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Mestrado em Estatística e Gestão de Informação
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PERFORMANCE AND ACTUAL PAY IN THE TOP 5 EUROPEAN FOOTBALL LEAGUES

The use of market value as a proxy variable for football players' salaries

João Pedro Fonseca Monteiro

Dissertation report presented as partial requirement for obtaining the Master's degree in Statistics and Information Management, specialization in Analysis and Information Management

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ABSTRACT

Until recently, it was difficult to obtain the real salary data of football players, however, with the expansion of sports economics, companies that work and commercialize this data began to emerge, so the salary data of players from different football leagues had become accessible. Numerous studies have been conducted on the factors that affect the value of each salary, however, due to the previous lack of data, researchers have used the players' market value as a proxy variable, substituting the actual salaries.

This Master's dissertation aimed to study whether there are differences in the conclusions of studies on performance and remuneration in football when using market values as a proxy variable for real salaries. This is something that had never been studied for a significant amount of data and for this, we used salaries, market values, performance indicators and personal characteristics of players from the five main European football leagues. Data were collected using web scraping techniques and were later treated and preliminarily analyzed using descriptive statistics techniques. Two-way fixed effect models for panel data were implemented, one for market values and one for salaries, estimated by three different estimators and, finally, a critical comparison was made between the models.

It was found that when market values were used as a proxy for salaries, differences were noted in the regression models, both in the impact on remuneration of the control variables and in the impact on remuneration of the variables measuring performance, regardless of the estimator used to calculate the model. The findings of this study suggest that researchers should only use real salaries if the aim is to study the relationship between performance and remuneration of football players.

KEYWORDS

Econometrics; Panel data; Football; Performance-Pay; Salaries; Market Value; Proxy variables

RESUMO

Até recentemente, era difícil obter os dados dos salariais reais dos jogadores de futebol, no entanto, com a expansão da economia do desporto, começaram a surgir empresas que os trabalham e comercializam, pelo que os dados salariais de jogadores de diferentes ligas de futebol tornaram-se acessíveis a qualquer pessoa. Foram realizados numerosos estudos sobre os fatores que afetam o valor de cada salário, no entanto, devido à anterior falta de dados, os investigadores utilizaram o valor de mercado dos jogadores como uma variável de substituição para os salários.

Esta dissertação de mestrado visou estudar se existiam diferenças nas conclusões dos estudos sobre o desempenho e remuneração no futebol quando se utilizam os valores de mercado como variável de substituição dos salários reais. Esta questão nunca tinha sido estudada para uma quantidade significativa de dados e para isso, utilizámos salários, valores de mercado, indicadores de desempenho e características pessoais de jogadores das cinco principais ligas europeias de futebol. Os dados foram recolhidos utilizando técnicas de web scraping e foram posteriormente tratados e analisados preliminarmente utilizando técnicas de estatística descritiva. Foram implementados modelos de efeito fixo bidirecionais para dados de painel, um para valores de mercado e outro para salários, estimados por três estimadores diferentes e, finalmente, foi feita uma comparação crítica entre os modelos.

Verificou-se que quando os valores de mercado foram utilizados como proxy para os salários, foram observadas diferenças nos modelos de regressão, tanto no impacto sobre a remuneração das variáveis de controlo como no impacto sobre a remuneração das variáveis que medem a performance, independentemente do estimador utilizado para calcular o modelo. Os resultados deste estudo sugerem que os investigadores devem apenas utilizar os salários reais, se o objetivo for estudar a relação entre o desempenho e a remuneração dos jogadores de futebol.

PALAVRAS-CHAVE

Econometria; Painel de dados; Futebol; Performance-remuneração; Salários; Valores de mercado; Variáveis proxy

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1. INTRODUCTION

Since the 1950s, academic interest in professional sports has been verified, largely due to their popularity among the population. Dobson & Goddard (2001) denoted that this beginning of research began in the United States so that the oldest academic literature is dominated by sports studies such as baseball, basketball, and American football. These authors stated that these empirical studies addressed several issues, such as the competitive balance, the uncertainty of the result, the distribution of talent in sports leagues, and the contribution of the coach or manager to the performance of the team.

The economic aspect focused on its relationship with the sport was then known as *sports economics*. Although there was greater interest from researchers in the 1950s and 1960s, it was only in the mid-1990s that there was an explosion of publications in the field of sports economics, where hundreds of articles and a set of important books were published (Andreff & Szymanski, 2006).

Since the development of pioneering studies, through the 1990s, the interest of researchers in professional sports has increased significantly (Santos & Garcia, 2011). Sloane (2015) states that this increasing attention can be explained by the growing economic importance of soccer competitions, as well as, by the awareness that soccer competitions are an excellent economic laboratory to obtain new knowledge on general economic issues. Frick (2007) attributes the growth in the number of empirical studies in the area since the mid-1990s to a series of different, but closely related events, such as the fact that the football industry has had unprecedented growth, the fact that the market of football players' work has changed its regulatory structure and the fact that there has been an increasing availability of information on player salaries, transfer fees and other statistics on players, which until then were not available.

Frick (2007) points to the Bosman Case (1995) as a determining role in changing the regulatory structure of the football players' labor market. The Bosman Case (1995) ended with the limitation on the number of foreign players in European clubs and, subsequently, favored an increase in transfers and salaries (Godechot, 2012). In 2012, The Guardian reported that the salaries of the best football players had increased by 1500% compared to 1992, in stark contrast to the 186% increase in the average salary in the United Kingdom over the same period. Frick (2007) also points to the increase in revenue from ticket sales, merchandising, and broadcasting rights, as preponderant factors for the increase in salaries in all major European leagues. The increase and diversification of team revenues combined with increased competition between clubs to present better teams had a strong impact on both transfer values and player salaries (Ante, 2019).

In 2020, among the 5 highest-paid athletes, 3 of them were football players. Cristiano Ronaldo (US $ 105 million), Lionel Messi (US $ 104 million), and Neymar (US $ 95.5 million) ranked second, third, and fourth on the list, respectively, surpassed only by the tennis player Roger Federer (Badenhausen, 2020). However, not all players are paid well above average, on the contrary, few players can enjoy the "superstar effect" (Rosen, 1981). Lucifora & Simmons (2003) also state that sometimes players have similar or slightly inferior talents, but are paid quite differently. So, what is it that explains the different salaries of football players?

1.1. BACKGROUND

Several studies have been carried out on football players' salaries to try to find the factors that influence their different values or salaries as an explanation of other topics. Some authors have tried to explain the different values of salaries with different variables and performance is identified by most of them as a differentiating factor. Several empirical studies inevitably show that professional athletes with better performance earn more money (Rosen & Sanderson, 2001). Most of the set of studies that tries to explain salaries considering performance, that is, performance and pay studies, are based on the model that Mincer (1974) studied and defined (Carrieri et al., 2018), a function that explains the value of a worker's salaries according to his level of education and experience. Salary regressions are used to study how remunerations relate to personal skills and human capital, however, unlike ordinary workers where there is no specific information on their performance, and who have therefore chosen to use the level of education and experience, professional sport offers a great opportunity to measure this characteristic (Rosen & Sanderson, 2001), which allows its use in the construction of the models. Deutscher & Büschemann (2016) state that in addition to performance, characteristics such as age, experience, talent, position, team effect, and country of origin were found by researchers to define the salaries of football players.

Dobson & Goddard (2001) report despite the abundance of football data, for a long time it was virtually impossible to access player salary data, and Weimar (2019) states that this lack of salary data is a general drawback of football research concerning salary determination. Currently, it is still very difficult to find reliable data for most players in the main European leagues. European clubs are required to pay the total amount spent on salaries annually, however, there is no obligation to clarify the individual salaries of each player. On the contrary, in the United States, there has always been a greater availability of salary data, largely because in most professional sports teams there is a salary cap, leading clubs to be more scrutinized. However, companies are beginning to better understand the importance of investing resources in developing sophisticated metrics that can be used to analyze employee performance (Moyes, 2016). In the case of sports analytics, this led to the emergence of data analysis companies and, subsequently, companies that commercialize and process data about transfers and performance statistics, such as Opta Sports, Transfermark, and WhoScored.com, and even salary databases, calculated using algorithms with minimal error rates and based on official club payment information, among other sources, such as Capology.

Sometimes, it is not possible to access specific data or some variables do not have enough statistical data, so researchers choose to use proxy variables in the construction of econometric models (Dziechciarz, 1989). A proxy variable is a variable used to measure an unobservable amount of interest and which must be strongly related to the unobserved variable (Clinton, 2004). Due to the lack of salary data, the researchers used the players' market value as a proxy variable for salaries, in performance and pay studies, where salaries were the dependent variable (see e.g. Battré et al., 2009; Bryson et al., 2013; Frick, 2011; Garcia-del-Barrio & Pujol, 2007b).

The researchers used the market values developed by sports websites, such as KICKER and Transfermarkt, or even by newspapers, such as the Spanish sports newspaper MARCA, and supported their use, as a proxy for salaries, in several ways. For example, Battré et al. (2009) mentioned Torgler et al. (2006) and his discovery that the market values of KICKER and Transfermarkt have a very strong correlation (0.75). The authors also used the study by Frick (2003), who mentions that there is a high correlation (0.80) between the market value calculated by KICKER and a set of real salary data for the Bundesliga. Also, Bryson et al. (2013) used studies, this time by Franck & Nüesch (2011, 2012), which show that there is a high correlation (0.89) between the market values of KICKER and Transfermarkt. Bryson et al. (2013) also used the previous fact that there is a high correlation between KICKER's market value and a set of real data, also claim that there are lots of sports articles and newspapers that use data from this portal, also note the fact that KICKER and Transfermarkt have a huge set of data from players and experts, who have established a consistent practice for a long time period and even that Transfermarkt has the help of a huge community of registered users, who recommend the market values.

Although researchers are perfectly aware that there is still a great lack of availability of salary data for football players, and that using market values as a proxy for salaries may not be the same as using salary data itself, only Thrane (2019) questioned whether the use of this proxy calls into question the conclusions drawn in the studies that used it. The author addressed this issue in the context of a salary determination study, but although he was the pioneer to raise doubts about the use of the proxy, he only used a relatively small data set, from the Norwegian Football League (Eliteserien), which is far from being one of the best European leagues and ranked 29th in the UEFA ranking at the time of the study's development. Still, Thrane (2019) concluded, for the Eliteserien data set, that the effects of performance and the characteristics of players on real earnings are qualitatively different from the analogous effects on market values. Thrane (2019) found that using market value as a proxy seems to underestimate the influence of career performance variables, exaggerate the influence of season performance variables and underestimate the influence of club membership on player pay about the use of real earnings. The author also notes that there are differences in the peak earnings, using the market value as a proxy, compared to the use of actual earnings and that the model suggests that there are no differences in the pay of players of different nationalities, whereas the analysis of the real earnings model suggests that it is.

Prockl & Frick (2018a) also questioned, in part, the validity of using market value as a proxy variable for salaries, in this case for Major League Soccer, the largest American football league, since players' salaries are public, but did not take into account players' performance in the construction of regressive models, so that the coefficients of determination of the models vary only between 50% and 60%, i.e., the models only explain between 50% and 60% of the variance of the dependent variable using the chosen independent variables. This study, although it questioned the use of the proxy, cannot be included in the scope of performance and pay studies, as it did not use, that is, performance to explain the salaries of football players.

Thus, there is still no study that addresses the use of this proxy, with a high number of data, for the main European football leagues and in the context of performance and pay. This dissertation will supply the lack of in-depth studies on the topic, studying whether there are differences between using the market value as a proxy variable for salaries and using the salaries of football players, and will also increase the literature on performance and pay studies. To this end, two regressive models will be built, with data from the five top European leagues (Spain, England, Germany, Italy and France) and, later, will be analyzed to understand the differences and similarities of the coefficients associated with the variables on both models. To make an appropriate choice of the independent variables that best explain salaries, studies that address salary determination will be considered (see e.g. Giangreco et al., 2021; Lucifora & Simmons, 2003; Lussier et al., 2022; Lehmann & Schulze, 2008; Kuethe & Motamed, 2010; Frick, 2011; Ribeiro et al, 2021).

1.2. STUDY RELEVANCE AND IMPORTANCE

With the appearance of platforms that collect and process data, football fans began to consume more and more statistics, looking for player evaluations, seeing their characteristics, and consulting their salaries. This motivated several researchers to develop new studies as more data became available. Frick (2011) claims that salaries in Europe remained private and confidential, which made him use athletes' market value as a proxy variable for their salaries. Like Frick (2011) and as previously stated, other authors have chosen to use a proxy variable for salaries, due to their inaccessibility.

But what if there are differences in the various studies' conclusions using market values as a proxy variable, instead of the actual salaries? According to Thrane (2019), “this research question could in principle have been answered by Lucifora & Simmons (2003), Lehmann & Schulze (2008), or Della Torre et al. (2018), who all had access to actual earnings for their football players, but neither of these studies compared the performance variables and control variables regression coefficient estimates on current earnings with the similar estimates on market values”.

The results of this study will not only increase the literature on performance and pay studies, more specifically salary determination studies, as well as confirming or not, depending on what is concluded, the validity of previous studies, which have used the market value as a proxy variable for salaries.

This study will mainly interest researchers who, in the future, intend to carry out research that addresses the performance and pay relationship in sports and who do not have access to athletes' salary data, so they will have to consider the results of this dissertation. If it is proven that there are no differences between the use of market value and the real value of salaries, in the construction of econometric models to explain the salaries of football players, researchers will, in the future, be sure of the validity of their conclusions and they will have literature that supports the use of market values as a proxy variable. On the contrary, if it is proven that there are differences in the models, according to the use of the two different variables, market values, and salaries, the researchers will have to be more careful in the elaboration of the study design and, they may even continue to use the proxy variables in question, but they will need to note that there may be differences in the conclusions and they can only conclude about market values. Some future research that needs to cite performance pay studies in sports other than football and that use the market value as a proxy variable for salary may have to refer to this study as well.

This study allows a generalization in the future for other sports or other football leagues.

1.3. STUDY OBJECTIVES

Proxy variables are chosen so that there is a greater correlation with the unobservable variable (Clinton, 2004). There are often unobservable variables in linear regression models and researchers are in a dilemma between eliminating variables or using proxy variables (Stahlecker & Trenkler, 1993), but when an unobservable variable is a variable that we want to explain, we must use a proxy or drop out of the study.

The main objective of this paper is to study whether, in the five major European leagues, there are differences in the results of the study of the factors affecting the value of football players' salaries, when using the market value of players, as a proxy variable for salaries. The study also aims to increase the literature on performance and pay studies in football. To achieve the objectives, we need to answer the following questions:

• What factors explain football players' salaries?

• What are the variables that other studies have identified as statistically significant to explain the value of football players' salaries?

• What is the impact of a player's characteristics on his salary?

• What are the impact of a player's performance and career on his salary?

• Are there any differences between the results of the regression model using market values as a proxy variable for salaries and using actual salary values?

The dissertation is organized as follows. In this first section, the framework of the study, its relevance and the respective objectives were presented. Section 2 is focused on the literature review on the factors that influence salaries of football players. Section 3 presents the main methodologies for estimating regression models. In Section 4, the research results are presented and discussed, including the results of OLS, fixed effects estimator and random effects estimator modeling, as well as a critical comparison between the models. Finally, in Section 5, the main conclusions are presented, as well as the limitations of the study and suggestions for future work.

2. LITERATURE REVIEW

The literature review is divided according to the factors, identified by the researchers, that affect the salary values of football players. Initially, the performance and variables that are most commonly used to measure this characteristic were addressed, and after that, a set of control variables was addressed, also whose use is quite recurrent in salary determination studies.

2.1. PERFORMANCE

As already mentioned in the introduction, athletes who perform better, earn better salaries (Rosen & Sanderson, 2001) and, according to Lehmann & Schulze (2008), performance is the biggest determinant of salaries. In almost all studies of the factors that influence salaries, performance always plays an important role in defining them, however, the way that performance is measured differs from researcher to researcher, who use different variables and metrics. Most of the authors used game statistics, with goals and assists being among the most used. The authors used these variables together in the models, such as Celik & Ince-Yenilmez (2017), Lee & Harris (2012), and Lucifora & Simmons (2003), or just the goals, such as Bryson et al. (2013), and mostly concluded that these characteristics have a positive and significant impact on salaries. Della Torre et al. (2018) affirm that, in addition to goals and assists, shots, passes, tackles, dribbles, and defenses are also among the most used variables to measure performance.

For Pappalardo et al. (2019), one of the biggest problems in sports analysis is the difficulty of measuring a player's performance, largely because there is no secret formula for measuring it. Also, Duch et al. (2010) state that the results of football games tend to be below, and as such, simple statistics, such as assists, shots, or goals do not measure the impact of a player on the final score. He et al. (2015) state that football is a collective sport, so it is very difficult to judge a player's performance since each position has different responsibilities, which makes the performance indicators also different.

Some of the studies mentioned above, such as Lucifora & Simmons (2003) and Lee & Harris (2012) excluded players who play the role of the goalkeeper from the models, while Celik & Ince-Yenilmez (2017) developed a specific model for players who play in this position, because the characteristics selected to measure performance, mostly goals and assists, are not relevant to the position. He et al. (2015), in their study of how the market value and performance of Spanish League players can be modeled, only included players who play the role of forwards in the developed model, leaving out all other positions, because, according to the authors, there are significant differences in performance between positions.

2.1.1. RATINGS

To solve the difficulty of measuring the performance of football players, algorithms with different metrics have been developed, which produce a rating for each player (see e.g. Kharrat & McHale, 2020; McHale et al., 2012; Pappalardo et al., 2019; Schultze & Wellbrock, 2018). A rating system is broadly defined as the process of assigning a numerical value to the individual and/or team performance on a predefined scale (Stefani & Pollard, 2007). Ratings are used to measure performance in various sports and, according to McHale et al. (2012), the task of assigning ratings is more complex in team sports. McHale et al. (2012) reinforce that in the specific case of football it is even more complex than other sports because the players have different positions, which require a different set of skills, there is complexity in the composition of the team, the dependence on external factors and especially the fact that players can change positions during the game. The ratings are not just the product of algorithms, based on game statistics since there are sports magazines that present ratings based on the opinion of journalists, who are usually subjective and imperfect because they vary according to the journalist and their preference (Gandelman, 2008). Still, as mentioned in Thrane (2019), these performance reviews have a positive impact on players' salaries.

It was also not just for research that ratings were developed, with the development of this performance measurement, it became common for sports websites to present a measure of performance evaluation and do business, based on their algorithms. Thrane (2019) used as a performance measure to explain the Norwegian League salaries, precisely the ratings developed by one of these sites, Whoscored.com, averaged them and concluded that they have a statistically significant and positive impact on remuneration. Likewise, Della Torre et al. (2018) and Swift (2017), Giangreco et al. (2021), and Ribeiro et al. (2021) used the ratings developed by WhoScored.com and concluded that this variable also has a positive impact on salaries. Deutscher & Büschemann (2016), Bryson et al. (2013), Drut & Duhautois (2017), Feess et al. (2004), and Frick (2011) chose to use ratings based on journalists' opinions, and while the former four used data from KICKER, the latter chose to use data from La Gazzetta dello Sport, and all of them concluded that there is a positive impact of performance ratings on salaries. In a different objective, Sæbø & Hvattum (2015) also used the ratings, in this case, with an algorithm developed by them, as a performance meter, to try to explain the value of the transfers of football players.

2.1.2. INTERNATIONAL STATUS

The fact that the players represent or not the national teams has been recurrently used as part of the explanatory variables in salary determination models, to measure performance, however, the researchers have chosen to measure this characteristic in different ways. Some authors have chosen to only use a dummy variable to inform whether the player is international (see e.g. Celik & Ince-Yenilmez, 2017; Drut & Duhautois, 2017; Feess et al., 2004; Kuethe & Motamed, 2010; Ribeiro et al., 2021), while other authors have chosen to use a variable to measure the number of international appearances for each player (see e.g. Deutscher & Büschemann, 2016; Eschweiler & Vieth, 2004; Frick, 2011; Giangreco et al., 2021; Prockl & Frick, 2018b).

There were still other different approaches, Bryson et al. (2013) also used a dummy variable but grouped the national teams geographically. Wicker et al. (2013) used two approaches in the same model to capture the effect of players' internationalization, a dummy variable to measure whether the player is international and a set of dummy variables to ascertain whether the player is a member of one of the best-rated national teams (Germany, Italy, France, Spain, England, Holland, Portugal, and Brazil). Franck & Nüuesch (2008) tried to weigh the dummy variable of participation in the national team of a player with the UEFA ranking of the team in question, to consider the quality differences between the national teams, however, the introduction of this variable did not change the results significantly, so the authors chose to use only a dummy variable to capture whether the player is international.

The internationalization of players, both in the main teams and in the under-21 teams, was identified by Rodríguez et al. (2019), as two of the variables that are part of a set of six, which are more likely to determine the market value of football players, in the top five European leagues. To arrive at this result, the authors considered the selection of variables, used a hedonic regression structure, and implemented the mean of the Bayesian model (BMA), through the composition of the Monte Carlo model of the Markov chain (MC3).

Only the best players in a country qualify for a national team (Eschweiler & Vieth, 2004), so according to Feess et al. (2004), Garcia-del-Barrio & Pujol (2007a), Frick (2007), and Prockl & Frick (2018b), being selected for a country's national team has a significant impact on salaries.

While it is almost generally agreed that international players win more than non-international players, there are some differences in the quantification of that salary gap. Celik & Ince-Yenilmez (2017), using the generalized least squares estimation technique, data from 2007 to 2016, coming from Major League Soccer, concluded that players who are called to the senior national team earn 51.4% more than the players who are not called. On the other hand, Kuethe & Motamed (2010), using the ordinary least squares estimation, data from 2007, from MLS, concluded that the experience of the national team increases salaries, ceteris paribus, by 63%. Frick (2011), using data covering six and thirteen consecutive seasons of the Bundesliga, from 1997-98 to 2002-03 and from 1995-96 to 2007-08, divided the international caps into a career and previous international caps and concluded both have a statistically significant non-linear influence on salaries.

2.1.3. GAMES PLAYED

According to Thrane (2019), the most talented players spend more time on the pitch and therefore are better paid than the less talented and, according to Swift (2017), the best performing players tend to play more minutes throughout the season.

The measurement of the number of games played has been used by researchers, as part of a series of variables to measure performance. On the other hand, the total number of games played in the career has been used to measure experience, which is why it was addressed in the respective section of the literature review.

Measuring the impact of games played in a season on salaries was addressed in several ways. Lee & Harris (2012), Prockl & Frick (2018b) and Ribeiro et al. (2021), in some of their models, used the number of minutes played by a player during the season and concluded that this variable has a significant and positive impact on salaries. However, unlike Prockl & Frick (2018b), who measured the number of minutes from the previous season, Lee & Harris (2012) used the minutes played from the same season as salaries, which can bring about biased results, since salary data are from the beginning of the season, while the minutes played occurred after that date, so the impact of the number of minutes played on the salary data used was not specifically measured.

On the other hand, Dobson & Gerrard (1999), Speight & Thomas (1997), Lehmann (2000), Frick (2011), Franck & Nüesch (2008) and Ribeiro et al. (2021), in some of their models, used the number of matches played and concluded that this feature has a significant and positive impact on football players' salaries. Like Lee & Harris (2012), and unlike the other authors mentioned, who used the previous season, Franck & Nüesch (2008) used a variable referring to the same season as salaries, which may have changed the conclusions, although the significant and positive impact is expected to continue.

Bryson et al. (2013) and Celik & Ince-Yenilmez (2017) used the number of games that a player started from the beginning of the match and the number of matches that he entered as a substitute, both concluding that there is a significant and positive impact of the matches he played at the beginning, however, the two studies differ as to the conclusion of the impact of the games in which the players acted as a substitute. Bryson et al. (2013) concluded that the number of games in which a player entered as a substitute has a positive impact on salaries, but is only statistically significant, at the 10% level of significance and Celik & Ince-Yenilmez (2017) concluded that this variable has a statistically significant negative impact, at the 1% significance level, on salaries. Celik & Ince-Yenilmez (2017) argue that the option to divide the games into games played from the beginning of the game and games in which a player entered as a substitute, is because an econometric estimate that uses only the number of games played, to treat the performance of a player who played 90 minutes and a player who entered the field after 89 minutes, in the same way.

Perhaps following the same line of thought, Thrane (2019) measured only the number of completed games for each player and concluded that this variable has a significant and positive impact on salaries. However, if Celik & Ince-Yenilmez (2017) warned that measuring only the number of games played could bring about changes in the results, Thrane (2019) when measuring only the complete games, is excluding all games in which players entered as substitutes, which may also influence the conclusions.

Lee & Harris (2012) as already mentioned, used the played minutes in the season, as part of the variables to measure performance, to explain the relationship of this characteristic with the salaries of MLS players, for the seasons 2007 to 2009. However, the authors also used the total number of games in which a player participated, such as those in which he started, although the variables measure very similar and possibly correlated characteristics, there is no mention, on the part of the authors, of multicollinearity problems. Celik & Ince-Yenilmez (2017) took exactly this situation, stated that these variables could be correlated, and attributed the use of Two-Stage Least Squares (2SLS) in the estimation of the models, the authors, as a remedy for this possible multicollinearity problem.

Rodríguez et al. (2019), whose study has already been explained in the international status section, also concluded that the games played last season, are part of a set of six variables, which are more likely to determine the market value of football players in the top five European leagues.

