table A.3: Second-stage Tobit regression for players younger than 24 years.

	Fraction of potential minutes played		
	Season 2	Season 3	Season 4
Predicted grade	-2.068	-0.367*	-0.751**
	(2.073)	(0.183)	(0.228)
Back-up grade$_{t-1}$	-0.0603	0.286***	0.00654
	(0.483)	(0.0605)	(0.146)
Fee-bound transfer	-0.0560	0.00586	-0.0801
	(0.151)	(0.0575)	(0.142)
Transfer fee (in millions)	0.0158	-0.00585	0.00914
	(0.0429)	(0.00979)	(0.0360)
Loan	-0.155		
	(0.163)		
Market value (in millions)	-0.0434	0.0116*	0.0104
	(0.0920)	(0.00494)	(0.00743)
Age	-0.345	-0.0197	0.573
	(1.669)	(0.442)	(0.974)
Age squared	0.00767	0.000284	-0.0137
	(0.0394)	(0.0105)	(0.0230)
German (1=German)	-0.467	0.0474	0.0437
	(0.563)	(0.0434)	(0.0980)
Google hits$_{t-1}$ (in thousands)	0.0623	0.00641	0.0228
	(0.0883)	(0.0296)	(0.0389)
Champions League	-0.430	0.0289	-0.0103
	(0.492)	(0.109)	(0.242)
Europa League	-0.506	0.00725	-0.201
	(0.537)	(0.0638)	(0.217)
Rank$_{t-1}$	-0.0257	-0.00957	0.0241
	(0.0346)	(0.00969)	(0.0316)
Constant	13.17	0.787	-4.963
	(24.60)	(4.433)	(10.01)
Position Effects	Yes	Yes	Yes
Team Effects	Yes	Yes	Yes
Season Effects	Yes	Yes	Yes
Observations	308	138	62

Standard errors clustered on the team level in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Only in Season 4, the Wald test of exogeneity of the instrumented variable (predicted grade) is significant (Season 2: $p = .380$, Season 3: $p = .657$).

Table A.4: Second-stage Tobit regression for players younger than 26 years.

	Fraction of potential minutes played			
	Season 2	Season 3	Season 4	Season 5
Predicted grade	-1.538*	-0.478***	-0.779*	-0.392***
	(0.673)	(0.112)	(0.338)	(0.100)
Back-up grade$_{t-1}$	-0.104	0.103	0.228	-0.0394
	(0.250)	(0.0744)	(0.152)	(0.112)
Fee-bound transfer	-0.0240	0.00581	0.0476	-0.284***
	(0.0792)	(0.0558)	(0.129)	(0.0740)
Transfer fee (in millions)	0.0162	-0.0101	0.00739	0.0146
	(0.0266)	(0.00618)	(0.0112)	(0.0102)
Loan	-0.0526			
	(0.112)			
Market value (in millions)	-0.0297	0.0132**	0.00644	0.00424
	(0.0384)	(0.00476)	(0.0107)	(0.00386)
Age	-0.341	-0.0566	-0.211	1.125*
	(0.560)	(0.215)	(0.442)	(0.573)
Age squared	0.00788	0.00139	0.00507	-0.0240
	(0.0129)	(0.00480)	(0.00968)	(0.0125)
German (1=German)	-0.229	0.0189	0.0688	-0.0912
	(0.131)	(0.0206)	(0.0726)	(0.0602)
Google hits$_{t-1}$ (in thousands)	0.0113	0.000277	-0.0357	0.0639**
	(0.0341)	(0.0203)	(0.0208)	(0.0248)
Champions League	-0.147	0.113	-0.0790	-0.0400
	(0.142)	(0.104)	(0.118)	(0.225)
Europa League	-0.283	0.0153	-0.191	-0.205
	(0.149)	(0.0613)	(0.106)	(0.110)
Rank$_{t-1}$	-0.0128	0.00370	-0.0155	-0.00913
	(0.0147)	(0.0115)	(0.0114)	(0.0164)
Constant	10.59	2.420	3.760	-10.98
	(8.526)	(2.379)	(5.560)	(6.901)
Position Effects	Yes	Yes	Yes	Yes
Team Effects	Yes	Yes	Yes	Yes
Season Effects	Yes	Yes	Yes	Yes
Observations	455	236	103	68

Standard errors clustered on the team level in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: None of the Wald tests of exogeneity of the instrumented variable (predicted grade) are significant (Season 2: $p = .056$, Season 3: $p = .109$, Season 4: $p = .231$, Season 5: $p = .720$).