2.2. CONTROL VARIABLES

2.2.1. AGE

According to Montanari et al. (2008), football players' salaries generally increase with experience, but they start to decrease when players reach a certain age, much because their physical condition begins to deteriorate. Several salary determination studies (see e.g. Battré et al., 2009; Della Torre et al., 2018; Deutscher & Büschemann, 2016; Hübl & Swieter, 2002; Ribeiro et al., 2021) have attempted to represent the relationship between age and salaries, using a quadratic variable to measure age, and have subsequently concluded that there is a non-linear, more specifically concave relationship (an inverted U-shaped relationship) between age and salaries.

Researchers have also found that there is a concave relationship between age and, market values and transfer prices (see e.g. Eschweiler & Vieth, 2004; Frick & Lehmann, 2001; Wicker et al., 2013).

An exceptional case seems to be the study by Kuethe & Motamed (2010), which examines the salary determination of professional football players in Major League Soccer (MLS), where the authors find that there is a convex relationship between players' ages and salaries. The authors attribute this contrast to the rest of the literature to the fact that MLS has the status of a less established league for top players, so the league chooses to compensate its fans by attracting those players at the end of their careers to earn salaries well above average and, the authors also point out, the fact that the league exhibits young talent before they earn much higher salaries in foreign markets. Lussier et al. (2022), in their study for MLS, concluded that the older a player is, the higher his salary will be, a conclusion that also goes against most of the literature.

There is a linear relationship between performance and salaries (Della Torre et al., 2018), which we can naturally expect and which has already been proven, considering that performance reaches a peak (Dendir, 2016), is that salaries also reach a peak. However, this salary peak is not consensual and differs from study to study and from league to league, which is not surprising either, since each league and the sample has its own characteristics, as was previously mentioned by Kuethe & Motamed (2010) study and the convex relationship between age and salaries in Major League Soccer.

2.2.2. EXPERIENCE

Mincer (1974), with its famous function of earnings, was the pioneer in trying to explain the salaries of workers, considering the level of education and experience. Researchers relied on Mincer's (1974) work to try to explain the salaries of professional athletes, having added many more variables related to the sport in question, to increase the variance explained by the models. The level of schooling has not been included in the models, but an exceptional case is Barros (2001), who tried to study the relationship between schooling and the salaries of players for Portuguese football and was unable to draw conclusions for the estimates of the Ordinary Least Squares method, due to endogeneity problems, however, the author used models of instrumental variables to get around these problems and was able to conclude that education plays no role in this market and that it is driven by talent.

Unlike not using schooling to explain salaries, the use of experience has been recurrent. In the United States, according to Lucifora & Simmons (2003), most researchers have only used experience, discarding the age of players, unlike some European studies that use the two variables together in models. This exclusion of the age variable is attributed by the authors to the fact that most US sports, unlike in Europe, have a recruitment system, a draft, in which players enter the major leagues with a uniform entry age, so inserting age and experience together in the models would bring problems of multicollinearity, in the function of salary gains.

There is no concrete way to measure a player's experience, so the way this measurement is done is up to each author, but according to Lucifora & Simmons (2003), the variables most used to measure this characteristic end up being the number of years a player plays in the studied league or the number of games played in his career. Lucifora & Simmons (2003), in their study with data from the first and second Italian division, opted to measure the experience in a quadratic way through the number of most recent matches, assigning variables to each league and, likewise, through the number of older matches, from the previous seasons, also in a quadratic way and for the two leagues. The authors concluded that the experience in the first division is more highly rewarded than in the second division, that there is a peak of matches in the previous seasons for the second division, but not for the first division, and that there is a peak in the most recent season for the first division, but not for the second division. Lucifora & Simmons (2003) finally conclude that extra games in the first division are more highly rewarded than extra games in the second division, while extra games in the most recent season have a greater impact on salaries than the appearances in previous seasons, thus concluding that the most recent experience has a greater impact on salaries.

Deutscher & Büschemann (2016), using data for the Bundesliga, took a different approach and tried to measure the experience by the number of matches in the league and by the number of international appearances of each player in the respective national team. The model brings again the confirmation that there is a quadratic relationship between the experience, in this case, the number of matches, and the salary of a football player, however, the same is not true with the number of international appearances, although they are statistically significant and have a positive influence, do not assume a quadratic relationship with salaries. In a way, since the number of international appearances does not assume a similar relationship to experience, as Mincer (1974) studied, although it has a positive impact on salaries, the variable should perhaps measure prestige instead of experience.

Eschweiler & Vieth (2004) and Frick (2011) used the number of matches played by players in the Bundesliga to measure experience, however, while the first authors concluded that there is a statistically significant quadratic relationship, the second concluded that there is a statistically significant cubic relationship between matches played and the salaries. Feess et al. (2004) used the number of games played in the career, while Thrane (2019) used the number of games played in the club, to measure the experience of the players. The first authors concluded that there is a quadratic relationship between the feature used and salaries, while Thrane (2019) concluded that the total number of games played by the club has a linear impact on salaries.

2.2.3. NATIONALITY

According to Wagner-Egger et al. (2012), racism in football is a problem that encompasses various social phenomena such as the sociological and political formation of fans, the culture of football, the economic discrimination of players, and the dynamics of the crowd or social judgment of the game. Frick (2007) states that discrimination occurs when a player's race or nationality, which does not affect his or her performance, influences pay, transfer rates, playing time, and career length.

Several authors have focused on racism and discrimination due to different nationalities in various sports and, according to Kahn (2000), the most studied form of discrimination in sports is salaried discrimination and this issue has been studied by building a regression, where the logarithm of the salaries are the dependent variable and the independent variables are, among other characteristics, performance, team characteristics, market characteristics and a dummy that informs whether the player is white or non-white.

Researchers started to realize early on, in sports economics, possible racial discrimination, and nationalities. For example, for baseball, Scully (1973), using MLB salary data, the North American League, concluded that athletes were not judged only by their merit, nor by their performance, but also by their skin color. The authors showed that black athletes were restricted to certain positions, that there were entry barriers and that they needed to perform better than white athletes to stay in the teams, just as they received less for their performance. Also for MLB, Mogull (1975), approached the issue of discrimination, with a different database from Scully (1973), but with a similar methodology. However, the author reached completely different conclusions from Scully (1973), stating that there was no evidence that black players in Major League Baseball were being discriminated against in terms of compensation. Also in baseball, Williams & Chambless (1997) also found that salary determination in MLB varied by race and ethnicity, while Holmes (2011) concluded that there was an 11% salary premium for Hispanic free baseball players and a 16% salary premium for white players, compared to black players.

Kahn (1991) produced a summary of studies that addressed salary discrimination in various sports. In the specific case of baseball, the author has assembled a set of studies that, like those mentioned above, have contradictory conclusions, but most of them show that there is no statistically significant salary discrimination, such as Medoff (1975), Mogull (1981), Raimondo (1983), and Rockwood & Asher (1976). For basketball, Kahn (1991) found evidence of salary discrimination, while for ice hockey, there is evidence that French-Canadians suffer salary discrimination in the defensive position.

The study of discrimination in sports is a well-documented case, however, brings many different conclusions, and the case of football is no exception. Szymanski (2000) opted not to use the most recurrent approach of regressing players' salaries according to performance variables, but rather to use the market test. The author found evidence of discrimination against black players in the English Football League during the period 1978-1993, where clubs with a higher proportion of black players playing performed better on average than clubs with a below-average proportion, after controlling the payroll. Pedace (2008) used the regional grouping of nationalities (African, South American, and North European) to study the existence of nationality discrimination in English football and concluded that South American players tend to be overpaid and that no other group of nationalities tends to be discriminated against or have a premium salary.

Within salary determination studies, some authors have used variables to control the nationality of players and thus can also study whether there is salary discrimination within the various leagues studied. Battré et al. (2009) built several models to explain the salaries of the German Football League players. In these models, the authors grouped nationalities by regions (South America, North America, Western Europe, Eastern Europe, Africa, and Asia-Australia) and used dummy variables to measure which players belong, using German nationality as a reference. The study by Battré et al. (2009) concludes that there is a salary premium for players from South America and Western Europe concerning German players and that there are no statistically significant differences between them and, African players and players from Asia and Australia. In some models, it was also noted that there is a salary premium for players from North America and Eastern Europe about German players, however, the various models bring contradictory conclusions, so not a single conclusion could be drawn. Della Torre et al. (2018), in a similar study, but for the Italian Football League, divided players between Italian and non-Italian, so they introduced a variable to control the different nationalities and included an interaction variable between performance and nationality, to better understand the problem. Della Torre et al. (2018) suggest, considering the models developed, that the pay gap between Italian and foreign players mainly penalizes older and better-performing foreign players.

Thrane (2019) uses in the salary determination models a variable that informs whether the players are Norwegian or foreign, and a later analysis of the model concludes that foreign players earn 29% more than Norwegians, in Norwegian Football League. Lussier et al. (2022), in a study using MLS data, used a variable that measures the impact of nationality on player salary, dividing players between US and foreign players, and concluded that foreign players earn higher salaries on average than US players. Ribeiro et al. (2021) did the same for the Portuguese League and concluded that foreign players earn on average more than Portuguese players.

Kuethe & Motamed (2010) collected the country of birth of each athlete and classified it according to continental football associations. It was concluded from the salary regression that in MLS, only the South Americans earn more, while the other groups of nationalities earn the same, compared to the North American players.

Eschweiler & Vieth (2004) also used a variable to control the nationality of players, in this case, to try to explain the market values of the Bundesliga. The authors divided the nationalities into groups considering the proportion of the nationalities of the players playing in Germany and concluded that there is a salary premium for South American and West European players compared to the other nationalities (apart from Germany) and concluded that there are no significant differences between the salaries of German and other nationalities (except for South American and West European players).

Although the use of the variable explaining the nationalities of players is recurrent, perhaps due to the contradictory conclusions of the subject, not all authors considered this characteristic when building models explaining the salaries and market values of football players, as was the case of Lucifora & Simmons (2003), Garcia-del-Barrio & Pujol (2007b), Franck & Nüesch (2008), Wicker et al. (2013) and Deutscher & Büschemann (2016).

2.2.4. POSITION

Several studies have included the players' positions in the explanatory variables and some of these studies note that there are differences in pay according to each of these positions. Frick (2007) states that, as far as the position of the player is concerned, the degree of specialization significantly affects remuneration. The author explains that goalkeepers are generally more specialized than the other positions, so that, they can only perform this function and therefore earn less, while the other positions, especially midfielders, can play outside their usual position and can be used in attack or defense, thus earning a significant salary premium.

Although there is a consensus that there are positions that on average earn more than others, researchers have come to different conclusions, so it is not possible to say with all certainty which position or positions have a salary advantage in football. Hübl & Swieter (2002), using salary data from the Bundesliga, and Frick (2006), using market value as a proxy for salaries, also for the Bundesliga, although for several different seasons, concluded that defenders, midfielders, and attackers earn a significantly higher salary than goalkeepers. On the other hand, Feess et al. (2004), also with data for the Bundesliga, concluded that there is only a positive effect on salary in midfielders and forwards compared to goalkeepers. Garcia-del-Barrio & Pujol (2007b) have some curious and significantly different conclusions from the previous authors, the authors, using a set of La Liga data, found evidence that there is a positive effect on the salaries of players playing the midfield and advanced roles and a negative effect on the salaries of defenders, with goalkeepers as a reference. Lehmann & Weigand (1999) also used Bundesliga data, this time from the 1998/1999 season, but unlike the other authors who considered goalkeepers as a reference in the models, the authors chose to use midfielders. Lehmann & Weigand (1999) then concluded that goalkeepers, defenders, and forwards earn less than midfielders. Celik & Ince-Yenilmez (2017), with data from the 2006 to 2017 MLS seasons, concluded that midfielders and forwards earn higher salaries than defenders and goalkeepers. Lussier et al. (2022), in their study for MLS, took a different approach and tried to find out only if there were differences between the salaries of forwards and the salaries of the other positions and concluded that the differences are not statistically significant.

2.2.5. TEAM

The effect of teams on players' pay has not been a major theme of football studies, most researchers have addressed the subject while conducting salary determination studies. Also in other sports, researchers have addressed salary inequality within each team and, rarely, between teams. Idson & Kahane (2000), being one of the exceptions, have studied salary inequality between teams in the National Hockey League, the major American hockey league, and have mainly concluded that team attributes have direct effects on players' pay and that the non-inclusion of teams in salary determination regressions causes individual attribute coefficients to be overestimated.

Unlike the United States, where there is a limited value that clubs can spend on salary, called the salary cap, the same does not exist in European football (Celik & Ince-Yenilmez, 2017), which creates a big gap between top and other teams. Although there is nothing similar in Europe, UEFA introduced Financial Fair Play in 2009, a program of the European body that regulates professional football, which investigates club accounts and aims, for example, to improve the economic and financial capacity of clubs, encourage clubs to operate on their revenues and discourage clubs from delaying payments, and can use heavy penalties for clubs that fail to comply ("Financial Fair Play | Inside UEFA", 2021). Although it limits foreign investment by requiring clubs to spend according to their revenues, the program does not combat the pay gap between the top and the other clubs.

According to Battré et al. (2009), clubs differ in their potential, with small and large clubs differing in their ability to pay. Richer football clubs usually pay higher salaries than other clubs (Della Torre et al., 2018).

Because of these pay differences between clubs, researchers have included dummy variables for teams in the respective leagues and have concluded that these variables have a statistically significant impact on salaries, so that there are statistically significant differences in the payment of salaries in the different teams, as we have seen, for example, in Battré et al. (2009), Bryson et al. (2013), Celik & Ince-Yenilmez (2017), Della Torre et al. (2018), or Deutscher & Büschemann (2016).

3. METHODOLOGIES

This chapter discusses the main methodologies used in the estimation of salary regression models. The variables that measure the players' characteristics, both in the respective seasons, as well as in the timeless characteristics, were chosen based on the previous literature on the subject and considering the available data. As previously mentioned, Deutscher & Büschemann (2016) state that performance, age, experience, talent, position and team have been identified by researchers as characteristics that define football players' salaries, so the variables used in this study will agree with this statement and with the remaining literature.

Figure 1 provides an overview of the methodological framework. After collecting and processing the data, such as joining the different databases coming from various sources, the research was developed in three stages. Firstly, using each of the estimators, the regression models that used football players' salaries as the dependent variable were calculated and, subsequently, these models were immediately interpreted. In the second stage, again for each estimator, new regression models were calculated, but this time using players' market values as the dependent variable. These models were also interpreted for each estimator. Finally, we compared the models for each estimator and assessed the statistical significance and impact of each explanatory variable used in the different dependent variables, noting the differences and similarities between the two models. To arrive at the final salary model, several models were tested, considering the maximization of the adjusted R^2. It was not possible to test all possible combinations, so we focused on maximizing the adjusted R^2, considering variables that had not yet been addressed by other researchers. The market value models used the same variables as the market value models. We chose to leave variables in the final salary model that were not shown to be statistically significant so that we could observe their behavior in the market value model.

Figure 1: Methodological framework.

3.1. DATA

To achieve the two types of regression models, one for salaries, and one for market values, using the same data and the same explanatory variables in both models, it was necessary to build a database, with data from several different sources and with different data extraction processes.

3.1.1. DEPENDENT VARIABLES

Two dependent variables were used, salaries and market values, in two model types. The players' salaries have been retrieved from Capology (www.capology.com). Capology commercializes players' salaries of several football leagues worldwide, where 30% of the total salaries of players (in 16 leagues) are directly verified through clubs, players' agencies, and journalists, while the remaining players' salaries are calculated through models that are based on the official payroll and have an error rate of less than 5% (Capology, 2020).

On the other hand, the market values were taken from Transfermarkt (www.transfermarkt.com). Several researchers have used the estimates produced by this platform in various football studies (e.g. Bryson et al., 2013; Della Torre et al.,2018; Franck & Nüesch, 2008). Transfermarkt is the leading website for football transfers and offers general football-related data such as scores and results, football news, transfer rumors, and market value estimates at individual and team levels for most professional football leagues (Muller et al., 2017). Muller et al. (2017) explain that any user of the site can propose an estimate of the market value of each player, considering their performance, and discuss with other members of the community their value. However, the authors further state that market values are not calculated using the average of users' estimates, but through a hierarchical approach, in which some elements of the community with more power review other users' estimates and select the most coherent and the most qualified, this to decrease the bias of the estimated market value. Salaries and market values are presented in euros.

3.1.2. EXPLANATORY VARIABLES

The choice of the explanatory variables considered previous literature and data availability. The aim was to cover most of the variables, which explain football players' salaries, identified by researchers in previous studies, so that all players could be analyzed, including, for example, those who play the goalkeeper position and who are often excluded from studies because of their performance is measured differently than other positions.

Most of the explanatory variables used in the models come essentially from the two sources mentioned above, Transfermarkt and Capology, however, another significant part of the variables were extracted from the sports statistics website, WhoScored.com (www.whoscored.com).

Among the explanatory variables extracted from WhoScored.com, there is the use of individual player ratings, as a uniform measure of performance for all positions. WhoScored.com is a website specialized in sports statistics and analysis, which uses and presents Opta statistics for the five main European football leagues and presents live results for hundreds of tournaments, thousands of teams, and thousands of players ("WhoScored Ratings Explained", 2021).

Dependent Variables				
Characteristic	**Variables**	**Source**	**Variable type**	**Description**
Salaries	Salaries	Capology	Numerical	Salary of each player.
Market Values	MV	Transfermarkt	Numerical	Market value of each player.
Explanatory Variables				
Age	Age	Capology	Numerical	Age of the player in years.
	Age2	Capology	Numerical	Age of the player squared.
Nationality	UEFA	WhosScored	Binary	Nationality grouped by confederations that manage football on each continent. 1 if the player has a nationality that is part of the confederation, 0 otherwise.
	CONMEBOL	WhoScored	Binary	
	CONCACAF	WhoScored	Binary	
	AFC	WhoScored	Binary	
	CAF	WhoScored	Binary	
Height	Height	WhoScored	Numerical	Height of the player in cm.
Weight	Weight	WhoScored	Numerical	Weight of the player in kg.
Position	Defender	Capology	Binary	1 if the player is a defender, 0 otherwise.
	Midfielder	Capology	Binary	1 if the player is a midfielder, 0 otherwise.
	Forward	Capology	Binary	1 if the player is a forward, 0 otherwise.
Performance	Ratings	WhoScored	Numerical	Performance rating in the season. From 0 to 10.
	Time Played	WhoScored	Numerical	Minutes of play in the previous season. Measured every 90 minutes.
	International Status	Transfermarkt	Binary	1 if the player has already played for his country's national team, 0 otherwise.
	Top 5	Transfermarkt/ WhoScored	Binary	1 if the player has played in the previous season in a team of the top 5 European leagues, 0 otherwise.

Table 1a: Initial study variables.

Caracteristic	Variables	Source	Variable type	Description
Explanatory Variables				
Team	Ajaccio; Alaves; Almeria; Amiens; Angers; Arsenal; AstonVilla; Atalanta; Athletic; AtleticoMadrid; Augsburg; Barcelona; Bastia; Bayern; Benevento; Bologna; Bordeaux; BorussiaDortmund; Bournemouth; Braunschweiger; Brescia; Brest; Brighton; Burnley; Caen; Cagliari; Cardiff; Carpi; Catania; CeltaVigo; Cesena; Chelsea; Chievo; Cordoba; Crtone; CrystalPalace; Darmstadt; Deportivo; Dijon; Dusseldorf; Eibar; Eintracht; Elche; Empoli; Espanyol; Everton; Evian; Fiorentina; Freiburg; Frosinone; Fulham; Gazelec; Genoa; Getafe; Girona; Granada; Guingamp; Hamburg; Hannover; Hellas; Hertha; Hoffenheim; Huddersfield; Huesca; Hull; Ingolstadt; Inter; Juventus; Koln; LasPalmas; Lazio; Lecce; Leganes; Leicester; Leipzig; Levante; Levante; Lille; Liverpool; Livorno; Lorient; Lyon; Mainz; Malaga; Mallorca; ManCity; ManUtd; Marseille; Middlesbrough; Monaco; Monchengladbach; Montpellier; Nancy; Nantes; Napoles; Nice; Nimes; Norwich; Nurnberg; Osasuna; Paderborn; Palermo; Parma; Pescara; PSG; QPR; Rayo; RealBetis; RealMadrid; RealSociedad; Reims; Rennes; Siena; Roma; Sassuolo; Schalke; Sevilla; Sheffield; Sochaux; Southampton; SPAL; SpGinjon; StEtienne; Stoke; Strasbourg; Stuttgart; Sunderland; Swansea; Torino; Tottenham; Toulouse; Troyes; Udinese; UnionBerlin; Valencia; Valenciennes; Valladolid; Villarreal; Watford; Werder; WestBrom; WestHam; Wolfsburg;	Capology	Binary	1 if the player plays in the team in the respective season, 0 otherwise.

Table 1b: Remaining initial study variables.

According to "WhoScored Ratings Explained" (2021), the ratings are based on a unique and comprehensive statistical algorithm, calculated live during the game, considering more than 200 raw and weighted statistics according to the player's influence on the game. The ratings range from 0 to 10, with 0 representing an extremely poor performance and 10, a perfect performance. Della Torre et al. (2018) used the WhoScored.com ratings in a salary determination study and, in an attempt to evaluate the algorithm used to calculate them, asked them to disclose it for research reasons, however, WhoScored.com, as expected, informed that the algorithm is not public and chose not to disclose it, so we had to rely on its consistency to evaluate players' performance.

All other explanatory variables chosen to be part of the models, as well as the dependent variables used, are specified in Tables 1a and 1b, where the variable's measurement characteristic, unit of measurement, type of variable, and description can be seen.

3.1.3. DATABASE

Seven sports seasons, more precisely the 2013/2014, 2014/2015, 2015/2016, 2016/2017, 2017/2018, 2018/2019, and 2019/2020 seasons, of the five main European football leagues, the Premier League (England), La Liga (Spain), Bundesliga (Germany), Serie A (Italy) and Ligue 1 (France), were considered for the study. Salary data and market values refer to these seasons, however, data measuring performance refer to the season immediately before the seasons of salaries and market values. In other words, for example, to try to explain the salaries of the 2013/2014 season, the performance of the player in the 2012/2013 season was used. The same has been done by almost all researchers who have developed studies of salary determination in football, for instance, Thrane (2019) explains that performances in one season do not affect remuneration in that same season but in the following season.

Only the performance of the season before the salaries was considered since the performance in the last season is much more important than the performance in the seasons before that one (Battré et al., 2009; Lucifora & Simmons, 2003). Also, regarding player performance, data from more leagues than the top five European leagues were used, since every season there are transfers of players from these leagues to the top five European leagues, and thus the number of players considered for the study could be increased. The leagues used were limited to the availability of data from WhoScored.com. The site does not provide the same performance statistics, namely ratings and minutes played, for the same leagues during the study period, so in some seasons the number of leagues used is higher than in others. In addition to players who played in the season before the seasons under study (seasons in which they played for a club in the five main European leagues), we used players who played in the Brasileirão (Brazilian first division), Bundesliga II (German second division), Championship (English second division), Eredivisie (Dutch first division), Liga NOS (Portuguese first division), Major League Soccer (North American first division), Super League (Greek first division), and Super Lig (Turkish first division).

The performance data of players who played in the Brasileirão and Major League Soccer in the season immediately before playing in one of the five major European leagues were considered from the 2012/2013 season to the 2018/2019 season. On the other hand, those who played in Bundesliga II and Super League were considered from the 2015/2016 season to the 2018/2019 season, those who played in Liga NOS were only considered from the 2016/2017 season to the 2018/2019 season, those who played in Super Lig were considered from the 2014/2015 season to the 2018/2019 season, while the data of players who played in the Championship and Eredivisie were considered from the 2013/2014 season to the 2018/2019 season.

To reach the final database, it was initially necessary to collect data from three different sources, Transfermarkt, WhoScored, and Capology. While for the data from Capology and WhoScored it was not necessary to establish any extraction process, as the data was already accessible in CSV files, the same did not happen with the data from Transfermarkt, where it was necessary to establish a web scraping process to extract the data, through the free and highly used software for statistical analysis, R. The merge of the three databases was also done through R, comparing the name of the players, as it was the only common information. This option, due to the differences in names in the different databases, required a manual check of the players with the same name, so that information from different players would not get mixed up and observations would not be lost. It was also necessary to calculate the ratings and minutes of players who played for more than one club in the performance season.

After merging the databases, data were pre-processed and cleaned, namely concerning cases that did not meet minimum requirements (such as the unavailability of salary or market value, or the minimum of 90 minutes played in the season). After this data cleaning and processing, the final dataset was obtained, which includes 11823 observations for all variables, from 4035 players, and which refers to 7 seasons.

The salary and market value data had as reference date the beginning of each season, i.e., in August. For example, when we approach the 2013/2014 season, the market values and salaries refer to August 2013, and the same happened for the other seasons under study.

3.2. ANALYSIS

3.2.1. PANEL DATA

According to Hsiao (2005), panel data or longitudinal data usually refers to data containing time-series observations of several individuals, so observations in panel data involve at least two dimensions, a cross-sectional dimension, and a time-series dimension. Panel data series can be composed of, for example, groups of countries, individuals, firms, clubs, etc.

There are two types of panel data, macro-panels, where there is a small number of sectional units observed over a large number of temporal units, and, micro-panels, where there are a large number of sectional units observed over a relatively short time period. In our case, we worked with a micro-panel, since we have a massive amount of individuals and a short number of time periods. Panels can also be balanced or unbalanced. In balanced panels, all individuals are measured in all periods, while in unbalanced panels there are individuals who have no observations for a given period. We analyzed an unbalanced panel, as expected when seven consecutive seasons are addressed, the number of players who played uninterruptedly during that period is minimal.