Table A.5: Second-stage Tobit regression for players younger than 28 years.

	Fraction of potential minutes played			
	Season 2	Season 3	Season 4	Season 5
Predicted grade	-1.314**	-0.511**	-0.779**	-1.117*
	(0.436)	(0.159)	(0.241)	(0.444)
Back-up grade$_{t-1}$	-0.0191	0.132	0.260**	-0.0512
	(0.133)	(0.0769)	(0.0984)	(0.174)
Fee-bound transfer	-0.0556	-0.0108	0.0125	-0.0602
	(0.0597)	(0.0410)	(0.0710)	(0.104)
Transfer fee (in millions)	0.0122	-0.00354	-0.0154***	0.00264
	(0.0110)	(0.00277)	(0.00413)	(0.00754)
Loan	-0.0711			
	(0.0952)			
Market value (in millions)	-0.0213	0.00772	0.00712	-0.0148
	(0.0174)	(0.00528)	(0.00567)	(0.0112)
Age	-0.144	0.0393	0.351	0.722
	(0.185)	(0.118)	(0.219)	(0.473)
Age squared	0.00334	-0.000769	-0.00715	-0.0159
	(0.00405)	(0.00253)	(0.00463)	(0.00986)
German (1=German)	-0.180*	0.0222	0.0555	-0.166
	(0.0849)	(0.0204)	(0.0567)	(0.132)
Google hits$_{t-1}$ (in thousands)	0.0171	-0.00433	0.0120	0.0853*
	(0.0236)	(0.0146)	(0.0133)	(0.0350)
Champions League	-0.169	0.0508	-0.114	0.195
	(0.128)	(0.114)	(0.106)	(0.265)
Europa League	-0.244*	0.00240	-0.127	-0.0554
	(0.115)	(0.0674)	(0.0667)	(0.0999)
Rank$_{t-1}$	-0.0124	0.000514	-0.0170	0.00790
	(0.0107)	(0.00978)	(0.0125)	(0.0183)
Constant	7.152*	1.183	-2.783	-3.490
	(3.635)	(1.398)	(2.555)	(6.213)
Position Effects	Yes	Yes	Yes	Yes
Team Effects	Yes	Yes	Yes	Yes
Season Effects	Yes	Yes	Yes	Yes
Observations	589	318	152	108

Standard errors clustered on the team level in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Only for Season 2 ($p = .018$), the Wald test of exogeneity of the instrumented variable (predicted grade) is significant (Season 2: $p = .225$, Season 4: $p = .052$, and Season 5: $p = .074$).

Table A.6: Second-stage Tobit regression for players older than 23 years.

	Fraction of potential minutes played			
	Season 2	Season 3	Season 4	Season 5
Predicted grade	-0.809***	-0.609***	-0.824***	-0.814*
	(0.161)	(0.122)	(0.237)	(0.355)
Back-up grade$_{t-1}$	-0.00755	0.0724	0.182	0.159
	(0.0609)	(0.0872)	(0.132)	(0.183)
Fee-bound transfer	0.00620	0.00879	0.0400	0.0251
	(0.0519)	(0.0411)	(0.0663)	(0.143)
Transfer fee (in millions)	0.000645	0.00142	-0.0144***	-0.00332
	(0.00388)	(0.00645)	(0.00309)	(0.00910)
Loan	0.0418			
	(0.156)			
Market value (in millions)	0.00180	0.00381	0.00649	-0.0136
	(0.00761)	(0.00486)	(0.00473)	(0.0147)
Age	0.0694	-0.0198	0.176	-0.0549
	(0.0989)	(0.105)	(0.157)	(0.226)
Age squared	-0.00125	0.0000787	-0.00312	0.000796
	(0.00173)	(0.00191)	(0.00270)	(0.00368)
German (1=German)	-0.0342	-0.0872**	0.0208	-0.0226
	(0.0317)	(0.0298)	(0.0399)	(0.128)
Google hits$_{t-1}$ (in thousands)	-0.00966	-0.00983	0.0102	0.0429
	(0.00907)	(0.0121)	(0.0123)	(0.0518)
Champions League	-0.142	0.00480	-0.362*	0.275
	(0.108)	(0.119)	(0.145)	(0.176)
Europa League	-0.151*	-0.0645	-0.217**	-0.00557
	(0.0671)	(0.0340)	(0.0779)	(0.136)
Rank$_{t-1}$	-0.0129*	-0.00000864	-0.0337**	0.00878
	(0.00541)	(0.00501)	(0.0129)	(0.0143)
Constant	2.742	2.365	-0.197	3.458
	(1.759)	(1.530)	(2.366)	(4.745)
Position Effects	Yes	Yes	Yes	Yes
Team Effects	Yes	Yes	Yes	Yes
Season Effects	Yes	Yes	Yes	Yes
Observations	459	311	172	107

Standard errors clustered on the team level in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Except for Season 5 ($p = .092$), the Wald tests of exogeneity of the instrumented variable (predicted grade) are significant (Season 2: $p = .002$, Season 3: $p = .008$, Season 4: $p = .020$).

Table A.7: Second-stage Tobit regression for players older than 25 years.

	Fraction of potential minutes played			
	Season 2	Season 3	Season 4	Season 5
Predicted grade	-0.832***	-0.685**	-1.002**	-0.114
	(0.141)	(0.216)	(0.348)	(0.304)
Back-up grade$_{t-1}$	0.0960	0.186	0.166	0.0343
	(0.0685)	(0.0999)	(0.189)	(0.0615)
Fee-bound transfer	0.00818	-0.0180	0.0146	0.0629
	(0.0605)	(0.0552)	(0.0842)	(0.0588)
Transfer fee (in millions)	0.000311	0.0108	-0.0205***	0.00434*
	(0.00430)	(0.00782)	(0.00523)	(0.00201)
Loan	-0.164			
	(0.203)			
Market value (in millions)	0.00433	-0.00643	0.0116	0.000692
	(0.00422)	(0.00671)	(0.00895)	(0.00908)
Age	-0.158	-0.200	0.495	0.186
	(0.201)	(0.202)	(0.253)	(0.152)
Age squared	0.00244	0.00295	-0.00817	-0.00319
	(0.00337)	(0.00344)	(0.00422)	(0.00245)
German (1=German)	-0.0284	-0.127**	0.00236	0.0689
	(0.0421)	(0.0462)	(0.0547)	(0.0555)
Google hits$_{t-1}$ (in thousands)	-0.0118	0.0188	0.00753	-0.0188
	(0.0110)	(0.0204)	(0.0290)	(0.0354)
Champions League	-0.190	-0.00798	-0.436	0.125
	(0.131)	(0.141)	(0.279)	(0.103)
Europa League	-0.219*	-0.0139	-0.232	0.0860
	(0.0883)	(0.0611)	(0.136)	(0.146)
Rank$_{t-1}$	-0.0169	-0.00145	-0.0369	0.0165
	(0.0103)	(0.00856)	(0.0208)	(0.0118)
Constant	5.958	4.693	-4.559	-2.207
	(3.141)	(2.802)	(4.131)	(1.421)
Position Effects	Yes	Yes	Yes	Yes
Team Effects	Yes	Yes	Yes	Yes
Season Effects	Yes	Yes	Yes	Yes
Observations	312	213	131	81

Standard errors clustered on the team level in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Except for Season 5 ($p = .938$), the Wald tests of exogeneity of the instrumented variable (predicted grade) are significant (Season 2: $p = .000$, Season 3: .035, Season 4: $p = .0.038$).

B Season level

Table B.8: Second-stage Tobit regression of the fraction of minutes played on predicted disaggregated measures for goalkeepers and defenders.