Baltagi & Song (2006) point out that there are obvious benefits to using panel data. Among these benefits is the fact that the use of panel data allows the use of a much larger data set, thus providing more efficient estimators than in cross-sectional data. This use of a larger amount of data allows more reliable estimates to be obtained and more sophisticated behavioral models with less restrictive assumptions to be tested. Yet another advantage of the panel data arrangement is its ability to control for individual heterogeneity. Not controlling for these unobserved individual-specific effects leads to biased and inconsistent estimators. Baltagi & Song (2006) also point out that panel data are better able to identify and estimate effects that are simply not detectable in cross-section or pure time-series data, namely, panel data sets are better able to study complex issues of dynamic behavior.

Panel data is widely used in football studies, particularly in salary determination studies. With the use of more than one season in the study for the same leagues and since many of the players are going to be the same, it is natural to use a panel data setup. Battré et al. (2009), Bryson et al. (2013), Celik & Ince-Yenilmez (2017), and Franck & Nüesch (2012) are some of the examples of authors who have used panel data in studies of football player salary determination.

The next sections were based on Baltagi & Song (2006), Baltagi (2008), and Woolridge (2010).

3.2.2. THE MODEL

One way to model individual heterogeneity is to assume that the error term has two separate components, one of which is individual-specific and does not change over time (Croissant & Millo, 2008). Similarly, it is possible to add another time-period-specific component. It makes sense that given a large number of individuals (players) considered and the considerable number of seasons, that heterogeneity exists between players and different seasons. We then studied a two-way error component regression model.

In unbalanced data panels, the two-way error component regression model, for individual *i = 1,…,* N_t which is observed over several time periods t = 1,..., T, is represented by:

$$y_{it} = X'_{it}\beta + u_{it}$$

$$u_{it} = \mu_i + \lambda_t + \nu_{it}$$

With *i* denoting generic i-th football player and t denotes the t-th season. β is the $k \times 1$ vector of regression coefficients, which includes the intercept. y_{it} denotes the output for the i-th player obverved at the t-th period, while X_{it} denotes the matrix of k inputs. The panel data is unbalanced in the sense that not all players can be observed for all time periods, so N_t represents the number of players that are observed at time t and n, which is the total number of player observations, is defined as $\sum_t N_t$.

A regression model with a two-way error component was considered for the study and thus this consists of the variable μ_i, which denotes the unobservable individual specific effect, λ_t, which denotes the unobservable time effect and by ν_{it}, which is the remaining stochastic disturbance term.

There are two types of effects models used in panel data estimation: fixed effects models and random effects models. The methods used in panel data regressions depend on the data.

For a better understanding of the estimators in the following sections, it is necessary to define the matrix Δ and to do so, we follow Baltagi's (2008) notation. Let D_t be the $N_t \times N$ matrix obtain from I_N by omitting the rows corresponding to the unobserved individuals in year t. Δ is defined as

$$\Delta = (\Delta_1, \Delta_2) = \begin{bmatrix} D_1 & D_1\iota_N & \\ \vdots & \ddots & \vdots \\ D_T & \cdots & D_T\iota_N \end{bmatrix}$$

where $\Delta_1 = (D'_1, \dots, D'_T)$ is $n \times N$, $\Delta_2 = diag[D_t\iota_N] = diag[\iota_N]$ is $n \times T$, I_N is an identity matrix of dimension N and ι_N is a vector of 1's of dimension N. The matrix Δ represents the dummy variable structure for the incomplete panel data model.

We estimated the models in three different ways. Initially we used the pooled OLS, then the fixed effects estimator, and finally the random effects estimator.

3.2.3. POOLED MODEL AND THE OLS

We assume that individual heterogeneity (μ_i) and the heterogeneity of the time periods (λ_t) did not exist, so it was no longer necessary to use a two-way error component regression model. A model with the form of

$$y_{it} = \alpha + X_{it}'\beta + \varepsilon_{it}$$

with strictly exogenous regressors X_{it}, spherical errors (homoscedastic and uncorrelated), independence among the *i* observations, and no multicollinearity among the independent variables, so that OLS produces consistent and efficient parameter estimators (Greene, 2012).

The OLS estimator of β, which includes the constant term α is defined by:

$$\hat{\beta} = (X'X)^{-1}X'y$$

Gil-García & Puron-Cid (2014) report that models using traditional OLS estimates show questionable results and that the history of regression analysis is replete with violations of its assumptions.

When it comes to estimating panel data models it is common to refer to OLS as Pooled OLS. The (Pooled) OLS is a pooled linear regression without fixed and/or random effects, which assumes a constant intercept and slopes regardless of group and period (Park, 2011). In case there is no homogeneity and thus a model with a two-sided error component is chosen, the Pooled OLS will be inconsistent if the individual component or the period component are correlated with the regressors (Croissant & Millo, 2008).

In panel data models, Pooled OLS stacks the observations for each individual over time one on top of the other, which does not result in distinctions between individuals and over time (Gil-García & Puron-Cid, 2014). The authors consider that, eventually, disregarding the effects on individuals and over time distorts the true picture of the relationships of the variables being studied between individuals and over time.

Gujarati & Porter (2011) consider that estimating panel data regression models using OLS is the most simplistic and naive way to do it, since it disregards the dimensions of time and spaces combined.

3.2.4. FIXED EFFECTS MODEL AND ESTIMATOR

Back to the two-way fixed effects error component model, we assume that μ_i and λ_t are fixed parameters to be estimated, while the stochastic disturbances we assume as ν_{it} ~ IID(0, σ_ν^2), that is, they must be distributed independently and identically. In this model, according to Baltagi (2008), X_{it} are considered independent of ν_{it} for all *i* and *t*, the inference in this case is dependent on the particular individuals *N* and over the specific time periods observed. The meaning of the term "fixed effects" refers to the fact that although the fixed variable μ_i varies between units, it remains constant over time, just as the variable λ_t that varies between time periods, but remains constant for each individual.

The simplest and most commonly used way to estimate fixed effects models is to add to the regression model *N-1* dummy variables, one for each individual minus one, to avoid collinearity problems and add *T-1* dummy variables, one for each season, minus one, also to avoid the same problem. After this addition, the model is estimated using OLS. This way of estimating fixed effects models is called Least Squares Dummy Variables (LSDV). However, according to Baltagi (2008), LSDV brings problems when *N* or *T* are very large, that is, when there are many observed individuals or time periods, since it becomes difficult to include and manage many dummy variables in the regression. This inclusion of many dummy variables also causes a huge loss of degrees of freedom.

To get around this unfeasibility of LSDV for large panes of data, it is necessary to perform a within transformation. According to Baltagi (2008) the within transformation is more complicated for unbalanced panels, but it is still manageable.

To understand the transformation, it is necessary to look at more matrices and understand the associated notation. $\Delta_N \equiv {\Delta_1}'\Delta_1 = diag[T_i]$ where T_i is the number of seasons in which player *i* is observed in the panel. $\Delta_T \equiv {\Delta_2}'\Delta_2 = diag[N_t]$ where $\Delta_{TN} \equiv {\Delta_2}'\Delta_1$ is the $T \times N$ matrix of 0's and 1's that indicate the presence or absence of a player in a certain season.

Baltagi et al. (2002) suggest the within transformation proposed by Wansbeek & Kapteyn (1989), which eliminates the effect of individuals and the effects of time periods. Defining $\bar{\Delta} \equiv \Delta_2 - \Delta_1\Delta_N^{-1}\Delta_{TN}'$ and $P \equiv \Delta_T - \Delta_{TN}\Delta_N^{-1}\Delta_{TN}' = \Delta_2'\bar{\Delta}$, Wansbeek & Kapteyn (1989) show that Q it is the matrix projection into the null space of $\Delta = (\Delta_1, \Delta_2)$.

$$Q \equiv (I_n - \Delta_1\Delta_N^{-1}\Delta_1') - \bar{\Delta}P^{-}\bar{\Delta}'$$

Where I_n is an identity matrix with dimension n. Q deletes the μ_i's and λ_t's, whether they are fixed or random and this produces the within or fixed effects estimator (Baltagi et al., 2002):

$$\tilde{\beta}_s = (X_s'QX_s)^{-1}X_s'Qy$$

where X_s denotes the exogenous regressors, excluding intercept and β_s denotes the vector of slope coefficients $(k-1)$.

3.2.5. RANDOM EFFECTS MODEL AND ESTIMATOR

We again approached a two-way error component model, but this time we assumed that the effects are random, i.e., μ_i, λ_t and ν_{it} are assumed to be random variables and follow their distributions, μ_i ~ IID(0,σ_μ^2), λ_t ~ IID(0,σ_λ^2) and ν_{it} ~ IID(0,σ_υ^2), i.e., should all be independently and identically distributed. In this model, according to Baltagi (2008), it is assumed that μ_i, λ_t and ν_{it} are independent of each other and, furthermore, X_{it}, which represents the explanatory variables, is independent of μ_i, λ_t and ν_{it} for all i and t.

In vector form, the incomplete two-way random effects model can be written as

$$u = \Delta_1\mu + \Delta_2\lambda + \nu$$

where $\mu' = \mu_1, \dots, \mu_N$, $\lambda' = \lambda_1, \dots, \lambda_T$ and $\nu' = \nu_{11}, \dots, \nu_{1T,} \dots, \nu_{N1}, \dots, \nu_{NT}$.

The variance-covariance matrix Ω for unbalanced data can be written as

$$\Omega = E(uu') = \sigma_v^2 I_n + \sigma_\mu^2 \Delta_1 \Delta_1{}' + \sigma_\lambda^2 \Delta_2 \Delta_2{}'$$

$$= \sigma_v^2 (I_n + \emptyset_1 \Delta_1 \Delta_1{}' + \emptyset_2 \Delta_2 \Delta_2{}') = \sigma_v^2 \Sigma$$

where *n* is the total number of observations ($\mathrm{n} = \Sigma_{\mathrm{t}=1}^{\mathrm{T}} \mathrm{N_t}$), $\emptyset_1 = \sigma_\mu^2 / \sigma_v^2$ and $\emptyset_2 = \sigma_\lambda^2 / \sigma_v^2$.

Baltagi (2008) notes that unlike in the case of balanced data panels, in this case it is not possible to perform spectral decomposition of Ω, developed by Fuller & Battese (1974). However, the author presents an alternative to this transformation, developed by Wansbeek & Kapteyn (1989), in which they derived the inverse of Ω in the following way:

$$\sigma_v^2 \Sigma = \Sigma^{-1} = V - V \Delta_2 \tilde{P}^{-1} \Delta_2{}' V$$

where

$$V = I_n - \Delta_1 \widetilde{\Delta}_N^{-1} \Delta_1{}' \qquad (n \times n)$$

$$\tilde{P} = \widetilde{\Delta}_T - \Delta_{TN} \widetilde{\Delta}_N^{-1} \Delta_{TN}{}' \qquad (T \times T)$$

$$\widetilde{\Delta}_N = \Delta_N + (\sigma_v^2 / \sigma_\mu^2) I_N \qquad (N \times N)$$

$$\widetilde{\Delta}_T = \Delta_T + (\sigma_v^2 / \sigma_\lambda^2) I_T \qquad (T \times T)$$

with $\Delta_N = \Delta_1{}' \Delta_1 = diag(\mathrm{T}_i)$, $\Delta_T = \Delta_2{}' \Delta_2 = diag(\mathrm{N}_t)$ and $\Delta_{TN} = \Delta_2{}' \Delta_1$. T_i is the number of times that individual *i* was observed in the panel with $(2 \leq \mathrm{T}_i \leq T)$.

According to Baltagi et al. (2002), if Σ is known, the GLS estimator of β is given by:

$$\hat{\beta}_{GLS} = (X' \Sigma^{-1} X)^{-1} X' \Sigma^{-1} y$$

The authors report that the GLS is the best unbiased estimator of β when the variance components σ_μ^2 e σ_λ^2 are known. Since these components are not known, it is necessary to estimate them first, to be able to estimate Σ and calculate the GLS. Some papers have suggested different approaches to obtain Feasible GLS (FGLS) estimates. We decided to use the Wallace & Hussain (1969) type estimators, which proposed to replace the real u by the residuals $\hat{u}_{OLS}$.

3.2.6. HAUSMAN TEST

To identify whether a model is a fixed-effects or random-effects model and thus check whether the estimators used are consistent or not, we used the Hausman's Test (Hausman, 1978).

The Hausman test is usually described for models with a one-sided error component, however, according to Baltagi (2008), the test can be based on the difference between the fixed effects estimator and the two-way random effects GLS estimator.

The GLS estimator is efficient if the individual effects, μ_i, and the time effects, λ_t, are uncorrelated with the explanatory variables, X_{it}, however, if these effects are correlated, the GLS estimator is inconsistent (Kang, 1985). If these effects are correlated with the explanatory variables, also the pooled OLS is inconsistent, while the fixed effects estimator (within estimator) is consistent.

According to Kang (1985), Hausman (1978) proposed a test to test the correlation between the unobserved effects and the explanatory variables. The test statistic is given by:

$$(\widehat{\beta_1} - \widehat{\beta_0})' var(\widehat{\beta_1} - \widehat{\beta_0})^{-1} (\widehat{\beta_1} - \widehat{\beta_0})$$

which asymptotically follows a chi-square distribution with k degrees of freedom, where $\widehat{\beta_1}$ is a consistent, but not efficient estimator, $\widehat{\beta_0}$ is the efficient estimator and k is the order of β.

In Hausman's test the two fixed and random effects estimators are compared under the null of no significant difference, that is, if this test is not rejected, the random effects estimator is chosen (Croissant & Millo, 2008).

3.2.7. SOFTWARE APPROACH

All extraction, data analysis, and model estimation methods were performed in R (programming language). R has many statistical/econometric tools available, is constantly updated, is free, and relatively fast (Racine & Hyndman, 2002). R also allows for the implementation of web scraping techniques, so it was a justified choice.

4. RESULTS AND DISCUSSION

FIRST, A BRIEF DESCRIPTIVE ANALYSIS OF THE VARIABLES WILL BE PRESENTED. NEXT, A BRIEF PRELIMINARY ANALYSIS OF THE RELATIONSHIPS BETWEEN THE EXPLANATORY VARIABLES AND THE DEPENDENT VARIABLES IN THE MODELS IS PRESENTED. THEN, THE REGRESSION MODELS THAT USE SALARIES AS THE DEPENDENT VARIABLE AND THE REGRESSION MODELS THAT USE MARKET VALUES AS THE DEPENDENT VARIABLE AND THAT WERE ESTIMATED BY THREE DIFFERENT ESTIMATORS ARE PRESENTED. FINALLY, THE INTERPRETATION OF THE MODELS AND THEIR COEFFICIENTS ARE PRESENTED, AS IS THE COMPARISON BETWEEN EACH OF THE MODELS ESTIMATED BY THE SAME ESTIMATOR AND THE INDICATION AND DESCRIPTION OF THE DIFFERENCES CAUSED BY USING MARKET VALUES OVER PLAYER SALARIES.

4.1. EXPLORATORY ANALYSIS

4.1.1. DESCRIPTIVE ANALYSIS

The 11823 observations of 4035 football players show that the average gross salaries over the seven seasons of understudy were 2121735 euros. Our database also shows that the average market value of the players over the seven seasons was 9352692 euros. The average salaries have been growing since the first season under study, 2013/2014, when they stood at €1704663 per year, and have risen to €2503525 in 2019/2020 (Figure 2). Market values have also grown positively during the same period, rising from €6345439 in 2013/2014, to €11743242 in 2019/2020. Although salaries and market values had a positive development, this growth happened at a different pace. The difference between average salaries and market values has increased from the 2013/2014 season to the 2018/2019 season and has decreased in 2019/2020 compared to the 2018/2019 season. While in the 2013/2014 season the average market values were 3.72 times higher than the average salaries, in 2019/2014 the average market values were already 4.69 times higher than the average salaries. According to our database, salaries have a minimum value of €2000 and a maximum value of €70758000, while market values have substantially higher minimum and maximum values, more specifically, a minimum value of €50000 and a maximum value of €200 million.

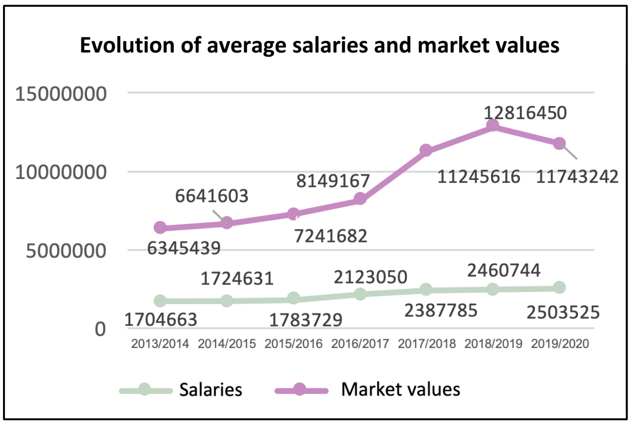

Figure 2: Evolution (in euros) of average salaries and market values over the seasons under study.

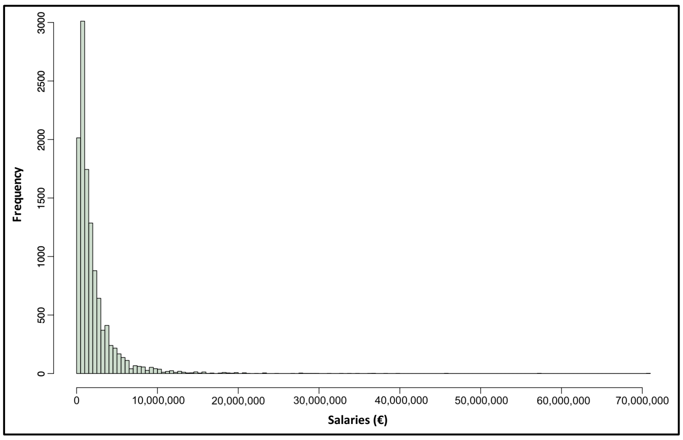

Figure 3: Histogram of the salaries. Salaries distribution, 2013-2014 until 2019-2020 seasons.

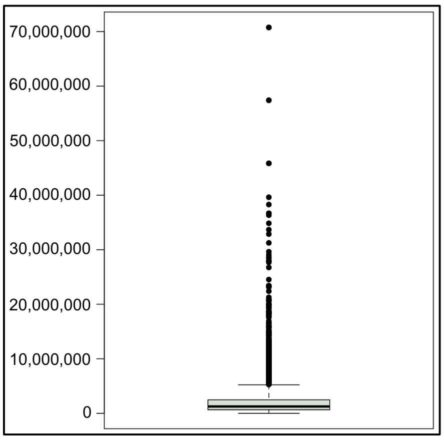

Figure 4: Box-plot of the salaries. Salaries distribution, 2013-2014 until 2019-2020 seasons.

Looking at the histogram of salaries (Figure 3), this variable has an asymmetric distribution. The histogram is asymmetric to the right since it has a tail on the right side of the distribution.

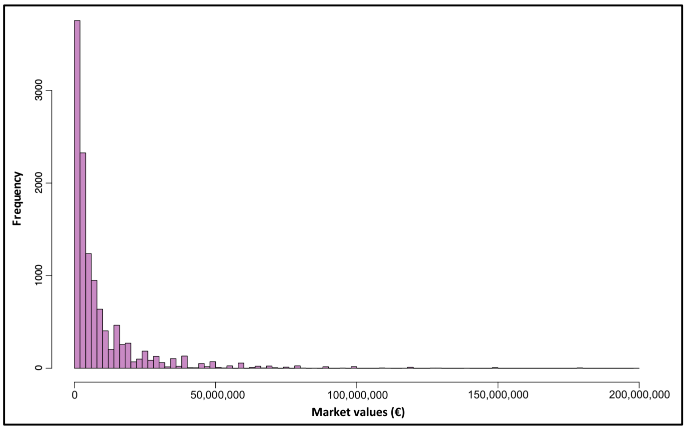

Figure 5: Histogram of the market values. Market values distribution, 2013-2014 until 2019-2020 seasons.

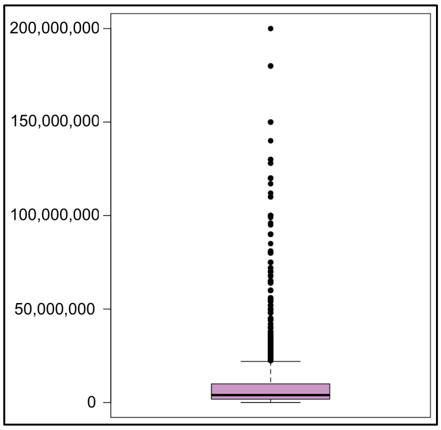

Figure 6: Box-plot of the market values. Market values distribution, 2013-2014 until 2019-2020 seasons.

Also, observing the histogram of the market values (Figure 5), we see that this variable presents an asymmetric distribution. The distribution has a tail on the right side, so we are again looking at an asymmetric histogram on the right. According to Pearson's correlation test (see appendix), the correlation between salaries and market values is 0.6807 ($p<0.0001$), a relatively strong correlation.

Given the kurtosis value, the distribution of salaries is more tailed than the distribution of market values and both are more tailed than the normal distribution. Concerning skewness, the distribution of salaries is more asymmetric than the distribution of market values, but both are skewed to the right side, i.e., the right tail of the distributions is long relative to the left tail. The values of kurtosis and skewness present in Table 2, confirm what was seen earlier in Figure 3 and Figure 5.

According to the classical definition of an outlier, 867 observations of salaries are considered outliers, i.e., 7.33% of total observations, and for market values, 1249 observations are considered outliers, 10.56% of all observations. According to the adjustment for asymmetric distributions, based on Hubert & Vandervieren (2008), 294 observations are considered outliers, 2.49% of the total observations. For market values, 555 observations are considered outliers, 4.69% of total observations, values from the box-plot also adjusted for asymmetric distributions and based again on Huberta & Vandervieren (2008).

We are facing a considerable number of outliers, so we checked the data again for measurement errors, experimental errors and/or inconsistencies, but we found that everything seemed to conform and that there seemed to be no data that came from errors and that would lead to outliers. There are indeed players who earn salaries and have market values far above the average, which makes their salaries and market values unusual compared to the rest of the data set. These players enjoy a "superstar effect", according to Rosen (1981). It did not seem consistent to us to choose to eliminate this amount of observations from the study, since no experimentation error provided this number of outliers. Eliminating these observations from the study would take some credibility away from the study and would cause us to ignore the existence of players who earn salaries well above average or have very high market values. We chose to leave all these observations in the study, always being aware that the presence of a high number of outliers in the study can have a negative impact on the regression models.

Variables	N	Mean	Variance	Median	IQR	Min	Max	Skewness	Kurtosis
Salaries	11823	2,121,735	2,993,561	1,248,000	1,833,500	2	70,758,000	6.98	99
Market values	11823	9,352,692	14,586,269	4,000,000	8,200,000	50	200,000,000	4.12	29.01
Age	11823	26.37	4.11	26	6	16	42	0.28	2.66
Weight	11823	77.02	7.05	77	10	55	101	0.18	3
Height	11823	182.43	6.47	183	9	161	203	-0.12	2.75
Time Played	11823	19.62	104.05	104.05	16.58	1	50.28	-0.03	2.03
Ratings	11823	6.82	0.33	6.81	0.42	5.21	8.95	0.39	4.28

Table 2: Descriptive statistics of continuous variables.

The ratings represent the average performance ratings of players during a season. The minimum rating value observed in our data is 5.21, while the maximum value is 8.95. The lowest value belongs to Johann Durand, player of Evian (Ligue 1), was achieved in the 2012/2013 season and the sum of only 121 minutes of play. The maximum value belongs to Neymar, player of Paris Saint Germain (Ligue 1), it was reached in the 2017/2018 season and in the sum of 1788 minutes. Within the 11823 observations, the average value of a player's performance rating is 6.82, a value also close to the median, 6.81.

Playing time was measured in minutes and then transformed into full games to enable a more intuitive analysis of the model. The minimum value that a player played during a season was 90 minutes, i.e., one full game, on the other hand, the maximum value was 4525 minutes of play, which amounts to 50.3 games, an extremely high value for a single season. In our data, the record number of minutes played in a season belongs to Blerim Dzemaili, a Swiss player who played for two teams in the 2016/2017 season, CF Montréal and Bologna FC. A player plays an average of 1765.82 minutes per season, or 19.6 full games. This value is also not far from the median value, 1796 minutes.

The average height of a player in our sample is 182.43 cm, while the average weight of a player is 77.02 kg. These average values are extremely close to the median for these characteristics, 183 cm, and 77 kg.

Variables	N	Percent
Position		
Goalkeeper	1031	8.72%
Defender	4251	35.96%
Midfielder	4259	36.02%
Forward	2282	19.30%
National Team		
International	7899	66.81%
Non-international	3924	33.19%
League Last Season		
Top 5	10790	91.26%
Out of Top 5	1033	8.74%
Nationality		
UEFA	8935	75.57%
CONMEBOL	1385	11.71%
CONCACAF	232	1.96%
AFC	106	0.90%
CAF	1155	9.77%
OFC	10	0.09%

Table 3: Descriptive statistics of categorical variables.