	Fraction of potential minutes played			
	Season 2	Season 3	Season 4	Season 5
Predicted conceded goals	0.0197***	0.0188***	0.0207	0.00611
	(0.00451)	(0.00415)	(0.0107)	(0.00461)
Predicted assists	-0.0483	-0.0236	-0.0196	0.0737
	(0.137)	(0.0520)	(0.0755)	(0.0685)
Predicted yellow cards	0.0245	0.102	0.0781	0.0199
	(0.0881)	(0.0906)	(0.0974)	(0.0243)
Predicted yellow-red cards	0.178	-1.245	-0.762	-0.300
	(0.410)	(0.646)	(1.999)	(0.827)
Predicted red cards	-0.324	-0.227	0.357	-0.630
	(2.058)	(1.297)	(0.612)	(0.344)
Back-up conceded goals$_{t-1}$	-0.00149	-0.00355	0.00121	-0.0150
	(0.00583)	(0.0160)	(0.0183)	(0.00943)
Back-up assists$_{t-1}$	0.0427	0.0670	0.0527	0.111
	(0.145)	(0.0669)	(0.235)	(0.145)
Back-up yellow cards$_{t-1}$	-0.00515	-0.0101	-0.0543	-0.0211
	(0.0800)	(0.0584)	(0.0701)	(0.0785)
Back-up yellow-red cards$_{t-1}$	0.270	0.150	-0.0133	0.334
	(0.264)	(0.450)	(1.777)	(0.654)
Back-up red cards$_{t-1}$	-0.145	-0.00876	-0.0379	-0.0897
	(0.158)	(0.345)	(0.435)	(0.428)
Fee-bound transfer	0.0192	0.0514	-0.0000407	-0.0633
	(0.0322)	(0.0512)	(0.117)	(0.0955)
Transfer fee (in millions)	-0.0207	-0.00585	-0.00399	0.00612
	(0.0131)	(0.0110)	(0.00756)	(0.00729)
Loan	0.0196			
	(0.238)			
Market value (in millions)	0.0389*	0.0167	0.0124	0.0229
	(0.0177)	(0.0121)	(0.0147)	(0.0152)
Age	-0.0312	-0.0915	-0.0308	0.0838
	(0.109)	(0.0527)	(0.143)	(0.109)
Age squared	0.000661	0.00145	0.000539	-0.00120
	(0.00218)	(0.000909)	(0.00258)	(0.00179)
German (1=German)	-0.0129	-0.0725	0.00595	0.0382
	(0.139)	(0.0648)	(0.168)	(0.107)
Google hits$_{t-1}$ (in thousands)	0.00828	-0.0101	-0.0354	-0.0266
	(0.0265)	(0.0505)	(0.0325)	(0.0335)
Champions League	0.124	-0.152	0.0987	-0.441**
	(0.310)	(0.198)	(0.257)	(0.155)
Europa League	0.105	-0.0898	-0.0768	-0.193
	(0.221)	(0.112)	(0.223)	(0.141)
Rank$_{t-1}$	0.00985	-0.0146	0.00851	-0.0180*
	(0.0225)	(0.0191)	(0.0229)	(0.00777)
Constant	0.706	1.955	0.525	-0.608
	(2.623)	(1.348)	(2.193)	(1.550)
Position Effects	Yes	Yes	Yes	Yes
Team Effects	Yes	Yes	Yes	Yes
Season Effects	Yes	Yes	Yes	Yes
Observations	421	246	145	92

Standard errors clustered on the team level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: All Wald tests of exogeneity of the instrumented variable (predicted conceded goals, assists, and cards) are significant.

C Match level

Table C.9: Ordinary Least Squares regression of minutes played per match using eight lagged variables.

	Minutes played	
Match grade$_{t-1}$ if graded	-4.921***	(0.494)
Match grade$_{t-2}$ if graded	-2.197***	(0.228)
Match grade$_{t-3}$ if graded	-1.310***	(0.106)
Match grade$_{t-4}$ if graded	-0.909***	(0.151)
Match grade$_{t-5}$ if graded	-0.956***	(0.139)
Match grade$_{t-6}$ if graded	-0.345*	(0.132)
Match grade$_{t-7}$ if graded	-0.554**	(0.185)
Match grade$_{t-8}$ if graded	-0.541**	(0.180)
Match graded$_{t-1}$	43.05***	(2.919)
Match graded$_{t-2}$	17.81***	(1.233)
Match graded$_{t-3}$	9.777***	(0.528)
Match graded$_{t-4}$	7.444***	(0.615)
Match graded$_{t-5}$	6.980***	(0.782)
Match graded$_{t-6}$	4.754***	(0.533)
Match graded$_{t-7}$	5.986***	(0.892)
Match graded$_{t-8}$	6.846***	(0.572)
Match played$_{t-1}$	8.460***	(0.490)
Match played$_{t-2}$	3.182***	(0.563)
Match played$_{t-3}$	1.912***	(0.402)
Match played$_{t-4}$	0.0780	(0.486)
Match played$_{t-5}$	0.0665	(0.405)
Match played$_{t-6}$	-0.687*	(0.337)
Match played$_{t-7}$	-0.539	(0.473)
Match played$_{t-8}$	0.309	(0.427)
Match backup grade$_{t-1}$ if graded	1.091***	(0.286)
Match backup grade$_{t-2}$ if graded	0.218	(0.162)
Match backup grade$_{t-3}$ if graded	0.183	(0.161)
Match backup grade$_{t-4}$ if graded	-0.0640	(0.138)
Match backup grade$_{t-5}$ if graded	0.0994	(0.155)
Fee-bound transfer	0.553	(0.644)
Transfer fee (in millions)	0.0824	(0.0430)
Loan	-0.403	(1.052)
Market value (in millions)	0.399**	(0.144)
Age	1.455**	(0.417)
Age squared	-0.0254**	(0.00815)
German (1=German)	0.521	(0.361)
Google hits previous season (in thousands)	-0.151	(0.168)
Hiring coach	0.0899	(0.340)
Tenure in team	0.0302**	(0.00876)
Tenure in team squared	-0.0000618	(0.0000322)
Number of players in team	0.0702	(0.0376)
Champions League	0.0467	(0.588)
Europa League	-0.0495	(0.421)
Rank difference	0.0877***	(0.0132)
Rank difference squared	0.00238	(0.00151)
Match day	0.181***	(0.0404)
Match day squared	-0.00379***	(0.000968)
Constant	-26.70***	(5.451)
Position Effects	Yes	
Team Effects	Yes	
Season Effects	Yes	
Adjusted R^2	0.531	
Observations	77563	

Standard errors clustered on the team level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.10: Second-stage Tobit regression of minutes played per match using lagged grades of five matches, interacting the transfer fee variables with the player's tenure in the team.

	Second stage Minutes per match	First stage Predicted grade
Predicted grade	-120.2***	
	(11.13)	
Fee-bound transfer	8.061	0.0171
	(5.603)	(0.0296)
Transfer fee (in millions)	1.086**	0.00373
	(0.351)	(0.00212)
Fee-bound transfer × Tenure in team	-0.0682	-0.000178
	(0.0534)	(0.000310)
Transfer fee (in millions) × Tenure in team	-0.0110***	-0.0000562*
	(0.00328)	(0.0000257)
Back-up match grade$_{t-1}$	-2.971***	-0.0254***
	(0.845)	(0.00510)
Loan	-9.129	-0.0675
	(8.667)	(0.0569)
Market value (in millions)	0.0189	-0.0109***
	(0.426)	(0.00178)
Age	9.047*	0.0369
	(4.343)	(0.0226)
Age squared	-0.179*	-0.000830
	(0.0838)	(0.000425)
German (1=German)	-4.079	-0.0596***
	(2.734)	(0.0153)
Google hits previous season (in thousands)	0.887	0.00586
	(1.030)	(0.00508)
Hiring coach	-2.546	-0.0318*
	(1.722)	(0.0147)
Tenure in team	0.155**	-0.000385
	(0.0523)	(0.000372)
Tenure in team squared	-0.000271	0.00000100
	(0.000170)	(0.000000788)
Number of players in team	1.305**	0.00879**
	(0.457)	(0.00296)
Champions League	-4.272	-0.00665
	(6.342)	(0.0364)
Europa League	-10.94**	-0.0762**
	(3.422)	(0.0247)
Rank difference	0.889***	0.00537***
	(0.110)	(0.000605)
Rank difference squared	-0.00369	-0.0000577
	(0.00930)	(0.0000378)
Match day	0.389*	-0.00126
	(0.178)	(0.000999)
Match day squared	-0.0133**	0.00000831
	(0.00474)	(0.0000271)
Constant	289.6***	3.540***
	(71.86)	(0.314)
Position Effects	Yes	Yes
Team Effects	Yes	Yes
Season Effects	Yes	Yes
Grades of previous 20 match days	No	Yes
Observations	71952	

Standard errors clustered on the team level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The player's tenure in team is measured in matches. The Wald test of exogeneity of the instrumented variable (predicted match grade) is significant.

Table C.11: Second-stage Tobit regression of minutes played per match on a seasonal level, interacting the transfer fee variables with the player's tenure in the team.