From the 11823 observations, 8.72% are observations of players playing the role of goalkeeper, 35.96% are of defenders, 36.02% are of midfielders and 19.30% are of forwards. Concerning players' internationalization, of the 11823 observations, 66.81% are of players who have been international for their country at least once, and 33.19% of the observations concern players who have never been international. Of the 11823 observations under study, 91.26% refer to players who played in one of the top 5 European leagues in the previous season, while 8.74% refer to players who played for a club that belonged to another football league and belonged to a league outside the European Top 5, also in the previous season and before moving to a top 5 European league club next season. As for the nationality of the players, which in our study was grouped according to the continental confederation to which each country belongs, 75.57% of the observations are of players whose country belongs to UEFA, 11.71% to CONMEBOL, 1.96% to CONCACAF, 0.90% to AFC, 9.77% to CAF and 0.09% to OFC.

4.1.2. PRELIMINARY STUDY ON THE RELATIONSHIP BETWEEN THE DEPENDENT VARIABLES AND THE QUANTITATIVE EXPLANATORY VARIABLES

Several scatter plots were computed, to preliminarily evaluate the relationship between the quantitative explanatory variables and the dependent variables that we will consider in the different models. These graphs were analyzed individually and compared to each other.

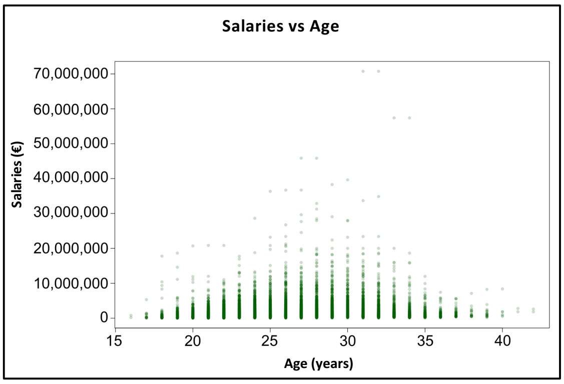

Figure 7: Scatter plot of the salary-age relationship.

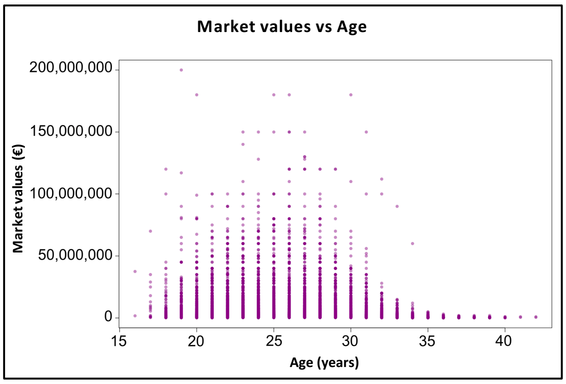

Figure 8: Scatter plot of the market value-age relationship.

According to Figure 7 and Figure 8, there seems to be a quadratic relationship between age and salary, just as there also seems to be the same relationship between age and market value, something that is in line with the literature on the subject that we have already covered. However, when we compare the two graphs, we can see that market values take higher values on average and seem to peak relatively earlier than salaries.

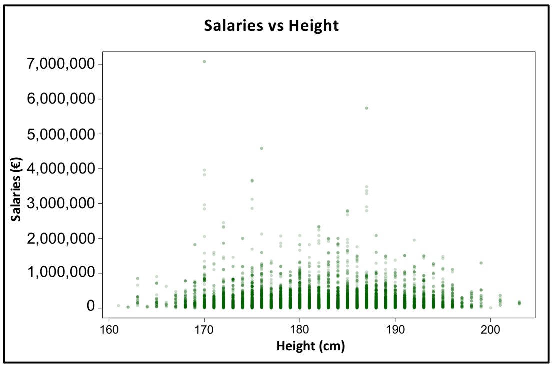

Figure 9: Scatter plot of the salary-height relationship.

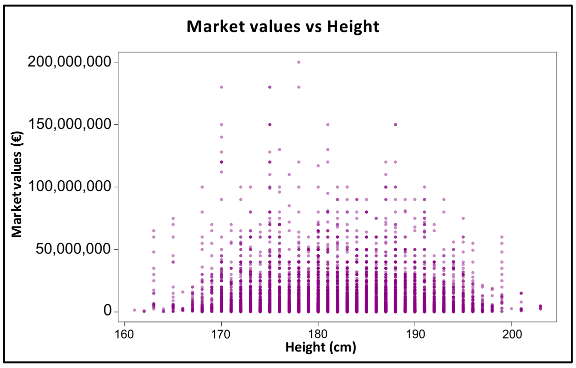

Figure 10: Scatter plot of the market value-height relationship.

There also appears to be a quadratic relationship between height and salary, as does a quadratic relationship between height and market value, although this relationship is much less noticeable in Figure 10 than in Figure 9, i.e., the quadratic relationship is sharper when we consider market values. According to the graphs, very short players and very tall players are penalized for their height in both their salaries and their market values.

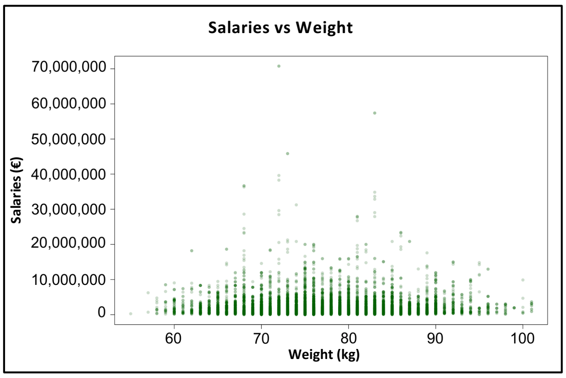

Figure 11: Scatter plot of the salary-weight relationship.

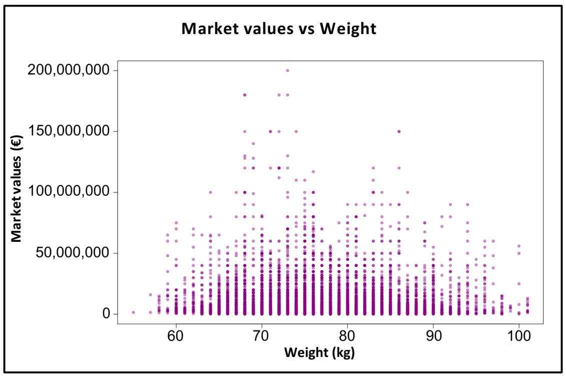

Figure 12: Scatter plot of the market value-weight relationship.

There again appears to be a quadratic relationship between weight and salary (Figure 11), just as there is between weight and a player's market value (Figure 12). The relationship between weight and salary is very similar to the relationship between height and salary, just as the relationship between weight and market value is very similar to the relationship between height and market value. This similarity between these graphs may indicate a correlation between the weight and height variables, which is confirmed by Pearson's correlation test (see appendix), which indicates that the correlation between the height variable and the age variable is 0.7631 ($p<0.0001$), a strong correlation.

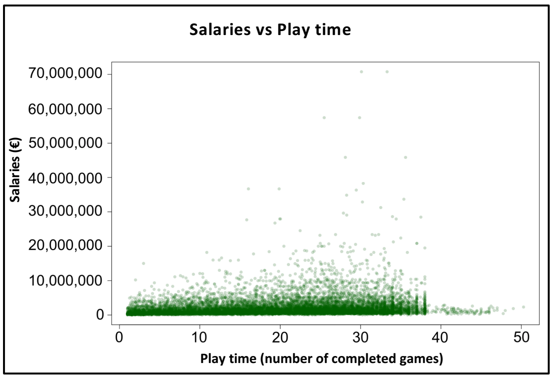

Figure 13: Scatter plot of the salary-play time relationship.

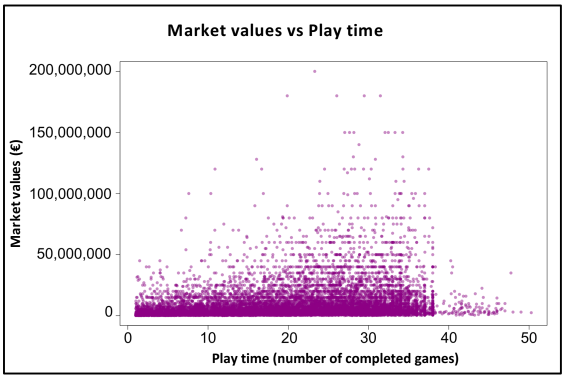

Figure 14: Scatter plot of the market value-play time relationship.

Looking at Figure 13, we cannot visualize the linear relationship, that the literature suggests, between the time a player spends on the field and his salary. It is not possible to verify that the more playing time a player spends, the higher his salary will be. On the contrary, in Figure 14, one can subtly verify that the more time a player spends on the field, the higher his market value will be. Comparing the two graphs, the impact of a player having more playing time on his market value seems to be greater than the impact on his salary.

Figure 15 seems to preliminarily confirm the theory that players with better performance receive higher salaries. In our study, one of the performance evaluators used were ratings, and it can be subtly seen that as rating increase, players' salaries also increase, although they seem to increase rather faintly.

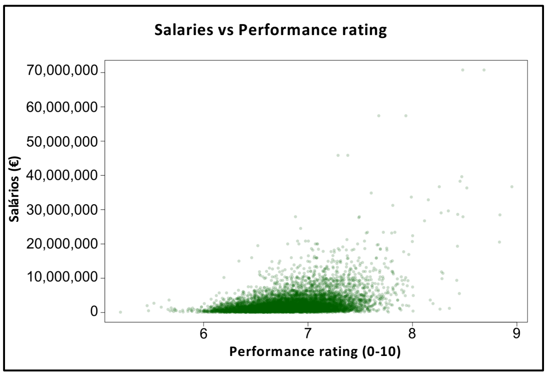

Figure 15: Scatter plot of the salary-performance rating relationship.

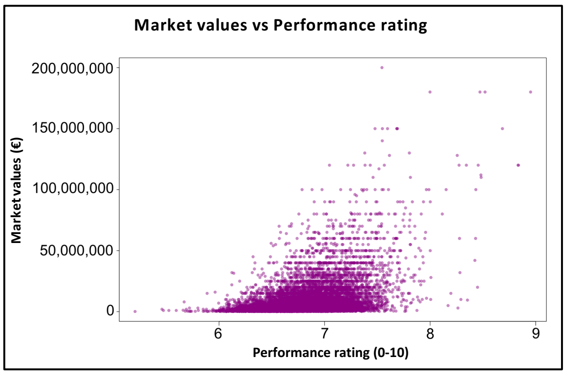

Figure 16: Scatter plot of the market value-performance rating relationship.

As far as market values are concerned, they seem to increase more noticeably as ratings also increase. As with playing time, comparing the two figures, the impact of a player having a higher performance rating on his market value seems to be greater than the impact on his salary.

4.2. REGRESSION MODELS

To represent the various methodologies used by researchers, we used the three most commonly used specifications in performance and pay studies, while the Hausman test (see appendix) indicated that the fixed effects estimator is the only consistent estimator (p-value<0.0001), within the estimators used.

We tested several models to find the final models for each of the estimators. To develop the final models, we considered the previous literature on the subject and our preliminary analysis of the relationship between salaries and the quantitative variables initially considered in the study. We also focused on variables that had not been used previously by the researchers and that brought us some doubts, such as weight and height, variables that as we saw earlier are even strongly correlated. We tested multiple models and chose to use those with the highest adjusted R^2. As we considered only the adjusted R^2, we chose not to eliminate variables that are not statistically significant in the regression model of salaries, not least because that way we could observe the significance of the same variables in the model of market values. Salaries and market values underwent a Log transformation in the regression models, due to their asymmetric distributions.

4.2.1. MODELS ESTIMATED BY THE POOLED OLS

The parameter estimates of the regression models estimated by pooled OLS, as well as the robust standard errors, are presented in **Table 4**.

4.2.1.1. SALARY MODEL

Model i) in Table 4 represents the salary regression model estimated by pooled OLS. The coefficient of determination of the model is 0.6446, i.e., 64.46% of the variability in salaries can be explained by the variables included in the regression.

Table 4: Regression models estimated by pooled OLS.

	i) Dependent variable: log(Salaries)				ii) Dependent variable: log(Market values)			
Explanatory variables	**Coefficient**	**Robust S.E.**	**t value**	**Pr(>|t|)**	**Coefficient**	**Robust S.E.**	**t value**	**Pr(>|t|)**
Intercept	6.5402	0.7932	8.2450	<0.0001 ***	8.0033	0.8606	9.2999	<0.0001 ***
Age	0.4051	0.0235	17.2576	<0.0001 ***	0.4750	0.0286	16.5920	<0.0001 ***
Age²	-0.0067	0.0004	15.5145	<0.0001 ***	-0.0112	0.0005	-21.1603	<0.0001 ***
Weight	-0.0233	0.0183	-1.2763	0.2019	-0.0552	0.0197	-2.8057	0.0050 ***
Weight²	0.0002	0.0001	1.3481	0.1777	0.0004	0.0001	2.7954	0.0052 ***
Playing Time	0.0105	0.0009	12.0371	<0.0001 ***	0.0315	0.0010	31.3246	<0.0001 ***
Ratings	0.2485	0.0316	7.8550	<0.0001 ***	0.5760	0.0326	17.6583	<0.0001 ***
League Last Season [a]								
Top 5	0.2899	0.0250	11.6072	<0.0001 ***	0.6601	0.0336	19.6547	<0.0001 ***
National Team [b]								
International	0.3504	0.0197	17.7559	<0.0001 ***	0.4636	0.0212	21.8401	<0.0001 ***
Position [c]								
Defender	0.0701	0.0338	2.0740	0.0381 **	-0.0295	0.0381	-0.7749	0.4384
Midfielder	0.2903	0.0350	8.3066	<0.0001 ***	0.2602	0.0389	6.6937	<0.0001 ***
Forward	0.4716	0.0367	12.8680	<0.0001 ***	0.4719	0.0408	11.5786	<0.0001 ***
Nationality [d]								
CAF	-0.2078	0.0285	-7.2851	<0.0001 ***	-0.3062	0.0337	-9.0937	<0.0001 ***
CONMEBOL	0.0809	0.0247	3.2757	0.0011 ***	0.0922	0.0280	3.2958	0.0010 ***
CONCACAF	-0.2062	0.0503	-4.0967	<0.0001 ***	-0.3264	0.0631	-5.1730	0.0000 ***
AFC	-0.1993	0.0589	-3.3833	0.0007 ***	-0.3542	0.0916	-3.8666	0.0001 ***
OFC	0.0997	0.0500	1.9950	0.0461 **	-0.0744	0.0793	-0.9378	0.3484
Teams [e]	jointly significant [f]							
R^2	0.6446				0.7148			
Adjusted R^2	0.6396				0.7108			
F statistic	129.736 on 163 and 11659 degrees of freedom				179.263 on 163 and 11659 degrees of freedom			
p-value	<0.0001 ***				<0.0001 ***			

*** significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.**
a) ref: Outside Top 5. b) ref: Non-international. c) ref: Goalkeeper. d) ref: UEFA.
e) 147 dummy variables, referring to the 147 teams (excluding the reference) that played in the top 5 European leagues between 2013/2014 and 2019/20, were hidden from the table, but available in the appendices. Ref: Wolverhampton.
f) a joint hypothesis test was performed using the robust version of the F-test (see appendix) which determined that the dummy variables referring to the teams were jointly significant in both models (p-value <0.0001*).**

This model confirmed the concave relationship between players' age and their salary earnings, as other authors had already claimed. According to model 4.i), real salaries peak at age 30.2.

The same model tells us that weight is not statistically significant in defining players' salaries. The model also tells us that the more minutes players play in the previous season, the higher their salary is the following season, and more specifically, that for every 90 minutes played, the time of a full game, players earn on average 1.06% more.

The better a player performs, the better his salary will be the following season. According to model 4.i), a 1 point change in a player's performance rating increases his salary on average by 28.21% the following season. For example, a player who had a rating of 8 the previous season will earn on average 28.21% more next season than a player who had a rating of 7.

On the other hand, the fact that the player has played in a European Top 5 team in the previous season weighs positively on his salary, as does the fact that a player is an international for his country. In case the player has played the previous season in a team of the top 5 European leagues, he receives on average 33.63% more than a player who has played in a team outside the Top 5, while a player who has already represented the national team of his country earns on average 41.96% more than a player who has never done so.

According to the model, also the position of each player has a statistically significant influence on his salary (see appendix). Defenders, midfielders, and forwards earn significantly higher salaries than goalkeepers, who were used as the reference in the study. The model shows that there are differences at a 5% significance level between the salaries of goalkeepers and defenders, and indicates that there are differences between the salaries of goalkeepers and midfielders and between the salaries of goalkeepers and forwards, but at a 1% significance level. Model 4.i) specifically tells us that a defender earns on average 7.26% more, a midfielder earns on average 33.69% more, and a forward earns on average 60.26% more, compared to a goalkeeper.

Finally, the nationalities of the players, which in all our models are grouped according to the continental football confederation to which each country belongs, also influence their remuneration (see appendix). A player whose nationality belongs to CAF has on average a 23.10% lower salary compared to a player whose home country belongs to UEFA. On the other hand, the model suggests that players whose home countries belong to CONMEBOL receive on average 8.42% more than players from UEFA countries. Players originating from CONCACAF countries have a salary 22.90% lower on average than players native to UEFA countries. AFC players are also disadvantaged relative to UEFA players, as the model suggests that they earn on average 22.05% less. Finally, one of the few sets of nationalities that appears to have a premium salary relative to UEFA is the OFC. Players whose countries are part of this organization are paid on average 10.48% more than players from UEFA countries. This result of the model is surprising and may be linked to the fact that there are very few players of these nationalities playing at a high level in the five major European leagues, so those that do exist are extremely highly valued and paid gold prices.

4.2.1.2. MARKET VALUE MODEL

Model 4.ii) represents the remuneration determination model, which uses market values instead of players' salaries. This model has a higher coefficient of determination than model 4.i), which is curious considering that the selection of variables considered the literature on salary determination in football and aimed to explain salaries rather than market values. Model 4.ii) is statistically significant and the variables included in the regression explain 71.48% of the variability in market values, compared to 64.46% of the variability in salaries, explained by the same variables in model 4.i).

Also, the peak market value of a player, 21.2 years according to model 4.ii), is quite different from the peak salary when salaries are used, 30.2 years. If, on the one hand, we consider 30.2 years to be a high value considering other studies, 21.2 years seems to us a very premature age for a player to reach his highest market value. This value can be explained by the fact that there are a lot of players that had a certain value and potential but never managed to realize it at a later stage of their career, but this is only a purely speculative reason, it is important to highlight the huge difference between using salaries and market values, when it comes to their peak, although the age of the players has a concave relation with both salaries and market values.

In model 4.ii), weight is statistically significant in defining market values, something contrary to what is found in model 4.i). There is thus a quadratic relationship between weight and market value, however, this relationship does not coincide with the conclusions drawn from Figure 12, where it was expected that there would be a concave rather than a convex relationship between these two variables.

Also, playing time has a not very different impact in model 4.ii) compared to model 4.i). In model 4.ii), for every 90 minutes played in the last season, players see their market value increase on average by 3.20% in the next season, while when using real salaries in model 4.i), they increase on average by 1.06% for the same number of minutes played.

The ratings have a much larger weight when using market values as the dependent variable than when using actual salaries. According to model 4.ii), a 1 point change in a player's performance rating in the previous season increases on average his market value by 77.90% in the following season, while that same 1 point change increases on average a player's salary by 28.21%, according to model 4.i).

The fact that a player in the previous season played in one of the top 5 European leagues and that he is an international for his country's national team has a greater influence on the market value than the player's salary. A player who has played in one of the European top 5 leagues has a 93.49% higher market value on average than a player who has not, compared to 33.63%, in model 4.i), while a player who is an international has a 58.98% higher market value on average, compared to 41.96% in model 4.i).

The impact of a player's position is essentially the same in the salary model and in the model that uses market values as a proxy for salaries, so as far as this feature is concerned, the use of market values could replace the real value of salaries. Still, some small differences need to be noted. Model 4.i) tells us that there are differences at a 10% significance level between the salaries of goalkeepers and defenders, but in model 4.ii) the same is not true, since there are no statistically significant differences between the market values of goalkeepers and the market values of defenders. The model also indicates that there are differences between the market values of goalkeepers and midfielders, and between the market values of goalkeepers and forwards, but only at a 1% significance level. More specifically, a midfielder will have a market value on average 29.72% higher than a goalkeeper, while a forward will have a market value on average 60.31% higher than a goalkeeper. Compared to model 4.i), the values are very similar, with a premium salary of on average 33.69% for defenders and on average 60.26% for forwards, compared to goalkeepers.

Concerning the influence of nationality, the model 4.ii) tells us that there are no statistically significant differences between the market values of UEFA and OFC players, contrary to what model 4.i) tells us about salaries. CAF, CONCACAF and AFC players have a lower market value on average than UEFA players, something that is also true in model 4.i), where players from countries belonging to these confederations have a lower salary on average than UEFA players. Although the impact is negative in both models, the percentage impact is different. A player whose home country belongs to CAF will have a market value on average 35.83% lower than a player whose home country belongs to UEFA. On the other hand, a player from a CONCACAF country will have a market value on average 38.60% less than a player from a UEFA country.

Players from AFC countries are even more disadvantaged, having a market value on average 42.50% less than players from UEFA countries. Players from CONMEBOL countries are the only ones to benefit compared to players from UEFA countries, having a market value on average 9.66% higher than the latter.

When using market values as a proxy for player salaries there are no major differences for players from CONMEBOL countries, as the two models show essentially similar results. A player from a CONMEBOL country receives on average 8.42% more than a player from a UEFA country, while his market value is on average 9.66% higher than a player from the same confederation.

However, using market values instead of salaries does not bring the same results for players from CAF, CONCACAF, AFC, or OFC countries. There are differences, as a CAF player receives on average 23.10% less than a UEFA player, but has a market value on average 35.83% less than the latter. A player from a CONCACAF country receives on average 23.10% less than a player from a UEFA country, but has a much lower market value, on average 38.60% less, according to the model that uses market values as the dependent variable. An AFC player, on the other hand, receives on average 22.05% less than a UEFA player, but has a much lower market value, on average 42.50% lower, according to model 4.ii). Using market value also implies that there is no statistical difference between the market values of OFC players and the market values of UEFA players, while model 4.i) tells us that not only are there salary differences between players from these confederations but there is a premium salary for OFC players.

4.2.2. MODELS ESTIMATED BY THE FIXED EFFECTS ESTIMATOR

The parameter estimates of the regression models estimated by the fixed effects estimator, as well as the robust standard errors, are presented in **Table 5**.

4.2.2.1. SALARY MODEL

Model i) in Table 5 represents the salary regression model that was estimated by the fixed effects estimator. This model has a coefficient of determination of 31.42%, that is, 31.42% of the variability in salaries is explained by the selected variables, which is a relatively low value within the universe of studies on the subject.

This model confirms the concave relationship between the age of players and their salaries. According to model 5.i), a player's peak salary occurs at age 25.3.

Playing time has a positive influence on players' pay. According to model 5.i), for every 90 minutes played in the previous season, players receive on average 0.37% more in the next season. Players who perform better in the previous season also have higher salaries in the following season. Model 5.i) confirms this thesis and tells us that a player who has a performance rating 1 point higher than another player will earn on average 10.24% more than the latter. For example, a player who had a rating of 8 will earn on average 10.24% more than a player who had a rating of 7.

The salary regression model estimated by the fixed effects estimator also tells us that there is a salary premium for players who have played the previous season in teams that are part of the top 5 European leagues. A player who has played the previous season in one of the top 5

European leagues will receive on average 9.71% more than a player who has not. According to the same model, the fact that a player is international for his country is not statistically significant in defining his salary.

Table 5: Regression models estimated by the fixed effects estimator.

	i) Dependent variable: log(Salaries)				**ii) Dependent variable: log(Market values)**			
Variáveis independentes	**Coefficient**	**Robust S.E.**	**t value**	**Pr(>|t|)**	**Coefficient**	**Robust S.E.**	**t value**	**Pr(>|t|)**
Intercept	-	-	-	-	-	-	-	-
Age	0.5658	0.0443	12.7830	<0.0001 ***	1.0923	0.0537	20.3325	<0.0001 ***
Age^2	-0.0112	0.0006	-17.4209	<0.0001 ***	-0.0205	0.0008	-26.8543	<0.0001 ***
Weight	-	-	-	-		-	-	-
$Weight^2$	-	-	-	-		-	-	-
Play Time	0.0037	0.0007	5.5533	<0.0001 ***	0.0123	0.0008	14.8175	<0.0001 ***
Ratings	0.0974	0.0256	3.8054	0.0001 ***	0.3727	0.0282	13.1932	<0.0001 ***
League Last Season [a)]								
Top 5	0.0926	0.0222	4.1694	<0.0001 ***	0.3431	0.0309	11.1085	<0.0001 ***
National Team [b)]								
International	0.0155	0.1429	0.1084	0.9137	-0.1393	0.1180	-1.1803	0.2379
Position								
Defender	-	-	-	-	-	-	-	-
Midfielder	-	-	-	-	-	-	-	-
Forward	-	-	-	-	-	-	-	-
Nationality								
CAF	-	-	-	-	-	-	-	-
CONMEBOL	-	-	-	-	-	-	-	-
CONCACAF	-	-	-	-	-	-	-	-
AFC	-	-	-	-	-	-	-	-
OFC	-	-	-	-	-	-	-	-
Teams [c)]	jointly significant [d)]							
R^2	0.3142				0.4547			
Adjusted R^2	-0.0622				0.1555			
F statistic	23.4698 on 149 and 7633 degrees of freedom				42.7189 on 149 and 7633 degrees of freedom			
p-value	<0.0001 ***				<0.0001 ***			

*** significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.**
a) ref: Outside Top 5. b) ref: Non-international. c) 143 non-constant dummy variables over time, referring to 143 teams that played in the top 5 European leagues between 2013/2014 and 2019/20, were hidden from the table, but made available in the appendix. Ref: Wolverhampton.
d) a joint hypothesis test was performed using the robust version of the F-test (see appendix) which determined that the dummy variables referring to the teams were jointly significant in both models (p-value <0.0001*).**

4.2.2.2. MARKET VALUE MODEL

Model 5.ii) represents the remuneration regression model estimated by the fixed effects estimator, which uses market values as a proxy for actual salaries. This model is statistically significant and has a coefficient of determination of 45.47%, a value that is even higher than the coefficient of determination of model 5.i), 31.42%. Given the coefficient of determination, the set of variables common to both models explains the variability of market values better than the variability of football players' salaries.