	Minutes per match				
	Season 1	Season 2	Season 3	Season 4	Season 5
Predicted grade	-114.7***	-97.09***	-88.07***	-82.34***	-94.25***
	(10.07)	(12.23)	(12.66)	(11.20)	(16.43)
Back-up match grade$_{t-1}$	-1.530	-0.797	-3.324*	-4.127*	-9.844**
	(1.080)	(1.060)	(1.340)	(1.889)	(3.080)
Fee-bound transfer	5.125	-5.092	-8.395	-3.861	44.11*
	(4.463)	(7.769)	(12.75)	(29.12)	(17.32)
Transfer fee (in millions)	0.441	2.336*	-1.138	8.896	11.51**
	(0.440)	(0.940)	(1.543)	(4.856)	(4.379)
Fee-bound transfer × Tenure in team	0.0311	0.143	0.178	0.0436	-0.304*
	(0.207)	(0.138)	(0.156)	(0.268)	(0.144)
Transfer fee (in millions) × Tenure in team	0.00255	-0.0340	0.00831	-0.0694	-0.0707*
	(0.0202)	(0.0175)	(0.0203)	(0.0390)	(0.0295)
Loan	2.954	-4.768			
	(4.072)	(6.230)			
Market value (in millions)	0.0598	-0.0779	-0.0629	0.813	-0.784
	(0.443)	(0.746)	(0.541)	(0.789)	(0.422)
Age	7.107	0.876	6.430	17.83*	-12.60
	(4.628)	(5.555)	(5.968)	(7.912)	(7.703)
Age squared	-0.120	-0.0198	-0.130	-0.331*	0.173
	(0.0902)	(0.104)	(0.118)	(0.153)	(0.134)
German (1=German)	-4.084	-6.396*	-1.676	0.669	-1.151
	(2.840)	(2.835)	(3.518)	(3.699)	(4.945)
Google hits current season (in thousands)	-0.916				
	(0.688)				
Google hits previous season (in thousands)		0.127	1.424	-2.826	3.882
		(1.081)	(2.345)	(1.870)	(2.129)
Hiring coach	-4.581	-0.616	-5.020	-2.107	18.09***
	(2.656)	(2.288)	(4.671)	(6.477)	(4.966)
Tenure in team	-2.449***	0.292	-0.0756	0.421	0.0966
	(0.671)	(0.612)	(0.587)	(0.595)	(0.492)
Tenure in team squared	0.0490***	-0.00178	-0.000418	-0.00183	0.00113
	(0.0148)	(0.00665)	(0.00426)	(0.00287)	(0.00229)
Number of players in team	1.007	0.734	0.998	2.108	0.0928
	(0.578)	(0.580)	(0.574)	(1.317)	(0.641)
Champions League	-0.693	0.999	-4.526	-10.29	-5.726
	(6.658)	(8.167)	(9.265)	(7.963)	(9.484)
Europa League	-7.852	-8.143	-2.158	-13.64	-24.77***
	(4.228)	(5.008)	(3.283)	(7.910)	(6.353)
Rank difference	0.851***	0.731***	0.284*	0.949***	0.370
	(0.158)	(0.133)	(0.129)	(0.218)	(0.316)
Rank difference squared	-0.00725	0.00766	-0.00408	-0.00383	-0.00177
	(0.0101)	(0.0157)	(0.0141)	(0.0211)	(0.0257)
Match day	1.868**	-0.0211	0.512	0.725	0.596
	(0.628)	(0.408)	(0.397)	(0.527)	(0.819)
Match day squared	-0.0404**	-0.000369	-0.0123	-0.0180	-0.0237
	(0.0141)	(0.0104)	(0.0129)	(0.0126)	(0.0208)
Constant	324.7***	327.8***	166.4*	-30.78	552.6***
	(63.25)	(89.24)	(84.80)	(105.2)	(145.0)
Position Effects	Yes	Yes	Yes	Yes	Yes
Team Effects	Yes	Yes	Yes	Yes	Yes
Season Effects	Yes	Yes	Yes	Yes	Yes
Observations	32449	23954	15092	9614	6746

Standard errors clustered on the team level in parentheses
Grade instrumented with grades of previous 20 (5 in the first season) match days.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The player's tenure in team is measured in matches. As in the first season, there are only a few players for whom I have a figure on their Google hits in the previous season, I use the Google hits for the current season in Season 1. All Wald tests of exogeneity of the instrumented variable (predicted match grade) are significant.

Table C.12: Second-stage Tobit regression of minutes played per match on relative transfer fees.

	Second stage	First stage
	Minutes per match	Predicted grade
Predicted grade	-85.87***	
	(9.166)	
Relative transfer fee	29.35	-0.230
	(19.69)	(0.118)
Back-up match grade$_{t-1}$	-3.370***	-0.0320***
	(0.736)	(0.00470)
Loan	-3.530	-0.0434
	(5.541)	(0.0513)
Market value (in millions)	0.166	-0.00540***
	(0.322)	(0.00112)
Age	7.616*	0.0286
	(3.683)	(0.0209)
Age squared	-0.155*	-0.000656
	(0.0711)	(0.000399)
German (1=German)	-2.151	-0.0493***
	(2.300)	(0.0143)
Google hits previous season (in thousands)	-0.0319	0.00157
	(0.820)	(0.00384)
Hiring coach	-1.134	-0.0335**
	(1.356)	(0.0119)
Tenure in team	0.0686	-0.000478
	(0.0380)	(0.000271)
Tenure in team squared	-0.000153	0.000000845
	(0.000133)	(0.000000822)
Number of players in team	0.978**	0.00548*
	(0.372)	(0.00238)
Champions League	-2.345	0.0225
	(4.830)	(0.0313)
Europa League	-7.429**	-0.0516*
	(2.560)	(0.0201)
Rank difference	0.649***	0.00416***
	(0.0801)	(0.000622)
Rank difference squared	-0.000414	-0.0000602
	(0.00796)	(0.0000335)
Match day	0.439**	-0.000534
	(0.149)	(0.00109)
Match day squared	-0.0123**	-0.00000847
	(0.00386)	(0.0000282)
Constant	179.7**	3.772***
	(57.54)	(0.300)
Position Effects	Yes	Yes
Team Effects	Yes	Yes
Season Effects	Yes	Yes
Grades of previous 20 match days	No	Yes
Observations	68067	

Standard errors clustered on the team level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The Wald test of exogeneity of the instrumented variable (predicted match grade) is significant.

Table C.13: Second-stage Tobit regression of minutes played per match, interacting the transfer fee variables with the coach's age.

	Second stage Minutes per match	First stage Predicted grade
Predicted grade	-85.73***	
	(9.187)	
Back-up match grade$_{t-1}$	-3.407***	-0.0321***
	(0.740)	(0.00476)
Fee-bound transfer	3.028	0.0534
	(12.35)	(0.0883)
Fee-bound transfer × Age in days of coach at match day	-0.000114	-0.00000289
	(0.000709)	(0.00000463)
Transfer fee (in millions)	0.497	-0.00248
	(0.464)	(0.00706)
Transfer fee (in millions) × Age in days of coach at match day	-0.0000189	-4.05e-08
	(0.0000246)	(0.000000311)
Loan	-3.976	-0.0446
	(5.548)	(0.0534)
Market value (in millions)	0.177	-0.00503***
	(0.303)	(0.00129)
Age	7.675*	0.0260
	(3.708)	(0.0215)
Age squared	-0.156*	-0.000602
	(0.0713)	(0.000408)
German (1=German)	-2.383	-0.0479***
	(2.368)	(0.0145)
Google hits previous season (in thousands)	-0.126	0.00324
	(0.850)	(0.00372)
Hiring coach	-1.102	-0.0313**
	(1.279)	(0.0121)
Tenure in team	0.0660	-0.000457
	(0.0378)	(0.000280)
Tenure in team squared	-0.000144	0.000000737
	(0.000135)	(0.000000868)
Number of players in team	0.952*	0.00559*
	(0.374)	(0.00238)
Champions League	-2.727	0.0241
	(4.737)	(0.0303)
Europa League	-7.591**	-0.0500*
	(2.578)	(0.0195)
Rank difference	0.648***	0.00419***
	(0.0801)	(0.000640)
Rank difference squared	-0.000406	-0.0000575
	(0.00787)	(0.0000345)
Match day	0.442**	-0.000528
	(0.149)	(0.00110)
Match day squared	-0.0123**	-0.00000823
	(0.00388)	(0.0000287)
Constant	179.8**	3.786***
	(58.10)	(0.312)
Position Effects	Yes	Yes
Team Effects	Yes	Yes
Season Effects	Yes	Yes
Grades of previous 20 match days	No	Yes
Observations	68007	

Standard errors clustered on the team level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The coach's age is measured in days. The Wald test of exogeneity of the instrumented variable (predicted match grade) is significant.