Using market values over salaries continues to note the concave relationship between players' ages and their salaries, however, the peak shifts from 25.3 years in model 5.i) to 26.6 years in model 5.ii).

Playing time continues to have a positive impact in model 5.ii) as in the previous model, and this impact is similar when the market value is used instead of the salary. In model 5.i), for every 90 minutes played, players receive on average 0.37% more, while in model 5.ii), for the addition of the same playing time, the increase is on average 1.24%.

The performance rating has a much larger impact when market values are used instead of salaries. According to model 5.ii), a player with a performance rating 1 point higher than another player will have a market value on average 45.16% higher, which contrasts with the results of model 5.i) where this same difference causes this time an impact of 10.24% on average on a player's salary. According to the models estimated by the fixed effects estimator, the use of market values instead of salaries exaggerates the influence of the performance rating on players' salaries, relative to the use of the salaries themselves.

Also, the fact that a player has played in a team of the top five European leagues in the previous season influences his remuneration much more when using market values in the study, than when using actual salaries. While model 5.i) points to a premium salary on average of 9.71% more for players who have played in one of the top five European leagues in the previous season, model 5.ii) points to a market value on average 40.93% higher compared to players who have not. The fact that a player's international career is not statistically significant in terms of remuneration when using market values as the dependent variable is something that agrees with model 5.i), but which contradicts the literature on the subject.

4.2.3. MODELS ESTIMATED BY THE RANDOM EFFECTS ESTIMATOR

The parameter estimates of the regression models estimated by the fixed effects estimator, as well as the robust standard errors, are presented in **Table 6**.

4.2.3.1. SALARY MODEL

Model i) in Table 6 represents the regression model estimated by the random effects estimator, where real salaries were used as the dependent variable. The linear model is statistically significant and the independent variables explain 62.72% of the variance in salaries.

The model shows that there is a concave relationship between the age of the players and their salaries. A player's peak salary, according to the model, is at age 30.1, a relatively late age compared to other studies, but which is even similar to the peak salary of model 4.i), 30.2 years, and a far cry from the 25.3 years of model 5.i).

The model indicates that weight is not statistically significant in defining player salaries. The longer a player's playing time in the previous season, the higher his salary is the following season. According to the model, for every 90 minutes played, time of 1 full game, a player's salary is on average 0.63% higher.

According to one of the characteristics chosen to measure performance in the study, the higher a player's rating in the previous season, the higher his salary will be in the following season. According to model 6.i), a player who had a performance rating 1 point higher than another player in the previous season, will have a salary on average 26.72% higher than the latter in the following season.

Table 6: Regressions models estimated by the random effects estimator.

	i) Dependent variable: log(Salaries)				ii) Dependent variable: log(Market values)			
Explanatory variables	**Coefficient**	**Robust S.E.**	**Coefficient**	**Robust S.E.**	**Coefficient**	**Robust S.E.**	**Coefficient**	**Robust S.E.**
Intercept	5.5554	0.9206	6.0345	<0.0001 ***	6.1496	1.0565	5.8209	<0.0001 ***
Age	0.4871	0.0262	18.5821	<0.0001 ***	0.5937	0.0337	17.6336	<0.0001 ***
Age^2	-0.0081	0.0005	-16.7010	<0.0001 ***	-0.0134	0.0006	-21.4006	<0.0001 ***
Weight	-0.0330	0.0209	-1.5811	0.1139	-0.0604	0.0239	-2.5235	0.0116 **
$Weight^2$	0.0002	0.0001	1.6294	0.1033	0.0004	0.0002	2.5678	0.0102 **
Play Time	0.0062	0.0009	6.6254	<0.0001 ***	0.0207	0.0011	18.7100	<0.0001 ***
Ratings	0.2368	0.0368	6.4394	<0.0001 ***	0.6033	0.0381	15.8462	<0.0001 ***
League Last Season [a]								
Top 5	0.2373	0.0253	9.3822	<0.0001 ***	0.5789	0.0330	17.5290	<0.0001 ***
National Team [b]								
International	0.4427	0.0213	20.7443	<0.0001 ***	0.5886	0.0236	24.9556	<0.0001 ***
Position [c]								
Defender	0.1101	0.0390	2.8238	0.0048 ***	-0.0190	0.0450	-0.4216	0.6733
Midfielder	0.3171	0.0401	7.9036	<0.0001 ***	0.2562	0.0458	5.5975	<0.0001 ***
Forward	0.4756	0.0421	11.2868	<0.0001 ***	0.4259	0.0481	8.8620	<0.0001 ***
Nationality [d]								
CAF	-0.2582	0.0326	-7.9143	<0.0001 ***	-0.3903	0.0401	-9.7307	<0.0001 ***
CONMEBOL	0.1309	0.0281	4.6641	<0.0001 ***	0.1356	0.0328	4.1317	<0.0001 ***
CONCACAF	-0.1942	0.0526	-3.6898	0.0002 ***	-0.3235	0.0726	-4.4571	<0.0001 ***
AFC	-0.1721	0.0630	-2.7327	0.0063 ***	-0.4427	0.1147	-3.8583	0.0001 ***
OFC	0.1540	0.0733	2.1005	0.0357 **	-0.0358	0.0886	-0.4040	0.6863
Teams [e]	jointly significant [f]							
R^2	0.6272				0.6967			
Adjusted R^2	0.6220				0.6925			
Chi-square statistic	2313.22 on 163 degrees of freedom				4513.45 on 163 degrees of freedom			
p-value	<0.0001 ***				<0.0001 ***			

*** significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.**
a) ref: Outside Top 5. b) ref: Non-international. c) ref: Goalkeeper. d) ref: UEFA.
e) 147 dummy variables, referring to the 147 teams (excluding the reference) that played in the top 5 European leagues between 2013/2014 and 2019/20, were hidden from the table, but available in the appendices. Ref: Wolverhampton.
f) a joint hypothesis test was performed using the robust version of the F-test (see appendix) which determined that the dummy variables referring to the teams were jointly significant in both models (p-value <0.0001*).**

Also, the fact that a player played for a club in the top five European leagues the previous year positively influences his salary the following season. There is then a premium salary on average of 26.78% more for such players, compared to players who did not play in a European Top 5 league the previous season. A player who is an international for his country's national team receives on average 55.68% more than a player who is not an international.

According to the model estimated by the random effects estimator, a player's position significantly influences his salary (see appendix). Defenders, midfielders, and forwards have on average higher salaries than goalkeepers. According to model 6.i), a defender earns on average 11.64% more, a midfielder earns on average 37.31% more, and a forward earns on average 60.90% more, compared to a goalkeeper.

Nationalities, grouped according to the continental football confederation to which each country belongs, significantly influence football players' salaries (see appendix). The different nationalities and respective continental confederations influence the salaries of players differently. A player from a country belonging to CAF, CONCACAF, or AFC is at a disadvantage compared to a player from a country belonging to UEFA, conversely, a player from a country belonging to CONMEBOL or OFC has a better salary than a player from a UEFA country. A player whose home country belongs to CAF receives on average 29.46% less, a player whose home country belongs to CONCACAF receives on average 21.43% less, and a player whose home country belongs to AFC receives on average 18.78% less, compared to a player whose home country belongs to UEFA. On the other hand, a player whose home country belongs to CONMEBOL gets on average 13.99% more and a player whose home country belongs to the OFC gets on average 16.65% more compared to a player whose home country belongs to UEFA.

4.2.3.2. MARKET VALUE MODEL

Model 6.ii) represents the regression model estimated by the random effects estimator and which attempts to explain the remuneration of football players, but using market values instead of the salaries. This model is also statistically significant and its coefficient of determination, 69.67%, is higher than that of model 6.i), i.e., once again this set of variables explains the variance of market values better than salaries.

The remuneration peak, shown in the model using market values as the dependent variable, differs greatly from the peak remuneration shown in the model using salaries. While in model 6.i) this peak is at age 30.1, in model 6.ii), the peak is at age 22.2. Regarding age and its peaks, there is a clear difference when using market values instead of salaries.

In regression model 6.ii), weight is statistically significant, i.e. it affects the market values of football players, something contrary to what is found in salaries in model 6.i). As in model 4.ii), there is again a convex relationship between weight and market value, something surprising given the observation in Figure 12, where the relationship between these two variables seemed to be concave.

Regarding the playing time of a player, measured every 90 minutes, there do not seem to be big differences between models. While in model 6.i), a player for every 90 minutes played earns on average 0.63% more, in model 6.ii), the influence of playing time is slightly greater, where a player for every 90 minutes played in the previous season earns on average 3.20% more in the following season.

The higher a player's rating in the previous season, the higher will be his salary and his market value in the following season, according to models 6.i) and 6.ii). However, the influence of this rating is much greater on market values than on salaries. When we use salaries, a player who had a performance rating 1 point higher than another player in the previous season will earn on average 26.72% more than the latter in the following season, while in the market values model, a player who had a performance rating 1 point higher than another player will have a market value on average 82.81% higher, a much higher impact than in model 6.i).

The fact that a player has played in one of the top 5 European leagues in the previous season and the fact that he has played for his country's national team has a positive influence in both models, however, when using market values instead of salaries the influence is much larger. A player who has played in one of the top 5 European leagues in the previous season will have a market value 78.40% higher on average than a player who has not, while in model 6.i) this impact on salary is 26.78% on average. A player who is international for his country's national team has a market value on average 80.16% higher than a player who is not, a high value compared to the premium salary of on average 55.68% for international players in model 6.i).

The influence of the position in which players usually play on their salaries is somewhat similar in both models, but there are still differences that should be noted. Model 6.i) tells us that there are differences at a 1% significance level between the salaries of defenders and the salaries of goalkeepers and that the first ones earn on average 11.64% more than the last ones, however, model 6.ii) tells us that there are no statistically significant differences between the market values of players playing on these two positions. Concerning midfielders and forwards, the two models show essentially similar results. We can conclude that there are statistically significant differences between the remuneration of midfielders and goalkeepers and between the remuneration of forwards and goalkeepers, whether we use salaries or market values as the dependent variable. According to model 6.ii), a midfielder will have a market value on average 29.20% higher than a goalkeeper, while a striker will have a market value on average 53.10% higher than a goalkeeper. These percentages are not far from what was presented in the model using salaries, where there is a salary premium of on average 37.31% for midfielders and on average 60.90% for forwards, relative to goalkeepers.

In model 6.ii), the nationality set to which each player belongs significantly influences not only a player's salary, but also his market value (see appendix). When market values are used, there is no statistically significant difference between the market values of players from OFC countries and the market values of players from UEFA countries, a difference that exists when the salaries themselves are used. There are then statistically significant differences between the market values of players from CAF and UEFA countries, between the market values of players from CONMEBOL and UEFA countries, between the market values of players from CONCACAF and UEFA countries, and between the market values of players from AFC and UEFA countries. Players originating from CAF, CONCACAF, and AFC countries have lower market values on average than players originating from UEFA countries, which coincides with that for salaries in model 6.i), however, although the effect on salaries is negative in both models, other differences should be noted. A player whose home country belongs to CAF will have a market value on average 47.74% lower, a player whose home country belongs to CONCACAF will have a market value on average 38.20% lower and a player whose home country belongs to AFC will have a market value on average 55.69% lower compared to players whose home countries belong to UEFA. These percentages differ from what could be concluded from model 6.i), where the differences in the salary of players from countries belonging to CAF, CONCACAF, and AFC, compared to players from countries belonging to UEFA, were respectively and on average less, 29.46%, 21.43%, and 18.78%. The use of market values rather than salaries exaggerates the negative differences in remuneration between players from CAF, CONCACAF, and CAF countries and players from UEFA countries.

When using market values instead of player salaries only there are no big differences for players from CONMEBOL countries. Players from CONMEBOL countries have a premium salary and a premium market value relative to players from UEFA countries. Model 6.i) tells us that these players earn on average 13.99% more than players from UEFA countries, while model 6.ii) tells us that these players enjoy a premium market value on average of 14.52%, relative to players from UEFA countries. Concerning players of these nationalities, there are almost no differences in the results of the pay and performance studies between the use of salaries and the use of market values.

5. CONCLUSION

We initially started the study with one main objective: to study whether using market values as a proxy for salaries would bring different results in the regression models used to study the factors that influence football players' salaries, since salaries are mostly unknown and authors have used market values as their replacement, without questioning whether this causes some changes in the conclusions of the studies. To achieve this goal, it was necessary to find out which factors affect football players' salaries and what is the relationship between performance and salaries, so increasing the literature on this subject was also one of the goals of this study.

To increase the literature within the factors influencing football players' salaries and to get to the main objective, initially, salary modeling was performed using multiple regression models estimated by three different estimators, the pooled OLS, the fixed effects estimator and the random effects estimator. Then, all models were interpreted individually. The selection of potential explanatory variables was based on the literature review, and their collection was limited by data availability.

Different salary regression models were obtained for each of the estimators. The regression models estimated by the pooled OLS and the random effects estimator were the models that showed the highest explanatory power, according to the R^2 criteria, while the regression model estimated by the fixed effects estimator was the one that showed the lowest explanatory power, with a very low R^2, only 31.42%. Even in the models estimated by the OLS and the random effects estimator, the R^2 takes values around 60%, which indicates that the variables available and included in the study do not explain about 40% of the variability of salaries.

The percentage impact of each variable on salaries changes from model to model depending on its estimator, yet most variables share the same negative or positive impact across the various models. The various models showed that there is a concave relationship between the age of the players and their salaries, however, they showed different ages for which players obtain their maximum salary. Regarding other personal characteristics of the players, the weight and height of the players were also included in the models, however, it was decided to leave out the height of one player, since its inclusion did not increase the adjusted R^2 in any of the models. Weight, although it was included in the final models, was found to not be statistically significant in defining salaries in all models.

Playing time, performance ratings and participation in the European Top 5 in the previous season proved to be statistically significant and to have a positive impact on salary determination in all models. The fact that a player has played for his country's national team has a statistically significant influence on salaries only in the models estimated by the OLS and the random effects estimator, and this characteristic showed a positive association with salaries in both models.

The models estimated by the OLS and the random effects estimator indicated that there are statistically significant differences between the salaries of defenders, midfielders, and forwards and the salaries of goalkeepers. According to these two models, defenders, midfielders, and forwards on average earn a higher salary than goalkeepers. The average salary is higher for forwards compared to goalkeepers, where both models point to an average salary around 60%

higher, while for midfielders the average salary is 33.69% higher in the OLS estimated model and 37.31% higher in the model estimated by the random effects estimator. Defenders, on the other hand, according to the OLS model, earn on average 7.26% more than goalkeepers, while the model estimated by the random effects estimator shows that defenders' salaries are on average 11.64% higher than goalkeepers'.

A player's nationality was another of the players' characteristics that were addressed in our study. To have a better interpretation of the model, nationalities were grouped according to the continental confederation that regulates football to which each country belongs, as Kuethe & Motamed (2010) did. The variables "CAF", "CONMEBOL", "CONCACAF", "AFC" and "OFC" proved to be statistically significant in the models estimated by the OLS and the random effects estimator, indicating that there are statistically significant differences between the salaries of players whose home countries belong to CAF, CONMEBOL, CONCACAF, AFC and OFC and the salaries of players whose home countries belong to UEFA. Again, these variables were not considered in the model estimated by the fixed effects estimator, since they are constant over time.

In the models estimated by OLS and the random effects estimator, players originating from countries belonging to CAF, CONCACAF and AFC are on average paid less than players from countries belonging to UEFA. This impact is on average 22% to 23% in the model estimated by OLS. In the model estimated by the random effects estimator, a player whose home country belongs to CAF receives on average 29.46% less, a player whose home country belongs to CONCACAF receives on average 21.43% less and a player whose home country belongs to AFC receives on average 18.78% less, compared to a player whose home country belongs to UEFA. In both models, the only players earning a premium salary compared to players from UEFA countries are players from CONMEBOL and OFC countries. These players respectively earn on average 8.42% and 10.48% higher salaries according to the model estimated by OLS and 13.99% and 16.65% according to the model estimated by the random effects estimator.

A possible explanation for the differences in pay depending on a player's nationality could be possible discrimination of Asian, African, and Central/North American players compared to European players. The topic has already been addressed by other researchers, however, it has never been addressed for these leagues nor with this size, so we have no possible comparison with other studies. On the other hand, players from Oceania and players from South America receive on average a premium salary compared to European players. Some studies report that South Americans tend to be overpaid, such as Pedace (2008), Battré et al. (2009), and Kuethe & Motamed (2010), however, these studies did not have players from UEFA countries as a reference, nor did they treat the five main European leagues.

Then, to achieve the main objective of the study, we computed the regression model that takes as dependent variable the market value of players, also estimated through the three estimators and with the same explanatory variables included in the regression models of salaries. The market value models were then interpreted individually and compared to the salary models, for each estimator, where the differences and similarities of the impact of each explanatory variable in the various models when using the market value instead of the real salary were noted.

Similar conclusions were obtained for the regression models estimated by the pooled OLS and the random effects estimator. The conclusions drawn from the fixed effects models were relatively different compared to the conclusions of the models estimated by the other two estimators.

In the models estimated by OLS and the random effects estimator, it was concluded that using market value as a proxy, causes the peak remuneration of a player to move from 30.2 years in the OLS estimated model and 30.1 years in the model estimated by the random effects estimator to 21.2 years in both models; using market value over salary makes a player's weight statistically significant in the model and suggests that there is a convex relationship between a player's weight and remuneration; the impact on compensation of minutes played in the previous season, does not seem to change very significantly when using market value as a proxy for salary; using market value as a proxy largely exaggerates the impact of a 1 point rise in performance rating, on a player's remuneration, compared to using actual salaries; using market value as a proxy also overstates the influence of a player having played for his country's national team on his remuneration; using market value as a proxy, compared to using actual salaries means that there is no longer a difference between goalkeepers' remuneration and defenders' remuneration, while the remuneration of midfielders and forwards remains higher, compared to goalkeepers' remuneration; when market value is used instead of salary, the remunerations of players from CAF, CONCACAF, and AFC countries are even more penalized compared to the remunerations of players from UEFA countries. For players from CONMEBOL countries there do not seem to be big differences when using market value as a proxy. Finally, the use of the proxy suggests that there are no longer differences between the remuneration of players originating from OFC countries and the remuneration of players originating from UEFA.

In the models estimated by the fixed effects estimator, it was concluded that using the market value as a proxy, makes a player's peak remuneration go from 25.3 years old to 26.6 years old; the impact on the remuneration of the minutes played on the previous season does not seem to have much difference when using the market value instead of the player's salary; using market value as a proxy for salary largely overestimates the impact of ratings and the impact of a player having played in one of the top five European leagues in the previous season on his remuneration; using market value rather than salary means that there are differences between the remuneration of players who have played for their country's national team and the remuneration of players who have never played.

Regardless of the estimator used, when market values were used as a proxy for salaries, differences were noted in the regression models, both in the impact on the remuneration of personal characteristics of the players and in the impact on the remuneration of variables that measure performance.

These results call into question the conclusions of studies that have attempted to explain football player remuneration and have used market values rather than actual salaries. The findings of our study suggest that researchers should use only real salaries if their goal is to study the relationship between football players' performance and pay. If actual salary data are not available, researchers should take into consideration that using market values as a proxy produces different results. If the researchers still want to use market values to try to study the relationship between performance and remuneration, they should be aware that any conclusions that can be drawn only concern market values and not salaries.

5.1. LIMITATIONS

One of the main limitations of the study was data availability. Although we considered an interesting number of seasons, a number much higher than previous studies within the subject, there was a huge lack of data regarding the number of explanatory variables. We also came across some unexpected results, such as the fact that the models explained market values better than actual salaries and the fact that the models estimated by the fixed effects estimator had such low explanatory power. Realizing the extent of our study, we chose not to study whether there were differences between the use of salaries and the use of market value, in groups of similar observations, as we had initially planned to study.

5.2. FURTHER WORKS

For future works that study which factors influence salaries and if the use of market value as a proxy variable for football players' salaries produces different conclusions, it is suggested that we try to consider more leagues to include in the study and try to include more explanatory variables, to try to increase the explanatory power of the regression models. Within the variables, we suggest trying to include more and different variables to measure performance and to measure other characteristics that were not included in our study and that can also explain players' salaries. We also suggest modeling the interaction between variables in the regression models, something that was left out in our study. Although our study has covered an interesting number of seasons, it is also suggested that a larger number of seasons be studied. Finally, it is suggested to try to model salaries on similar groups of observations and to observe if there are differences in the models when using market values instead of real salaries.

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7. APPENDIX

Appendix 1: Pearson correlation test between salaries and market values.

```
        Pearson's product-moment correlation


t = 101.02, df = 11821, p-value < 2.2e-16
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 0.6708939 0.6902443
sample estimates:
      cor
0.6806878
```

Appendix 2: Pearson's correlation test between a player's weight and height.

```
        Pearson's product-moment correlation


t = 128.37, df = 11821, p-value < 2.2e-16
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 0.7554386 0.7705008
sample estimates:
      cor
0.7630733
```

Appendix 3: Hausman specification test for the salaries model.

```
chisq = 467.44, df = 149, p-value < 2.2e-16
alternative hypothesis: one model is inconsistent
```

Appendix 4: Full regression model of salaries estimated by pooled OLS.

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	6.54022481	0.79323444	8.2450	< 2.2e-16	***
Age	0.40508804	0.02347296	17.2576	< 2.2e-16	***
Age2	-0.00666021	0.00042929	-15.5145	< 2.2e-16	***
Weight	-0.02332969	0.01827984	-1.2763	0.2018918	
Weight2	0.00016058	0.00011912	1.3481	0.1776612	
PlayingTime	0.01049804	0.00087214	12.0371	< 2.2e-16	***
RATINGS	0.24850546	0.03163678	7.8550	4.350e-15	***
LeagueLastSeason	0.28991096	0.02497684	11.6072	< 2.2e-16	***
InternationalStatus	0.35036161	0.01973217	17.7559	< 2.2e-16	***
Defender	0.07011704	0.03380746	2.0740	0.0381002	*
Midfielder	0.29034220	0.03495318	8.3066	< 2.2e-16	***
Forward	0.47163130	0.03665146	12.8680	< 2.2e-16	***
CAF	-0.20779983	0.02852378	-7.2851	3.420e-13	***
CONMEBOL	0.08085444	0.02468321	3.2757	0.0010571	**
CONCACAF	-0.20618678	0.05032979	-4.0967	4.219e-05	***
AFC	-0.19926104	0.05889488	-3.3833	0.0007185	***
OFC	0.09970687	0.04997904	1.9950	0.0460690	*
ACMilan	0.47782145	0.17619818	2.7118	0.0067009	**
Ajaccio	-1.01487456	0.18381468	-5.5212	3.439e-08	***
Alaves	-0.57435264	0.19587057	-2.9323	0.0033711	**
Almeria	-1.76180549	0.28841134	-6.1087	1.037e-09	***
Amiens	-1.08722670	0.21384971	-5.0841	3.752e-07	***
Angers	-1.07866854	0.17302043	-6.2343	4.694e-10	***
Arsenal	0.65440213	0.17603870	3.7174	0.0002022	***
AstonVilla	-0.10856887	0.17699420	-0.6134	0.5396215	
Atalanta	-0.64410305	0.17308638	-3.7213	0.0001991	***
Athletic	-0.23139978	0.18963181	-1.2203	0.2223917	
AtleticoMadrid	0.70408039	0.19141878	3.6782	0.0002359	***
Augsburg	-0.73131371	0.17597201	-4.1559	3.264e-05	***
Barcelona	1.25300184	0.17897580	7.0010	2.682e-12	***
Bastia	-1.19988151	0.17680670	-6.7864	1.205e-11	***
Bayer	0.11037638	0.18646942	0.5919	0.5539106	
Bayern	1.00855710	0.18659362	5.4051	6.605e-08	***
Benevento	-0.64619682	0.29369252	-2.2002	0.0278087	*
Bologna	-0.42572021	0.17991804	-2.3662	0.0179885	*
Bordeaux	-0.81527780	0.18743141	-4.3497	1.375e-05	***
Dortmund	0.43670582	0.18279395	2.3891	0.0169073	*
Bournemouth	-0.01851521	0.17619222	-0.1051	0.9163099	
Braunschweiger	-0.94664888	0.33351416	-2.8384	0.0045418	**

Brescia	-0.66402315	0.36791974	-1.8048	0.0711311	.
Brest	-0.62649100	0.18737266	-3.3436	0.0008297	***
Brighton	0.00928563	0.17090409	0.0543	0.9566713	
Burnley	-0.35466278	0.17948827	-1.9760	0.0481821	*
Caen	-1.14005499	0.17909168	-6.3658	2.016e-10	***
Cagliari	-0.68941577	0.18463035	-3.7340	0.0001893	***
Cardiff	-0.27337344	0.18112913	-1.5093	0.1312559	
Carpi	-1.27773202	0.25451798	-5.0202	5.238e-07	***
Catania	-0.94348964	0.19281868	-4.8931	1.006e-06	***
CeltaVigo	-0.58335634	0.18394121	-3.1714	0.0015208	**
Cesena	-1.29379748	0.24093933	-5.3698	8.033e-08	***
Chelsea	0.64684126	0.17624747	3.6701	0.0002436	***
Chievo	-1.04314333	0.17613258	-5.9225	3.260e-09	***
Cordoba	-0.98591417	0.24076373	-4.0949	4.251e-05	***
Crotone	-1.21167235	0.18807911	-6.4424	1.223e-10	***
CrystalPalace	0.13519714	0.18296323	0.7389	0.4599640	
Darmstadt	-1.07735958	0.18743996	-5.7478	9.270e-09	***
Deportivo	-0.69883853	0.22986574	-3.0402	0.0023694	**
Dijon	-1.00824945	0.18624344	-5.4136	6.299e-08	***
Dusseldorf	-0.95765302	0.18467088	-5.1857	2.188e-07	***
Eibar	-0.84670752	0.22160258	-3.8208	0.0001337	***
Eintracht	-0.45841046	0.17352074	-2.6418	0.0082572	**
Elche	-1.32879909	0.21319635	-6.2327	4.741e-10	***
Empoli	-0.98559559	0.18957917	-5.1989	2.039e-07	***
Espanyol	-0.49527791	0.21312570	-2.3239	0.0201492	*
Everton	0.31179604	0.17297747	1.8025	0.0714888	.
Evian	-1.09403307	0.17546374	-6.2351	4.671e-10	***
Fiorentina	-0.22942269	0.17386489	-1.3195	0.1870126	
Freiburg	-0.89705155	0.17400388	-5.1554	2.573e-07	***
Frosinone	-0.78500300	0.18425807	-4.2603	2.057e-05	***
Fulham	-0.25726903	0.20923180	-1.2296	0.2188760	
Gazelec	-0.98123013	0.21666755	-4.5287	5.993e-06	***
Genoa	-0.44677305	0.17422963	-2.5643	0.0103515	*
Getafe	-0.78859015	0.19163561	-4.1151	3.898e-05	***
Girona	-0.35186650	0.22380619	-1.5722	0.1159330	
Granada	-0.82773401	0.18601358	-4.4499	8.672e-06	***
Guingamp	-1.17440141	0.17661781	-6.6494	3.074e-11	***
Hamburg	-0.11341872	0.17954683	-0.6317	0.5275990	
Hannover	-0.47395479	0.18150397	-2.6113	0.0090324	**
Hellas	-0.80322724	0.18358393	-4.3753	1.223e-05	***

Hertha	-0.43139371	0.18099911	-2.3834	0.0171693	*
Hoffenheim	-0.38510309	0.17883329	-2.1534	0.0313062	*
Huddersfield	-0.13601236	0.17631807	-0.7714	0.4404835	
Huesca	-0.63325728	0.17795740	-3.5585	0.0003745	***
Hull	-0.38554135	0.17943355	-2.1487	0.0316820	*
Ingolstadt	-1.00803325	0.18541052	-5.4368	5.535e-08	***
Inter	0.41832174	0.17555730	2.3828	0.0171964	*
Juventus	0.75523005	0.17770865	4.2498	2.156e-05	***
Koln	-0.26570152	0.19197297	-1.3841	0.1663675	
LasPalmas	-0.86977603	0.24199720	-3.5942	0.0003268	***
Lazio	0.00218453	0.17499388	0.0125	0.9900401	
Lecce	-0.20266600	0.19020412	-1.0655	0.2866635	
Leganes	-0.38223579	0.21449437	-1.7820	0.0747701	.
Leicester	0.18910385	0.17849756	1.0594	0.2894306	
Leipzig	0.13157318	0.19293281	0.6820	0.4952754	
Levante	-0.96349655	0.18326751	-5.2573	1.488e-07	***
Lille	-0.48288074	0.19543284	-2.4708	0.0134943	*
Liverpool	0.59876436	0.17351609	3.4508	0.0005610	***
Livorno	-0.86332378	0.35574146	-2.4268	0.0152465	*
Lorient	-1.00611695	0.17403546	-5.7811	7.612e-09	***
Lyon	-0.08348570	0.18065174	-0.4621	0.6439923	
Mainz	-0.63742309	0.17675607	-3.6062	0.0003120	***
Malaga	-0.58672613	0.17923927	-3.2734	0.0010656	**
Mallorca	-0.12780061	0.51940256	-0.2461	0.8056455	
ManCity	0.96861823	0.17207132	5.6292	1.853e-08	***
ManUtd	0.89321290	0.18415401	4.8504	1.248e-06	***
Marseille	0.03721191	0.18097017	0.2056	0.8370878	
Metz	-0.89326190	0.18425327	-4.8480	1.263e-06	***
Middlesbrough	-0.02943717	0.18582499	-0.1584	0.8741338	
Monaco	-0.01363312	0.18170108	-0.0750	0.9401917	
Monchengladbach	-0.16699447	0.19110527	-0.8738	0.3822261	
Montpellier	-0.85333291	0.17525752	-4.8690	1.136e-06	***
Nancy	-1.49453828	0.32834658	-4.5517	5.375e-06	***
Nantes	-1.08672177	0.18627327	-5.8340	5.555e-09	***
Napoles	0.13561469	0.17855860	0.7595	0.4475708	
Newcastle	0.08605344	0.17429836	0.4937	0.6215179	
Nice	-0.69557196	0.18342545	-3.7921	0.0001501	***
Nimes	-1.45794733	0.22199834	-6.5674	5.338e-11	***
Norwich	-0.44599993	0.19001405	-2.3472	0.0189320	*
Nurnberg	-0.88669117	0.19935772	-4.4477	8.758e-06	***

Osasuna	-1.04148474	0.22235284	-4.6839	2.846e-06	***
Paderborn	-1.52082907	0.20861748	-7.2900	3.299e-13	***
Palermo	-0.84111308	0.17390704	-4.8366	1.338e-06	***
Parma	-0.67745619	0.18305362	-3.7009	0.0002159	***
Pescara	-0.82888894	0.21171738	-3.9151	9.089e-05	***
PSG	0.77249068	0.19121603	4.0399	5.382e-05	***
QPR	-0.04611930	0.19398566	-0.2377	0.8120823	
Rayo	-0.82182867	0.18720775	-4.3899	1.144e-05	***
RealBetis	-0.45703203	0.18590616	-2.4584	0.0139701	*
RealMadrid	1.17784633	0.19420995	6.0648	1.362e-09	***
RealSociedad	-0.45488318	0.19258185	-2.3620	0.0181917	*
Reims	-1.16872512	0.17681139	-6.6100	4.011e-11	***
Rennes	-0.69720460	0.17782565	-3.9207	8.879e-05	***
Siena	-1.03596067	0.16730211	-6.1922	6.134e-10	***
Roma	0.45981125	0.17814623	2.5811	0.0098610	**
Sampdoria	-0.45331963	0.17646852	-2.5688	0.0102162	*
Sassuolo	-0.51752731	0.17378624	-2.9780	0.0029078	**
Schalke	0.04581574	0.19602645	0.2337	0.8152047	
Sevilla	-0.12272873	0.18989013	-0.6463	0.5180885	
Sheffield	-1.08526062	0.23908375	-4.5392	5.702e-06	***
Sochaux	-0.95941599	0.19817102	-4.8414	1.306e-06	***
Southampton	0.21925123	0.17443046	1.2570	0.2087951	
SPAL	-0.58699128	0.19348447	-3.0338	0.0024203	**
SportingGinjon	-1.10876155	0.21381609	-5.1856	2.189e-07	***
StEtienne	-0.66732713	0.17349997	-3.8463	0.0001206	***
Stoke	-0.07715326	0.18232673	-0.4232	0.6721868	
Strasbourg	-0.95685284	0.18205884	-5.2557	1.500e-07	***
Stuttgart	-0.31709180	0.17847406	-1.7767	0.0756465	.
Sunderland	0.08936559	0.17302893	0.5165	0.6055306	
Swansea	-0.13764256	0.17470140	-0.7879	0.4307869	
Torino	-0.47218991	0.17980360	-2.6261	0.0086471	**
Tottenham	0.42989616	0.17389889	2.4721	0.0134462	*
Toulouse	-0.86717649	0.18131154	-4.7828	1.750e-06	***
Troyes	-1.24139559	0.19596637	-6.3347	2.465e-10	***
Udinese	-0.69110975	0.17206358	-4.0166	5.942e-05	***
UnionBerlin	-0.66131747	0.19411533	-3.4068	0.0006594	***
Valencia	0.26849023	0.18468365	1.4538	0.1460330	
Valenciennes	-1.26313227	0.26592270	-4.7500	2.058e-06	***
Valladolid	-1.22526539	0.26304032	-4.6581	3.227e-06	***
Villarreal	-0.39033524	0.23105246	-1.6894	0.0911735	.

```
Watford             -0.05927415  0.17890598  -0.3313 0.7404129
Werder              -0.46650196  0.18115544  -2.5751 0.0100319 *
WestBrom            -0.10539028  0.17731413  -0.5944 0.5522759
WestHam              0.15577256  0.17765036   0.8768 0.3805867
Wolfsburg            0.22846046  0.17959320   1.2721 0.2033631
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Appendix 5: Full regression model of market values estimated by pooled OLS.

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	8.00329678	0.86057861	9.2999	< 2.2e-16	***
Age	0.47497873	0.02862698	16.5920	< 2.2e-16	***
Age2	-0.01120674	0.00052961	-21.1603	< 2.2e-16	***
Weight	-0.05522367	0.01968263	-2.8057	0.0050290	**
Weight2	0.00035748	0.00012788	2.7954	0.0051914	**
PlayingTime	0.03154515	0.00100704	31.3246	< 2.2e-16	***
RATINGS	0.57602371	0.03262055	17.6583	< 2.2e-16	***
LeagueLastSeason	0.66005588	0.03358264	19.6547	< 2.2e-16	***
InternationalStatus	0.46358510	0.02122635	21.8401	< 2.2e-16	***
Defender	-0.02953780	0.03811755	-0.7749	0.4384066	
Midfielder	0.26021651	0.03887466	6.6937	2.275e-11	***
Forward	0.47193665	0.04075923	11.5786	< 2.2e-16	***
CAF	-0.30624508	0.03367649	-9.0937	< 2.2e-16	***
CONMEBOL	0.09218040	0.02796901	3.2958	0.0009843	***
CONCACAF	-0.32640633	0.06309867	-5.1730	2.342e-07	***
AFC	-0.35417474	0.09159850	-3.8666	0.0001110	***
OFC	-0.07435675	0.07928648	-0.9378	0.3483543	
ACMilan	-0.50395776	0.16593979	-3.0370	0.0023948	**
Ajaccio	-1.63627043	0.18932174	-8.6428	< 2.2e-16	***
Alaves	-1.07766789	0.20070549	-5.3694	8.052e-08	***
Almeria	-1.44409541	0.18557291	-7.7818	7.751e-15	***
Amiens	-1.33521926	0.19736018	-6.7654	1.393e-11	***
Angers	-1.28659129	0.17248727	-7.4591	9.333e-14	***
Arsenal	-0.00378243	0.16827656	-0.0225	0.9820675	
AstonVilla	-0.90300152	0.17625528	-5.1233	3.051e-07	***
Atalanta	-1.00265360	0.17661895	-5.6769	1.404e-08	***
Athletic	-0.70413313	0.17072657	-4.1243	3.744e-05	***
AtleticoMadrid	0.22472522	0.17334327	1.2964	0.1948574	
Augsburg	-1.30571373	0.17220848	-7.5822	3.656e-14	***
Barcelona	0.45246770	0.17365168	2.6056	0.0091829	**
Bastia	-1.83036373	0.16898596	-10.8315	< 2.2e-16	***
Bayer	-0.53861219	0.18922860	-2.8464	0.0044300	**
Bayern	0.31779358	0.18434945	1.7239	0.0847587	.
Benevento	-1.51162341	0.26103982	-5.7908	7.187e-09	***
Bologna	-1.30409358	0.16197469	-8.0512	8.992e-16	***
Bordeaux	-1.16900383	0.16520092	-7.0763	1.566e-12	***
Dortmund	-0.15870251	0.17795689	-0.8918	0.3725169	
Bournemouth	-0.60879411	0.16773146	-3.6296	0.0002851	***
Braunschweiger	-1.57429251	0.49959707	-3.1511	0.0016305	**

Brescia	-1.18020739	0.23045497	-5.1212	3.084e-07	***
Brest	-1.37405795	0.24054074	-5.7124	1.141e-08	***
Brighton	-0.52215665	0.16294368	-3.2045	0.0013565	**
Burnley	-0.82633306	0.17550191	-4.7084	2.525e-06	***
Caen	-1.51855688	0.17868675	-8.4984	< 2.2e-16	***
Cagliari	-1.15112132	0.17414507	-6.6101	4.007e-11	***
Cardiff	-0.88745001	0.18236355	-4.8664	1.152e-06	***
Carpi	-1.67949886	0.26018059	-6.4551	1.124e-10	***
Catania	-1.41951364	0.19038471	-7.4560	9.548e-14	***
CeltaVigo	-1.08513303	0.16820295	-6.4513	1.153e-10	***
Cesena	-2.26743904	0.25720214	-8.8158	< 2.2e-16	***
Chelsea	0.18462204	0.16325124	1.1309	0.2581173	
Chievo	-1.58470356	0.17414142	-9.1001	< 2.2e-16	***
Cordoba	-1.58430776	0.18890147	-8.3870	< 2.2e-16	***
Crotone	-1.90885492	0.19392084	-9.8435	< 2.2e-16	***
CrystalPalace	-0.59968220	0.16540674	-3.6255	0.0002896	***
Darmstadt	-1.95022981	0.21892443	-8.9082	< 2.2e-16	***
Deportivo	-1.25762669	0.17179625	-7.3205	2.634e-13	***
Dijon	-1.15722809	0.18472807	-6.2645	3.872e-10	***
Dusseldorf	-1.38021248	0.18474049	-7.4711	8.521e-14	***
Eibar	-1.01351493	0.16898368	-5.9977	2.061e-09	***
Eintracht	-1.06369044	0.16821238	-6.3235	2.651e-10	***
Elche	-1.34781762	0.20739521	-6.4988	8.427e-11	***
Empoli	-1.48675472	0.21391644	-6.9502	3.843e-12	***
Espanyol	-1.04548024	0.17419954	-6.0016	2.012e-09	***
Everton	-0.29339094	0.16609977	-1.7664	0.0773627	.
Evian	-1.83271182	0.18615169	-9.8453	< 2.2e-16	***
Fiorentina	-0.68891654	0.16576293	-4.1560	3.261e-05	***
Freiburg	-1.29825172	0.17705455	-7.3325	2.409e-13	***
Frosinone	-1.61675049	0.25786016	-6.2699	3.741e-10	***
Fulham	-0.68465569	0.18171084	-3.7678	0.0001655	***
Gazelec	-1.51887507	0.27456892	-5.5319	3.237e-08	***
Genoa	-1.23246746	0.16480193	-7.4785	8.058e-14	***
Getafe	-1.06949811	0.17215520	-6.2124	5.396e-10	***
Girona	-1.09628785	0.20256329	-5.4121	6.353e-08	***
Granada	-1.25798046	0.16605863	-7.5755	3.847e-14	***
Guingamp	-1.59469076	0.17132891	-9.3078	< 2.2e-16	***
Hamburg	-1.57129438	0.16880550	-9.3083	< 2.2e-16	***
Hannover	-1.44574542	0.16870540	-8.5696	< 2.2e-16	***
Hellas	-1.49828127	0.17998565	-8.3244	< 2.2e-16	***
Hertha	-0.97239114	0.17780361	-5.4689	4.622e-08	***

Hoffenheim	-0.95112192	0.17194550	-5.5315	3.243e-08	***
Huddersfield	-0.86447663	0.17621552	-4.9058	9.431e-07	***
Huesca	-1.63613818	0.24792601	-6.5993	4.310e-11	***
Hull	-0.99569728	0.17967518	-5.5417	3.061e-08	***
Ingolstadt	-1.88955028	0.19895259	-9.4975	< 2.2e-16	***
Inter	-0.25642226	0.16797711	-1.5265	0.1269048	
Juventus	0.16711362	0.16990430	0.9836	0.3253449	
Koln	-1.14960920	0.17722341	-6.4868	9.124e-11	***
LasPalmas	-1.25423881	0.22513226	-5.5711	2.587e-08	***
Lazio	-0.62431865	0.17200063	-3.6297	0.0002849	***
Lecce	-1.23089599	0.29857905	-4.1225	3.774e-05	***
Leganes	-0.63452759	0.22046783	-2.8781	0.0040081	**
Leicester	-0.46800710	0.17864774	-2.6197	0.0088116	**
Leipzig	-0.28221130	0.19231853	-1.4674	0.1422899	
Levante	-1.29115928	0.17489490	-7.3825	1.659e-13	***
Lille	-0.98037544	0.17192189	-5.7024	1.210e-08	***
Liverpool	0.00317872	0.17278849	0.0184	0.9853228	
Livorno	-1.87661014	0.22639911	-8.2889	< 2.2e-16	***
Lorient	-1.66328042	0.17573204	-9.4649	< 2.2e-16	***
Lyon	-0.71423268	0.17449848	-4.0931	4.286e-05	***
Mainz	-1.24096711	0.17016687	-7.2926	3.236e-13	***
Malaga	-1.21191917	0.16536376	-7.3288	2.475e-13	***
Mallorca	-1.36733160	0.33287601	-4.1076	4.025e-05	***
ManCity	0.44391549	0.16580368	2.6774	0.0074310	**
ManUtd	0.12047628	0.16671306	0.7227	0.4699054	
Marseille	-0.71300709	0.17606658	-4.0496	5.163e-05	***
Metz	-1.58342520	0.19297770	-8.2052	2.543e-16	***
Middlesbrough	-1.05380912	0.22823354	-4.6172	3.930e-06	***
Monaco	-0.55476878	0.16551005	-3.3519	0.0008052	***
Monchengladbach	-0.77878718	0.16697570	-4.6641	3.135e-06	***
Montpellier	-1.39080136	0.16655432	-8.3504	< 2.2e-16	***
Nancy	-1.54275985	0.56551835	-2.7280	0.0063806	**
Nantes	-1.41143883	0.17461235	-8.0833	6.927e-16	***
Napoles	-0.31690331	0.17810951	-1.7793	0.0752230	.
Newcastle	-0.60858093	0.16462111	-3.6969	0.0002193	***
Nice	-1.07624730	0.17778486	-6.0537	1.460e-09	***
Nimes	-1.55076980	0.20113578	-7.7101	1.360e-14	***
Norwich	-0.87562092	0.17132493	-5.1109	3.257e-07	***
Nurnberg	-1.30517755	0.18332845	-7.1193	1.148e-12	***
Osasuna	-1.36922987	0.18571721	-7.3727	1.786e-13	***
Paderborn	-1.60392493	0.17204926	-9.3225	< 2.2e-16	***

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Palermo           -1.71425044  0.20095631  -8.5305 < 2.2e-16 ***
Parma             -1.21847342  0.20520355  -5.9379 2.970e-09 ***
Pescara           -2.06001601  0.22666116  -9.0885 < 2.2e-16 ***
PSG               -0.00778546  0.18111345  -0.0430 0.9657129
QPR               -0.97011985  0.18320520  -5.2953 1.210e-07 ***
Rayo              -1.37500870  0.18572663  -7.4034 1.419e-13 ***
RealBetis         -0.70264355  0.17215439  -4.0815 4.505e-05 ***
RealMadrid         0.54480849  0.16967682   3.2109 0.0013270 **
RealSociedad      -0.57764161  0.16865912  -3.4249 0.0006171 ***
Reims             -1.58714279  0.16502561  -9.6176 < 2.2e-16 ***
Rennes            -1.18051367  0.17184095  -6.8698 6.756e-12 ***
Siena             -2.34062529  0.15124380 -15.4758 < 2.2e-16 ***
Roma              -0.31917593  0.17190362  -1.8567 0.0633770 .
Sampdoria         -1.10643480  0.17123957  -6.4613 1.079e-10 ***
Sassuolo          -1.10449735  0.16897728  -6.5364 6.566e-11 ***
Schalke           -0.64529605  0.17367817  -3.7155 0.0002038 ***
Sevilla           -0.61027840  0.16199802  -3.7672 0.0001659 ***
Sheffield         -0.61449557  0.22480334  -2.7335 0.0062763 **
Sochaux           -1.96704076  0.17884352 -10.9987 < 2.2e-16 ***
Southampton       -0.54790387  0.16509751  -3.3187 0.0009072 ***
SPAL              -1.45210703  0.19281019  -7.5313 5.395e-14 ***
SportingGinjon    -1.40306615  0.17907737  -7.8350 5.096e-15 ***
StEtienne         -1.07050937  0.16490151  -6.4918 8.825e-11 ***
Stoke             -0.80808811  0.17192194  -4.7003 2.627e-06 ***
Strasbourg        -1.11734698  0.19395460  -5.7609 8.580e-09 ***
Stuttgart         -1.23926075  0.16694814  -7.4230 1.224e-13 ***
Sunderland        -0.92628073  0.16625812  -5.5713 2.584e-08 ***
Swansea           -0.89298497  0.17226127  -5.1839 2.209e-07 ***
Torino            -1.09694786  0.17564294  -6.2453 4.376e-10 ***
Tottenham          0.07825176  0.17127145   0.4569 0.6477605
Toulouse          -1.45363808  0.16791120  -8.6572 < 2.2e-16 ***
Troyes            -1.48189113  0.19555724  -7.5778 3.781e-14 ***
Udinese           -1.14913070  0.15974146  -7.1937 6.693e-13 ***
UnionBerlin       -1.40486624  0.18162467  -7.7350 1.119e-14 ***
Valencia          -0.16634917  0.17213495  -0.9664 0.3338700
Valenciennes      -1.51977217  0.16945711  -8.9685 < 2.2e-16 ***
Valladolid        -1.34489640  0.21427131  -6.2766 3.583e-10 ***
Villarreal        -0.67955308  0.17527927  -3.8770 0.0001063 ***
Watford           -0.60735094  0.16938287  -3.5857 0.0003376 ***
Werder            -1.28242280  0.17018662  -7.5354 5.229e-14 ***
WestBrom          -0.95543034  0.17154182  -5.5697 2.609e-08 ***

WestHam           -0.53203985  0.16711390  -3.1837 0.0014579 **
Wolfsburg         -0.85800759  0.16363999  -5.2433 1.605e-07 ***
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Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
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Appendix 6: Full regression model of salaries estimated by the fixed effects estimator.

	Estimate	Std. Error	t value	Pr(>|t|)	
Age	0.56577120	0.04425971	12.7830	< 2.2e-16	***
Age2	-0.01115330	0.00064023	-17.4209	< 2.2e-16	***
PlayingTime	0.00368163	0.00066296	5.5533	2.897e-08	***
RATINGS	0.09744663	0.02560731	3.8054	0.0001427	***
LeagueLastSeason	0.09264606	0.02222044	4.1694	3.088e-05	***
InternationalStatus	0.01549354	0.14293010	0.1084	0.9136817	
ACMilan	0.60944702	0.17937894	3.3975	0.0006834	***
Ajaccio	-0.17195834	0.31098315	-0.5530	0.5803134	
Alaves	-0.07072987	0.31096345	-0.2275	0.8200769	
Almeria	-1.95731178	0.75592919	-2.5893	0.0096360	**
Amiens	-0.38928910	0.22818355	-1.7060	0.0880423	.
Angers	-0.13842972	0.22814304	-0.6068	0.5440235	
Arsenal	0.74531125	0.18502604	4.0281	5.676e-05	***
AstonVilla	0.42994707	0.18159183	2.3677	0.0179259	*
Atalanta	-0.00762588	0.18333820	-0.0416	0.9668230	
Athletic	0.47514843	0.24703467	1.9234	0.0544660	.
AtleticoMadrid	0.49239750	0.18650825	2.6401	0.0083054	**
Augsburg	-0.13149561	0.18104623	-0.7263	0.4676713	
Barcelona	0.91619240	0.18116175	5.0573	4.351e-07	***
Bastia	-0.04538507	0.20109310	-0.2257	0.8214472	
Bayer	0.37769407	0.18462888	2.0457	0.0408208	*
Bayern	0.76513721	0.18294383	4.1824	2.917e-05	***
Benevento	-0.14357790	0.26408429	-0.5437	0.5866761	
Bologna	-0.03346562	0.18134585	-0.1845	0.8535945	
Bordeaux	-0.12953931	0.21942598	-0.5904	0.5549699	
Dortmund	0.61128744	0.18469014	3.3098	0.0009380	***
Bournemouth	0.51307318	0.19057736	2.6922	0.0071136	**
Brescia	-0.61815440	0.37228421	-1.6604	0.0968677	.
Brest	-0.09898529	0.17943034	-0.5517	0.5811946	
Brighton	0.26601607	0.18873942	1.4094	0.1587471	
Burnley	-0.01380037	0.18132907	-0.0761	0.9393361	
Caen	-0.25567587	0.20403662	-1.2531	0.2102120	
Cagliari	-0.07899063	0.20788211	-0.3800	0.7039723	
Cardiff	0.38658687	0.20253171	1.9088	0.0563290	.

Carpi	-0.76730825	0.23905061	-3.2098	0.0013337	**
Catania	0.21762713	0.21989391	0.9897	0.3223563	
CeltaVigo	-0.09688843	0.20310214	-0.4770	0.6333452	
Cesena	-0.36672861	0.19009684	-1.9292	0.0537471	.
Chelsea	0.66843963	0.18267001	3.6593	0.0002546	***
Chievo	-0.20148516	0.18742714	-1.0750	0.2824064	
Cordoba	0.16029154	0.18611252	0.8613	0.3891211	
Crotone	-0.57704023	0.33105951	-1.7430	0.0813720	.
CrystalPalace	0.45807345	0.18843093	2.4310	0.0150806	*
Darmstadt	-0.35575841	0.23066774	-1.5423	0.1230426	
Deportivo	0.00962464	0.20920055	0.0460	0.9633061	
Dijon	-0.27966483	0.22930274	-1.2196	0.2226423	
Dusseldorf	-0.13205069	0.24486888	-0.5393	0.5897156	
Eibar	-0.29150240	0.22549615	-1.2927	0.1961486	
Eintracht	-0.07052100	0.19924976	-0.3539	0.7233991	
Elche	-0.53847228	0.25328908	-2.1259	0.0335419	*
Empoli	-0.24926170	0.18728207	-1.3309	0.1832476	
Espanyol	0.06854771	0.20531862	0.3339	0.7384942	
Everton	0.56912316	0.18322540	3.1061	0.0019024	**
Evian	0.18846907	0.20845450	0.9041	0.3659573	
Fiorentina	0.20159634	0.17861312	1.1287	0.2590700	
Freiburg	-0.40231034	0.20306124	-1.9812	0.0476017	*
Frosinone	-0.17655240	0.20637166	-0.8555	0.3922974	
Fulham	0.34477676	0.22199889	1.5531	0.1204512	
Gazelec	0.92556697	0.19037326	4.8619	1.186e-06	***
Genoa	-0.00532367	0.17846060	-0.0298	0.9762026	
Getafe	0.20982719	0.23585972	0.8896	0.3736942	
Girona	-0.07603425	0.21078481	-0.3607	0.7183189	
Granada	-0.09944288	0.20082320	-0.4952	0.6204900	
Guingamp	-0.31278159	0.20821337	-1.5022	0.1330825	
Hamburg	0.44268986	0.19916339	2.2227	0.0262620	*
Hannover	0.03916715	0.21200867	0.1847	0.8534354	
Hellas	-0.10008968	0.19773469	-0.5062	0.6127437	
Hertha	0.08587664	0.20654828	0.4158	0.6775898	
Hoffenheim	0.11885018	0.19276009	0.6166	0.5375365	

Huddersfield	0.26027139	0.20598086	1.2636	0.2064227	
Huesca	0.63637403	0.28465387	2.2356	0.0254064	*
Hull	0.15920983	0.21401420	0.7439	0.4569467	
Ingolstadt	0.13145193	0.21770858	0.6038	0.5459961	
Inter	0.69976696	0.17672937	3.9595	7.578e-05	***
Juventus	0.63049986	0.17846824	3.5328	0.0004136	***
Koln	0.02870562	0.20175828	0.1423	0.8868647	
LasPalmas	0.01925156	0.26334299	0.0731	0.9417249	
Lazio	0.28611820	0.20353055	1.4058	0.1598316	
Lecce	-0.08951182	0.30500345	-0.2935	0.7691648	
Leganes	0.07808353	0.20322776	0.3842	0.7008284	
Leicester	0.31830252	0.18141326	1.7546	0.0793728	.
Leipzig	0.59342060	0.22099758	2.6852	0.0072645	**
Levante	-0.39410949	0.20852401	-1.8900	0.0587964	.
Lille	-0.14133840	0.22438402	-0.6299	0.5287820	
Liverpool	0.60173494	0.18531048	3.2472	0.0011706	**
Lorient	-0.04716193	0.18397417	-0.2564	0.7976869	
Lyon	0.25380624	0.20474181	1.2396	0.2151465	
Mainz	-0.11696977	0.19546189	-0.5984	0.5495725	
Malaga	0.03673491	0.19153025	0.1918	0.8479064	
Mallorca	-0.32956738	0.30440245	-1.0827	0.2789892	
ManCity	0.87916032	0.17533041	5.0143	5.442e-07	***
ManUtd	0.90862044	0.17911018	5.0730	4.009e-07	***
Marseille	0.30015803	0.19006877	1.5792	0.1143299	
Metz	-0.47625015	0.19005101	-2.5059	0.0122344	*
Middlesbrough	0.45695817	0.18700670	2.4435	0.0145665	*
Monaco	0.15818977	0.18805740	0.8412	0.4002745	
Monchengladbach	0.18114162	0.21660208	0.8363	0.4030193	
Montpellier	-0.13886636	0.18901470	-0.7347	0.4625536	
Nantes	-0.28806139	0.19476936	-1.4790	0.1391850	
Napoles	0.33864051	0.19054334	1.7772	0.0755692	.
Newcastle	0.52977913	0.19673311	2.6929	0.0070992	**
Nice	-0.15928648	0.18544048	-0.8590	0.3903880	
Nimes	-0.36402473	0.18772589	-1.9391	0.0525224	.
Norwich	0.13631141	0.18257670	0.7466	0.4553292	

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Nurnberg          0.18213841 0.31059897  0.5864 0.5576172
Osasuna          -0.29225905 0.33534924 -0.8715 0.3835051
Paderborn        -0.36218898 0.25991838 -1.3935 0.1635177
Palermo          -0.23480920 0.20279463 -1.1579 0.2469546
Parma             0.03155451 0.18748067  0.1683 0.8663454
Pescara          -0.09011864 0.27491425 -0.3278 0.7430671
PSG               0.84515781 0.19735744  4.2824 1.872e-05 ***
QPR               0.39161991 0.20214375  1.9373 0.0527414 .
Rayo             -0.17857563 0.21101447 -0.8463 0.3974276
RealBetis        -0.06696373 0.19093850 -0.3507 0.7258168
RealMadrid        0.80240224 0.19290210  4.1596 3.223e-05 ***
RealSociedad      0.06733803 0.22880871  0.2943 0.7685379
Reims            -0.10215491 0.22472415 -0.4546 0.6494250
Rennes           -0.18652251 0.18783283 -0.9930 0.3207297
Roma              0.55555953 0.18297989  3.0362 0.0024041 **
Sampdoria         0.08610121 0.18403940  0.4678 0.6399115
Sassuolo         -0.01831110 0.19226002 -0.0952 0.9241256
Schalke           0.53734223 0.19443622  2.7636 0.0057306 **
Sevilla           0.34049258 0.18499437  1.8406 0.0657254 .
Sheffield         0.52513559 0.32262843  1.6277 0.1036342
Sochaux           0.09600821 0.24867328  0.3861 0.6994469
Southampton       0.44966835 0.18634652  2.4131 0.0158419 *
SPAL             -0.08110684 0.19405220 -0.4180 0.6759852
SportingGinjon   -0.51546918 0.21784617 -2.3662 0.0179962 *
StEtienne         0.00216975 0.19780159  0.0110 0.9912482
Stoke             0.35979739 0.18429372  1.9523 0.0509386 .
Strasbourg       -0.31721717 0.20521620 -1.5458 0.1222014
Stuttgart         0.12144929 0.20595025  0.5897 0.5554078
Sunderland        0.43126236 0.18374235  2.3471 0.0189454 *
Swansea           0.38138686 0.18177081  2.0982 0.0359225 *
Torino            0.03637319 0.18824856  0.1932 0.8467926
Tottenham         0.54406595 0.18457371  2.9477 0.0032113 **
Toulouse         -0.08905577 0.18948100 -0.4700 0.6383696
Troyes           -0.55743355 0.24909419 -2.2378 0.0252601 *
Udinese          -0.24014474 0.18714446 -1.2832 0.1994592
UnionBerlin      -0.18157027 0.26878557 -0.6755 0.4993653
Valencia          0.38034330 0.18209700  2.0887 0.0367691 *
Valenciennes     -0.49345400 0.46669578 -1.0573 0.2903920
Valladolid       -0.14281742 0.24119978 -0.5921 0.5537927
Villarreal        0.18131366 0.21592878  0.8397 0.4011074
Watford           0.15559042 0.18024135  0.8632 0.3880361
Werder            0.10732020 0.18916568  0.5673 0.5705037
WestBrom          0.51401825 0.18342702  2.8023 0.0050867 **
WestHam           0.57328651 0.18560056  3.0888 0.0020168 **
Wolfsburg         0.64116674 0.18007790  3.5605 0.0003724 ***
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Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
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Appendix 7: Full regression model of market values estimated by the fixed effects estimator.

	Estimate	Std. Error	t value	Pr(>|t|)	
Age	1.09232186	0.05372284	20.3325	< 2.2e-16	***
Age2	-0.02053128	0.00076454	-26.8543	< 2.2e-16	***
PlayingTime	0.01229116	0.00082950	14.8175	< 2.2e-16	***
RATINGS	0.37266397	0.02824662	13.1932	< 2.2e-16	***
LeagueLastSeason	0.34306897	0.03088346	11.1085	< 2.2e-16	***
InternationalStatus	-0.13929238	0.11801118	-1.1803	0.2379049	
ACMilan	0.10110791	0.14065315	0.7188	0.4722580	
Ajaccio	-0.65085730	0.16020310	-4.0627	4.899e-05	***
Alaves	-0.17911875	0.18187527	-0.9848	0.3247320	
Almeria	0.15532892	0.21069695	0.7372	0.4610143	
Amiens	-0.32994264	0.16661662	-1.9803	0.0477112	*
Angers	-0.40754355	0.16213287	-2.5136	0.0119697	*
Arsenal	0.30787112	0.14149645	2.1758	0.0295991	*
AstonVilla	0.07033068	0.14984750	0.4693	0.6388340	
Atalanta	-0.09064826	0.15270837	-0.5936	0.5527948	
Athletic	0.01191977	0.14041149	0.0849	0.9323497	
AtleticoMadrid	0.17671145	0.14782758	1.1954	0.2319722	
Augsburg	-0.25107648	0.15985824	-1.5706	0.1163125	
Barcelona	0.27429775	0.14746078	1.8601	0.0629041	.
Bastia	-0.53070343	0.16966583	-3.1279	0.0017670	**
Bayer	-0.01107805	0.15841006	-0.0699	0.9442490	
Bayern	0.36028714	0.15759589	2.2861	0.0222730	*
Benevento	-0.44715274	0.20387007	-2.1933	0.0283142	*
Bologna	-0.35443737	0.15221182	-2.3286	0.0199073	*
Bordeaux	-0.12921009	0.13945680	-0.9265	0.3542029	
Dortmund	0.07789623	0.14625623	0.5326	0.5943252	
Bournemouth	0.31840959	0.21466560	1.4833	0.1380408	
Brescia	-0.73226805	0.20916897	-3.5008	0.0004664	***
Brest	-0.26713903	0.15065404	-1.7732	0.0762362	.
Brighton	0.12023390	0.17326856	0.6939	0.4877558	
Burnley	0.13550259	0.21209777	0.6389	0.5229276	
Caen	-0.20932640	0.16805968	-1.2455	0.2129686	
Cagliari	-0.29598649	0.15319810	-1.9321	0.0533902	.
Cardiff	0.16955301	0.16550773	1.0244	0.3056592	

Carpi	-0.41065919	0.34971968	-1.1743	0.2403306	
Catania	0.06477079	0.19615479	0.3302	0.7412561	
CeltaVigo	-0.12711129	0.16064943	-0.7912	0.4288320	
Cesena	-0.51861359	0.19382553	-2.6757	0.0074739	**
Chelsea	0.31759774	0.15229307	2.0854	0.0370627	*
Chievo	-0.23426372	0.15357362	-1.5254	0.1271967	
Cordoba	0.06912033	0.25223929	0.2740	0.7840714	
Crotone	-0.44575835	0.19363382	-2.3021	0.0213581	*
CrystalPalace	-0.01112525	0.14029218	-0.0793	0.9367956	
Darmstadt	-0.36927909	0.23302700	-1.5847	0.1130748	
Deportivo	-0.45692436	0.17181785	-2.6594	0.0078454	**
Dijon	-0.13352667	0.17263754	-0.7735	0.4392795	
Dusseldorf	-0.17931062	0.20209756	-0.8872	0.3749734	
Eibar	-0.19245308	0.16683506	-1.1536	0.2487196	
Eintracht	-0.05449175	0.16420595	-0.3319	0.7400116	
Elche	-0.37110347	0.22476298	-1.6511	0.0987617	.
Empoli	-0.23092055	0.18133005	-1.2735	0.2028858	
Espanyol	-0.29231562	0.14159784	-2.0644	0.0390128	*
Everton	0.19453622	0.13355694	1.4566	0.1452738	
Evian	-0.79543494	0.21161415	-3.7589	0.0001719	***
Fiorentina	-0.00392639	0.14469798	-0.0271	0.9783527	
Freiburg	-0.21553656	0.16770099	-1.2852	0.1987463	
Frosinone	-0.75491169	0.20553898	-3.6728	0.0002415	***
Fulham	0.08006227	0.15645587	0.5117	0.6088588	
Gazelec	-0.29541942	0.16361007	-1.8056	0.0710154	.
Genoa	-0.37198807	0.15549775	-2.3922	0.0167699	*
Getafe	-0.30397524	0.19154214	-1.5870	0.1125566	
Girona	-0.62344421	0.23902785	-2.6082	0.0091184	**
Granada	-0.23313691	0.16248605	-1.4348	0.1513817	
Guingamp	-0.44724299	0.14910601	-2.9995	0.0027130	**
Hamburg	-0.27888355	0.17130428	-1.6280	0.1035659	
Hannover	-0.29585043	0.14913700	-1.9837	0.0473196	*
Hellas	-0.35805724	0.16489095	-2.1715	0.0299257	*
Hertha	-0.06730247	0.17133100	-0.3928	0.6944624	
Hoffenheim	-0.12392538	0.14499151	-0.8547	0.3927397	

Huddersfield	0.17174967	0.20233578	0.8488	0.3959998	
Huesca	-0.76552614	0.67623811	-1.1320	0.2576547	
Hull	-0.28416228	0.16724125	-1.6991	0.0893381	.
Ingolstadt	-0.32922151	0.21023725	-1.5660	0.1174012	
Inter	0.19853736	0.14237507	1.3945	0.1632172	
Juventus	0.18524065	0.13616066	1.3605	0.1737257	
Koln	-0.31813805	0.17445729	-1.8236	0.0682536	.
LasPalmas	-0.06484222	0.22420081	-0.2892	0.7724248	
Lazio	0.10477491	0.14923666	0.7021	0.4826555	
Lecce	-0.66576313	0.26316934	-2.5298	0.0114330	*
Leganes	0.02617718	0.20621147	0.1269	0.8989886	
Leicester	0.01988830	0.15680827	0.1268	0.8990768	
Leipzig	0.06612938	0.19963484	0.3313	0.7404635	
Levante	-0.22514286	0.15873244	-1.4184	0.1561208	
Lille	-0.21873984	0.16163286	-1.3533	0.1759958	
Liverpool	0.27113982	0.14148502	1.9164	0.0553534	.
Lorient	-0.48907705	0.16280270	-3.0041	0.0026722	**
Lyon	-0.03174515	0.14147741	-0.2244	0.8224651	
Mainz	-0.25135928	0.16471051	-1.5261	0.1270346	
Malaga	-0.14390120	0.14986876	-0.9602	0.3369943	
Mallorca	-0.68941588	0.34631131	-1.9907	0.0465450	*
ManCity	0.51695000	0.13267321	3.8964	9.846e-05	***
ManUtd	0.28301125	0.13637401	2.0753	0.0379960	*
Marseille	-0.25084312	0.15333350	-1.6359	0.1018951	
Metz	-0.60481793	0.17245019	-3.5072	0.0004554	***
Middlesbrough	-0.08718588	0.15815661	-0.5513	0.5814696	
Monaco	-0.01102807	0.12734831	-0.0866	0.9309936	
Monchengladbach	0.10469483	0.16005426	0.6541	0.5130536	
Montpellier	-0.29680096	0.18511709	-1.6033	0.1089066	
Nantes	-0.42897558	0.13772803	-3.1147	0.0018484	**
Napoles	0.08507404	0.14984683	0.5677	0.5702282	
Newcastle	0.06643639	0.13906076	0.4778	0.6328412	
Nice	-0.02919592	0.16244149	-0.1797	0.8573678	
Nimes	0.17974465	0.37861787	0.4747	0.6349866	
Norwich	-0.07541128	0.14366583	-0.5249	0.5996627	

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Nurnberg          -0.24265473  0.17066151  -1.4218 0.1551112
Osasuna           -0.25940758  0.19096238  -1.3584 0.1743698
Paderborn         -0.13170232  0.27653972  -0.4763 0.6339092
Palermo           -0.32537359  0.20146159  -1.6151 0.1063379
Parma             -0.16834066  0.14885959  -1.1309 0.2581459
Pescara           -0.59782446  0.24179769  -2.4724 0.0134420 *
PSG                0.11221958  0.13759239   0.8156 0.4147576
QPR                0.15623358  0.17272886   0.9045 0.3657579
Rayo              -0.38949175  0.16587512  -2.3481 0.0188947 *
RealBetis         -0.03410048  0.15767715  -0.2163 0.8287849
RealMadrid         0.16807542  0.14459811   1.1624 0.2451246
RealSociedad      -0.01864574  0.17817260  -0.1046 0.9166564
Reims             -0.60054618  0.17995848  -3.3371 0.0008505 ***
Rennes            -0.20567792  0.15655988  -1.3137 0.1889755
Roma              -0.05618230  0.14296064  -0.3930 0.6943368
Sampdoria         -0.14206910  0.13875836  -1.0239 0.3059340
Sassuolo          -0.27342050  0.15375338  -1.7783 0.0753935 .
Schalke            0.18215693  0.13971466   1.3038 0.1923485
Sevilla            0.01062748  0.13670615   0.0777 0.9380372
Sheffield          0.55204288  0.51622100   1.0694 0.2849267
Sochaux           -0.59974573  0.30108379  -1.9920 0.0464114 *
Southampton       -0.07204275  0.14454019  -0.4984 0.6181974
SPAL              -0.38432078  0.15958898  -2.4082 0.0160553 *
SportingGinjon    -0.40723550  0.17924371  -2.2720 0.0231163 *
StEtienne         -0.19608480  0.15583343  -1.2583 0.2083227
Stoke             -0.01673724  0.15271470  -0.1096 0.9127310
Strasbourg        -0.13263420  0.20285898  -0.6538 0.5132445
Stuttgart         -0.07744900  0.17392006  -0.4453 0.6561057
Sunderland         0.01134667  0.14779735   0.0768 0.9388071
Swansea            0.04854963  0.15052173   0.3225 0.7470507
Torino            -0.09324849  0.14115935  -0.6606 0.5088950
Tottenham          0.02904307  0.15006485   0.1935 0.8465437
Toulouse          -0.45388249  0.16164491  -2.8079 0.0049993 **
Troyes            -0.46350598  0.15810859  -2.9316 0.0033826 **
Udinese           -0.17223036  0.16663489  -1.0336 0.3013657
UnionBerlin       -0.37416381  0.25512767  -1.4666 0.1425330
Valencia           0.21714880  0.13648462   1.5910 0.1116481
Valenciennes      -0.39287106  0.43980022  -0.8933 0.3717277
Valladolid        -0.42156497  0.21115177  -1.9965 0.0459147 *
Villarreal        -0.03119837  0.15328022  -0.2035 0.8387199
Watford            0.06343534  0.14224159   0.4460 0.6556323
Werder            -0.16375118  0.17221503  -0.9509 0.3417091
WestBrom           0.10348244  0.14399413   0.7187 0.4723741
WestHam            0.11471401  0.15360102   0.7468 0.4551885
Wolfsburg         -0.01971433  0.16516917  -0.1194 0.9049946
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Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
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Appendix 8: Full regression model of salaries estimated by the random effects estimator.

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	5.55544954	0.92060803	6.0345	1.643e-09	***
Age	0.48710976	0.02621393	18.5821	< 2.2e-16	***
Age2	-0.00805110	0.00048207	-16.7010	< 2.2e-16	***
Weight	-0.03299785	0.02086963	-1.5811	0.1138727	
Weight2	0.00022137	0.00013586	1.6294	0.1032629	
PlayingTime	0.00623402	0.00094092	6.6254	3.615e-11	***
RATINGS	0.23680120	0.03677380	6.4394	1.247e-10	***
LeagueLastSeason	0.23731901	0.02529461	9.3822	< 2.2e-16	***
InternationalStatus	0.44265590	0.02133872	20.7443	< 2.2e-16	***
Defender	0.11007182	0.03897944	2.8238	0.0047532	**
Midfielder	0.31708851	0.04011963	7.9036	2.954e-15	***
Forward	0.47559409	0.04213731	11.2868	< 2.2e-16	***
CAF	-0.25821803	0.03262680	-7.9143	2.711e-15	***
CONMEBOL	0.13093783	0.02807381	4.6641	3.135e-06	***
CONCACAF	-0.19416066	0.05262096	-3.6898	0.0002255	***
AFC	-0.17213408	0.06298948	-2.7327	0.0062904	**
OFC	0.15400046	0.07331581	2.1005	0.0357056	*
ACMilan	0.60639452	0.19922930	3.0437	0.0023421	**
Ajaccio	-0.47451881	0.21412377	-2.2161	0.0267042	*
Alaves	-0.36885537	0.21762277	-1.6949	0.0901154	.
Almeria	-1.29749392	0.30525759	-4.2505	2.150e-05	***
Amiens	-0.88645537	0.22903902	-3.8703	0.0001093	***
Angers	-0.76571411	0.19420361	-3.9428	8.099e-05	***
Arsenal	0.76103076	0.20044020	3.7968	0.0001473	***
AstonVilla	0.23662696	0.19723578	1.1997	0.2302740	
Atalanta	-0.27238200	0.19388144	-1.4049	0.1600808	
Athletic	0.13769232	0.20935350	0.6577	0.5107423	
AtleticoMadrid	0.70841098	0.22422762	3.1593	0.0015853	**
Augsburg	-0.39505629	0.19709440	-2.0044	0.0450502	*
Barcelona	1.16152026	0.21480041	5.4074	6.519e-08	***
Bastia	-0.59633236	0.20342031	-2.9315	0.0033795	**
Bayer	0.27861315	0.20964016	1.3290	0.1838718	
Bayern	0.93557414	0.22281728	4.1988	2.703e-05	***
Benevento	-0.46800068	0.31335162	-1.4935	0.1353250	

Bologna	-0.19839872	0.20179771	-0.9832	0.3255509	
Bordeaux	-0.49666286	0.20656021	-2.4044	0.0162125	*
Dortmund	0.57514263	0.20442358	2.8135	0.0049090	**
Bournemouth	0.22983963	0.19785218	1.1617	0.2453919	
Braunschweiger	-0.40534144	0.36738741	-1.1033	0.2699162	
Brescia	-0.74008835	0.43777572	-1.6906	0.0909466	.
Brest	-0.40009152	0.20283913	-1.9725	0.0485810	*
Brighton	0.09253624	0.19769533	0.4681	0.6397397	
Burnley	-0.17299668	0.20296244	-0.8524	0.3940329	
Caen	-0.76940185	0.20066281	-3.8343	0.0001266	***
Cagliari	-0.34331909	0.20400801	-1.6829	0.0924269	.
Cardiff	-0.05784534	0.20260960	-0.2855	0.7752651	
Carpi	-0.83318096	0.27904908	-2.9858	0.0028344	**
Catania	-0.26280194	0.23397947	-1.1232	0.2613826	
CeltaVigo	-0.33481052	0.20421765	-1.6395	0.1011406	
Cesena	-0.69767148	0.28590929	-2.4402	0.0146945	*
Chelsea	0.76302933	0.19984511	3.8181	0.0001352	***
Chievo	-0.55485970	0.20113238	-2.7587	0.0058126	**
Cordoba	-0.36520384	0.28422155	-1.2849	0.1988434	
Crotone	-0.96962018	0.21094000	-4.5967	4.338e-06	***
CrystalPalace	0.37178221	0.20436903	1.8192	0.0689110	.
Darmstadt	-0.63470956	0.21392846	-2.9669	0.0030141	**
Deportivo	-0.33955719	0.24725645	-1.3733	0.1696856	
Dijon	-0.82294109	0.21031678	-3.9129	9.173e-05	***
Dusseldorf	-0.69730070	0.20283661	-3.4377	0.0005886	***
Eibar	-0.61441701	0.23981088	-2.5621	0.0104169	*
Eintracht	-0.21667455	0.19384623	-1.1178	0.2636904	
Elche	-0.78607518	0.24635226	-3.1909	0.0014223	**
Empoli	-0.54705953	0.21118373	-2.5904	0.0095972	**
Espanyol	-0.18036561	0.23016070	-0.7837	0.4332610	
Everton	0.50803553	0.19448800	2.6122	0.0090085	**
Evian	-0.43161047	0.20720408	-2.0830	0.0372710	*
Fiorentina	0.05250601	0.19474179	0.2696	0.7874585	
Freiburg	-0.61412033	0.19546528	-3.1418	0.0016831	**
Frosinone	-0.42811556	0.19990911	-2.1416	0.0322503	*

Fulham	0.00779046	0.22796372	0.0342	0.9727389	
Gazelec	-0.24280596	0.31407249	-0.7731	0.4394854	
Genoa	-0.14997529	0.19539450	-0.7676	0.4427694	
Getafe	-0.35417057	0.21217851	-1.6692	0.0951025	.
Girona	-0.34229065	0.26015760	-1.3157	0.1882990	
Granada	-0.42843988	0.20583774	-2.0814	0.0374150	*
Guingamp	-0.77617759	0.19755034	-3.9290	8.579e-05	***
Hamburg	0.22952736	0.19914909	1.1525	0.2491227	
Hannover	-0.20715319	0.20236450	-1.0237	0.3060154	
Hellas	-0.39078938	0.20438007	-1.9121	0.0558915	.
Hertha	-0.17653141	0.20216243	-0.8732	0.3825635	
Hoffenheim	-0.10763858	0.19929119	-0.5401	0.5891335	
Huddersfield	0.02761782	0.19913130	0.1387	0.8896963	
Huesca	-0.24534761	0.20310935	-1.2080	0.2270878	
Hull	0.04787610	0.20141360	0.2377	0.8121176	
Ingolstadt	-0.57313455	0.20904368	-2.7417	0.0061216	**
Inter	0.62829488	0.19722006	3.1858	0.0014476	**
Juventus	0.76656436	0.20488186	3.7415	0.0001838	***
Koln	-0.12607939	0.21877193	-0.5763	0.5644201	
LasPalmas	-0.45832368	0.25709401	-1.7827	0.0746598	.
Lazio	0.20658788	0.19626109	1.0526	0.2925381	
Lecce	-0.20620516	0.24587092	-0.8387	0.4016704	
Leganes	-0.23795749	0.23400125	-1.0169	0.3092188	
Leicester	0.31988772	0.20311142	1.5749	0.1152981	
Leipzig	0.31305214	0.21562615	1.4518	0.1465763	
Levante	-0.61514319	0.20244897	-3.0385	0.0023828	**
Lille	-0.25173581	0.21492661	-1.1713	0.2415166	
Liverpool	0.68863659	0.19787900	3.4801	0.0005031	***
Livorno	-0.37105329	0.39431377	-0.9410	0.3467191	
Lorient	-0.47364930	0.19722155	-2.4016	0.0163386	*
Lyon	0.13601010	0.20169974	0.6743	0.5001215	
Mainz	-0.33936510	0.19826255	-1.7117	0.0869794	.
Malaga	-0.20599432	0.20118724	-1.0239	0.3059068	
Mallorca	-0.13649273	0.53408699	-0.2556	0.7982930	
ManCity	0.98325718	0.20023191	4.9106	9.203e-07	***

ManUtd	0.98335374	0.20965368	4.6904	2.758e-06	***
Marseille	0.20914740	0.20488917	1.0208	0.3073784	
Metz	-0.71799287	0.20444526	-3.5119	0.0004466	***
Middlesbrough	0.29487720	0.20038448	1.4716	0.1411675	
Monaco	0.12490957	0.20016390	0.6240	0.5326158	
Monchengladbach	0.04765521	0.21207313	0.2247	0.8222079	
Montpellier	-0.51212133	0.19674782	-2.6029	0.0092547	**
Nancy	-1.24136328	0.33239453	-3.7346	0.0001889	***
Nantes	-0.71003426	0.20670960	-3.4349	0.0005948	***
Napoles	0.28872729	0.20180091	1.4308	0.1525278	
Newcastle	0.36989792	0.19511121	1.8958	0.0580071	.
Nice	-0.39331546	0.20428257	-1.9254	0.0542099	.
Nimes	-1.21977966	0.24670562	-4.9443	7.749e-07	***
Norwich	-0.13584758	0.20520319	-0.6620	0.5079747	
Nurnberg	-0.49648337	0.21839858	-2.2733	0.0230268	*
Osasuna	-0.56075124	0.24165101	-2.3205	0.0203310	*
Paderborn	-1.28484596	0.22837712	-5.6260	1.887e-08	***
Palermo	-0.43253494	0.19775624	-2.1872	0.0287468	*
Parma	-0.23276274	0.20363772	-1.1430	0.2530522	
Pescara	-0.38018804	0.23471393	-1.6198	0.1053037	
PSG	0.84687507	0.21398034	3.9577	7.612e-05	***
QPR	0.36336466	0.21497071	1.6903	0.0909976	.
Rayo	-0.39754722	0.20882002	-1.9038	0.0569635	.
RealBetis	-0.24116005	0.20564779	-1.1727	0.2409462	
RealMadrid	1.10862547	0.22937420	4.8333	1.360e-06	***
RealSociedad	-0.12458220	0.21042379	-0.5921	0.5538260	
Reims	-0.68332048	0.19969128	-3.4219	0.0006240	***
Rennes	-0.42088758	0.19975248	-2.1070	0.0351349	*
Siena	-0.44212233	0.28775208	-1.5365	0.1244504	
Roma	0.56488366	0.20182796	2.7988	0.0051371	**
Sampdoria	-0.14803210	0.19751147	-0.7495	0.4535794	
Sassuolo	-0.19356125	0.19506496	-0.9923	0.3210761	
Schalke	0.25798980	0.21651948	1.1915	0.2334692	
Sevilla	0.13152050	0.20909259	0.6290	0.5293575	
Sheffield	-0.87738463	0.25502818	-3.4403	0.0005830	***

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Sochaux           -0.37647263  0.22286177  -1.6893 0.0911954 .
Southampton        0.39613422  0.19681471   2.0127 0.0441663 *
SPAL              -0.40523972  0.21541755  -1.8812 0.0599720 .
SportingGinjon    -0.81732403  0.23197882  -3.5233 0.0004279 ***
StEtienne         -0.35357001  0.19423960  -1.8203 0.0687423 .
Stoke              0.27486536  0.20358506   1.3501 0.1770020
Strasbourg        -0.78367686  0.20354084  -3.8502 0.0001186 ***
Stuttgart         -0.05516763  0.19954669  -0.2765 0.7821960
Sunderland         0.37811688  0.19484752   1.9406 0.0523335 .
Swansea            0.19207006  0.19604428   0.9797 0.3272408
Torino            -0.12614792  0.20046733  -0.6293 0.5291852
Tottenham          0.56233609  0.19833961   2.8352 0.0045873 **
Toulouse          -0.49719245  0.20229268  -2.4578 0.0139940 *
Troyes            -0.92303513  0.21391709  -4.3149 1.610e-05 ***
Udinese           -0.40870745  0.19367610  -2.1103 0.0348570 *
UnionBerlin       -0.51381145  0.21464266  -2.3938 0.0166906 *
Valencia           0.37258661  0.20845780   1.7873 0.0739072 .
Valenciennes      -0.68556670  0.28879025  -2.3739 0.0176162 *
Valladolid        -0.81738688  0.28158958  -2.9028 0.0037058 **
Villarreal        -0.05771407  0.24632496  -0.2343 0.8147558
Watford            0.08580011  0.20191617   0.4249 0.6708960
Werder            -0.15480546  0.19989399  -0.7744 0.4386876
WestBrom           0.32270619  0.19977104   1.6154 0.1062554
WestHam            0.41501328  0.19801303   2.0959 0.0361136 *
Wolfsburg          0.47060562  0.19903942   2.3644 0.0180764 *
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Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
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Appendix 9: Full regression model of market values estimated by the random effects estimator.

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	6.14960507	1.05647651	5.8209	6.009e-09	***
Age	0.59373488	0.03367074	17.6336	< 2.2e-16	***
Age2	-0.01335037	0.00062383	-21.4006	< 2.2e-16	***
Weight	-0.06035763	0.02391853	-2.5235	0.0116336	*
Weight2	0.00039869	0.00015527	2.5678	0.0102482	*
PlayingTime	0.02074287	0.00110865	18.7100	< 2.2e-16	***
RATINGS	0.60325583	0.03806955	15.8462	< 2.2e-16	***
LeagueLastSeason	0.57886164	0.03302315	17.5290	< 2.2e-16	***
InternationalStatus	0.58864778	0.02358777	24.9556	< 2.2e-16	***
Defender	-0.01898958	0.04503817	-0.4216	0.6733007	
Midfielder	0.25618862	0.04576811	5.5975	2.223e-08	***
Forward	0.42594514	0.04806442	8.8620	< 2.2e-16	***
CAF	-0.39026110	0.04010601	-9.7307	< 2.2e-16	***
CONMEBOL	0.13555603	0.03280905	4.1317	3.627e-05	***
CONCACAF	-0.32349840	0.07257989	-4.4571	8.384e-06	***
AFC	-0.44268301	0.11473479	-3.8583	0.0001148	***
OFC	-0.03578065	0.08857491	-0.4040	0.6862501	
ACMilan	-0.22861403	0.20552870	-1.1123	0.2660228	
Ajaccio	-0.99193576	0.22662498	-4.3770	1.214e-05	***
Alaves	-0.71118668	0.23720055	-2.9983	0.0027211	**
Almeria	-0.66964522	0.23831702	-2.8099	0.0049641	**
Amiens	-1.11566715	0.23851603	-4.6775	2.936e-06	***
Angers	-0.99123888	0.21635511	-4.5815	4.664e-06	***
Arsenal	0.19840278	0.21128791	0.9390	0.3477419	
AstonVilla	-0.38158555	0.21272271	-1.7938	0.0728683	.
Atalanta	-0.61423893	0.21232613	-2.8929	0.0038241	**
Athletic	-0.34694696	0.21029862	-1.6498	0.0990144	.
AtleticoMadrid	0.32390064	0.22428039	1.4442	0.1487160	
Augsburg	-0.89628274	0.21121561	-4.2434	2.218e-05	***
Barcelona	0.45442860	0.22978290	1.9776	0.0479925	*
Bastia	-1.16301223	0.20875668	-5.5711	2.587e-08	***
Bayer	-0.34295045	0.23057868	-1.4873	0.1369503	
Bayern	0.35214791	0.23493539	1.4989	0.1339231	
Benevento	-1.13239706	0.27803720	-4.0728	4.675e-05	***

Bologna	-0.94367492	0.20135227	-4.6867	2.808e-06	***
Bordeaux	-0.71881363	0.20431225	-3.5182	0.0004361	***
Dortmund	-0.02771296	0.21840471	-0.1269	0.8990312	
Bournemouth	-0.24909170	0.20667850	-1.2052	0.2281454	
Braunschweiger	-0.88781926	0.53321093	-1.6650	0.0959310	.
Brescia	-1.17930546	0.30895907	-3.8170	0.0001358	***
Brest	-0.98840036	0.28677638	-3.4466	0.0005697	***
Brighton	-0.37698235	0.21408498	-1.7609	0.0782814	.
Burnley	-0.43922396	0.21650879	-2.0287	0.0425150	*
Caen	-0.99036460	0.21900926	-4.5220	6.186e-06	***
Cagliari	-0.78479345	0.21077493	-3.7234	0.0001975	***
Cardiff	-0.59807732	0.22430484	-2.6664	0.0076783	**
Carpi	-1.02642989	0.29940428	-3.4282	0.0006096	***
Catania	-0.65628958	0.24608975	-2.6669	0.0076667	**
CeltaVigo	-0.68121320	0.20737250	-3.2850	0.0010229	**
Cesena	-1.48799822	0.32855779	-4.5289	5.989e-06	***
Chelsea	0.32887937	0.20819986	1.5796	0.1142181	
Chievo	-0.94752711	0.21885698	-4.3294	1.507e-05	***
Cordoba	-0.70068136	0.28339230	-2.4725	0.0134321	*
Crotone	-1.46027960	0.24108176	-6.0572	1.428e-09	***
CrystalPalace	-0.26392297	0.20564637	-1.2834	0.1993836	
Darmstadt	-1.23278929	0.27501640	-4.4826	7.444e-06	***
Deportivo	-0.78280759	0.20882533	-3.7486	0.0001787	***
Dijon	-0.93649917	0.23031812	-4.0661	4.812e-05	***
Dusseldorf	-1.18110821	0.22485574	-5.2527	1.525e-07	***
Eibar	-0.68323739	0.20928829	-3.2646	0.0010994	**
Eintracht	-0.65513326	0.20635763	-3.1747	0.0015036	**
Elche	-0.66414347	0.24309974	-2.7320	0.0063050	**
Empoli	-0.86542053	0.25107375	-3.4469	0.0005691	***
Espanyol	-0.66638629	0.21343770	-3.1222	0.0017997	**
Everton	-0.03572204	0.20665291	-0.1729	0.8627644	
Evian	-1.10181854	0.23029092	-4.7845	1.735e-06	***
Fiorentina	-0.34612830	0.20429117	-1.6943	0.0902371	.
Freiburg	-0.93105269	0.21716224	-4.2874	1.823e-05	***
Frosinone	-1.24507544	0.27560620	-4.5176	6.316e-06	***

Fulham	-0.35753187	0.22033425	-1.6227	0.1046850	
Gazelec	-0.91683919	0.27189495	-3.3720	0.0007486	***
Genoa	-0.83305134	0.20356029	-4.0924	4.298e-05	***
Getafe	-0.65919212	0.21149789	-3.1168	0.0018328	**
Girona	-0.98547836	0.25571867	-3.8538	0.0001169	***
Granada	-0.71190841	0.20607856	-3.4545	0.0005532	***
Guingamp	-1.11981539	0.20967983	-5.3406	9.438e-08	***
Hamburg	-0.99276268	0.20812029	-4.7701	1.863e-06	***
Hannover	-0.97271103	0.20948129	-4.6434	3.464e-06	***
Hellas	-0.95277565	0.21998232	-4.3311	1.496e-05	***
Hertha	-0.60531888	0.21510659	-2.8140	0.0049005	**
Hoffenheim	-0.62618561	0.21094790	-2.9684	0.0029993	**
Huddersfield	-0.56148935	0.21655755	-2.5928	0.0095318	**
Huesca	-1.54289427	0.30994538	-4.9780	6.518e-07	***
Hull	-0.44099242	0.21728999	-2.0295	0.0424289	*
Ingolstadt	-1.27438722	0.22774927	-5.5956	2.249e-08	***
Inter	-0.03073592	0.20994132	-0.1464	0.8836063	
Juventus	0.20781546	0.21748459	0.9555	0.3393240	
Koln	-0.88239746	0.22136934	-3.9861	6.758e-05	***
LasPalmas	-0.70170455	0.25172755	-2.7876	0.0053193	**
Lazio	-0.33826859	0.21124033	-1.6013	0.1093277	
Lecce	-1.20088658	0.34799839	-3.4508	0.0005608	***
Leganes	-0.51927518	0.26672817	-1.9468	0.0515787	.
Leicester	-0.20614083	0.21779986	-0.9465	0.3439290	
Leipzig	-0.18273441	0.23844022	-0.7664	0.4434693	
Levante	-0.78033218	0.21097708	-3.6987	0.0002177	***
Lille	-0.57432149	0.20922274	-2.7450	0.0060599	**
Liverpool	0.17876251	0.21551000	0.8295	0.4068465	
Livorno	-1.23914270	0.30359669	-4.0815	4.504e-05	***
Lorient	-1.05727660	0.21473975	-4.9235	8.616e-07	***
Lyon	-0.34641272	0.21249414	-1.6302	0.1030815	
Mainz	-0.83345923	0.21097416	-3.9505	7.844e-05	***
Malaga	-0.62093441	0.20607339	-3.0132	0.0025909	**
Mallorca	-1.28801753	0.35291116	-3.6497	0.0002637	***
ManCity	0.52934138	0.21369831	2.4770	0.0132614	*

ManUtd	0.26069372	0.21280127	1.2251	0.2205784	
Marseille	-0.48515655	0.22051242	-2.2001	0.0278170	*
Metz	-1.20349013	0.22677752	-5.3069	1.135e-07	***
Middlesbrough	-0.51303025	0.25004478	-2.0518	0.0402159	*
Monaco	-0.29176135	0.20173053	-1.4463	0.1481221	
Monchengladbach	-0.39169450	0.20644169	-1.8974	0.0578049	.
Montpellier	-0.90804519	0.20587802	-4.4106	1.040e-05	***
Nancy	-1.06532151	0.54004030	-1.9727	0.0485567	*
Nantes	-1.01993503	0.21308852	-4.7864	1.719e-06	***
Napoles	-0.17985111	0.22573580	-0.7967	0.4256225	
Newcastle	-0.24385340	0.20374317	-1.1969	0.2313829	
Nice	-0.60953816	0.21567988	-2.8261	0.0047195	**
Nimes	-1.29367534	0.25742383	-5.0255	5.097e-07	***
Norwich	-0.43775065	0.20932753	-2.0912	0.0365296	*
Nurnberg	-0.94077575	0.21948921	-4.2862	1.832e-05	***
Osasuna	-0.73302189	0.22611181	-3.2419	0.0011909	**
Paderborn	-1.36536255	0.21214643	-6.4359	1.275e-10	***
Palermo	-1.06302077	0.24297077	-4.3751	1.224e-05	***
Parma	-0.72436576	0.23561164	-3.0744	0.0021141	**
Pescara	-1.28270606	0.28529164	-4.4961	6.987e-06	***
PSG	0.09429968	0.22349651	0.4219	0.6730846	
QPR	-0.28552707	0.22219039	-1.2851	0.1987983	
Rayo	-0.86460253	0.22306785	-3.8760	0.0001068	***
RealBetis	-0.37293372	0.21041972	-1.7723	0.0763655	.
RealMadrid	0.51562029	0.22941595	2.2475	0.0246245	*
RealSociedad	-0.17749216	0.20674037	-0.8585	0.3906193	
Reims	-1.07006643	0.20534839	-5.2110	1.911e-07	***
Rennes	-0.74556180	0.21052055	-3.5415	0.0003994	***
Siena	-1.56480198	0.32906181	-4.7553	2.005e-06	***
Roma	-0.20759801	0.21664653	-0.9582	0.3379648	
Sampdoria	-0.71012972	0.20951366	-3.3894	0.0007027	***
Sassuolo	-0.71225263	0.20885268	-3.4103	0.0006511	***
Schalke	-0.31752098	0.21259775	-1.4935	0.1353257	
Sevilla	-0.27993443	0.20130398	-1.3906	0.1643716	
Sheffield	-0.41672684	0.25740152	-1.6190	0.1054795	

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Sochaux            -1.25152129  0.22018691  -5.6839 1.348e-08 ***
Southampton        -0.27876627  0.20647466  -1.3501 0.1770026
SPAL               -1.21643817  0.23318817  -5.2166 1.854e-07 ***
SportingGinjon     -0.87346953  0.21178471  -4.1243 3.744e-05 ***
StEtienne          -0.71125603  0.20531170  -3.4643 0.0005336 ***
Stoke              -0.31377543  0.21055937  -1.4902 0.1361989
Strasbourg         -0.89387213  0.23747420  -3.7641 0.0001680 ***
Stuttgart          -0.72594335  0.20512498  -3.5390 0.0004032 ***
Sunderland         -0.33803132  0.20470926  -1.6513 0.0987093 .
Swansea            -0.38209340  0.21075907  -1.8129 0.0698669 .
Torino             -0.61717708  0.21246297  -2.9049 0.0036810 **
Tottenham           0.11438047  0.22596262   0.5062 0.6127314
Toulouse           -1.01757986  0.20816208  -4.8884 1.030e-06 ***
Troyes             -0.99599384  0.24621049  -4.0453 5.259e-05 ***
Udinese            -0.75501638  0.19944217  -3.7856 0.0001541 ***
UnionBerlin        -1.25815135  0.22156423  -5.6785 1.391e-08 ***
Valencia            0.07057922  0.21162424   0.3335 0.7387538
Valenciennes       -0.81458744  0.22506706  -3.6193 0.0002966 ***
Valladolid         -0.91643142  0.25276491  -3.6256 0.0002895 ***
Villarreal         -0.39082569  0.21694190  -1.8015 0.0716464 .
Watford            -0.34847736  0.21060234  -1.6547 0.0980184 .
Werder             -0.84922642  0.20749196  -4.0928 4.290e-05 ***
WestBrom           -0.34827121  0.21199060  -1.6429 0.1004385
WestHam            -0.20090243  0.20715136  -0.9698 0.3321494
Wolfsburg          -0.49422991  0.20267635  -2.4385 0.0147625 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Appendix 10: robust version of the F-test, used to test the joint significance of the team dummy variables, in the salaries model, estimated by pooled OLS.

```
Model 1: restricted model
Model 2: LOGSALGROSS ~ Age + Age2 + Weight + Weight2 + PlayingTime + RATINGS +
    LeagueLastSeason + InternationalStatus + Defender + Midfielder +
    Forward + CAF + CONMEBOL + CONCACAF + AFC + OFC + ACMilan +
    Ajaccio + Alaves + Almeria + Amiens + Angers + Arsenal +
    AstonVilla + Atalanta + Athletic + AtleticoMadrid + Augsburg +
    Barcelona + Bastia + Bayer + Bayern + Benevento + Bologna +
    Bordeaux + Dortmund + Bournemouth + Braunschweiger + Brescia +
    Brest + Brighton + Burnley + Caen + Cagliari + Cardiff +
    Carpi + Catania + CeltaVigo + Cesena + Chelsea + Chievo +
    Cordoba + Crotone + CrystalPalace + Darmstadt + Deportivo +
    Dijon + Dusseldorf + Eibar + Eintracht + Elche + Empoli +
    Espanyol + Everton + Evian + Fiorentina + Freiburg + Frosinone +
    Fulham + Gazelec + Genoa + Getafe + Girona + Granada + Guingamp +
    Hamburg + Hannover + Hellas + Hertha + Hoffenheim + Huddersfield +
    Huesca + Hull + Ingolstadt + Inter + Juventus + Koln + LasPalmas +
    Lazio + Lecce + Leganes + Leicester + Leipzig + Levante +
    Lille + Liverpool + Livorno + Lorient + Lyon + Mainz + Malaga +
    Mallorca + ManCity + ManUtd + Marseille + Metz + Middlesbrough +
    Monaco + Monchengladbach + Montpellier + Nancy + Nantes +
    Napoles + Newcastle + Nice + Nimes + Norwich + Nurnberg +
    Osasuna + Paderborn + Palermo + Parma + Pescara + PSG + QPR +
    Rayo + RealBetis + RealMadrid + RealSociedad + Reims + Rennes +
    Siena + Roma + Sampdoria + Sassuolo + Schalke + Sevilla +
    Sheffield + Sochaux + Southampton + SPAL + SportingGinjon +
    StEtienne + Stoke + Strasbourg + Stuttgart + Sunderland +
    Swansea + Torino + Tottenham + Toulouse + Troyes + Udinese +
    UnionBerlin + Valencia + Valenciennes + Valladolid + Villarreal +
    Watford + Werder + WestBrom + WestHam + Wolfsburg

  Res.Df  Df  Chisq Pr(>Chisq)
1  11806
2  11659 147 8731.2  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Appendix 11: robust version of the F-Test, used to test the joint significance of the team dummy variables, in the market values model, estimated by pooled OLS.

```
Model 1: restricted model
Model 2: LOGVM ~ Age + Age2 + Weight + Weight2 + PlayingTime + RATINGS +
    LeagueLastSeason + InternationalStatus + Defender + Midfielder +
    Forward + CAF + CONMEBOL + CONCACAF + AFC + OFC + ACMilan +
    Ajaccio + Alaves + Almeria + Amiens + Angers + Arsenal +
    AstonVilla + Atalanta + Athletic + AtleticoMadrid + Augsburg +
    Barcelona + Bastia + Bayer + Bayern + Benevento + Bologna +
    Bordeaux + Dortmund + Bournemouth + Braunschweiger + Brescia +
    Brest + Brighton + Burnley + Caen + Cagliari + Cardiff +
    Carpi + Catania + CeltaVigo + Cesena + Chelsea + Chievo +
    Cordoba + Crotone + CrystalPalace + Darmstadt + Deportivo +
    Dijon + Dusseldorf + Eibar + Eintracht + Elche + Empoli +
    Espanyol + Everton + Evian + Fiorentina + Freiburg + Frosinone +
    Fulham + Gazelec + Genoa + Getafe + Girona + Granada + Guingamp +
    Hamburg + Hannover + Hellas + Hertha + Hoffenheim + Huddersfield +
    Huesca + Hull + Ingolstadt + Inter + Juventus + Koln + LasPalmas +
    Lazio + Lecce + Leganes + Leicester + Leipzig + Levante +
    Lille + Liverpool + Livorno + Lorient + Lyon + Mainz + Malaga +
    Mallorca + ManCity + ManUtd + Marseille + Metz + Middlesbrough +
    Monaco + Monchengladbach + Montpellier + Nancy + Nantes +
    Napoles + Newcastle + Nice + Nimes + Norwich + Nurnberg +
    Osasuna + Paderborn + Palermo + Parma + Pescara + PSG + QPR +
    Rayo + RealBetis + RealMadrid + RealSociedad + Reims + Rennes +
    Siena + Roma + Sampdoria + Sassuolo + Schalke + Sevilla +
    Sheffield + Sochaux + Southampton + SPAL + SportingGinjon +
    StEtienne + Stoke + Strasbourg + Stuttgart + Sunderland +
    Swansea + Torino + Tottenham + Toulouse + Troyes + Udinese +
    UnionBerlin + Valencia + Valenciennes + Valladolid + Villarreal +
    Watford + Werder + WestBrom + WestHam + Wolfsburg

  Res.Df  Df  Chisq Pr(>Chisq)
1  11806
2  11659 147 5922.5  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Appendix 12: robust version of the F-test, used to test the joint significance of the team dummy variables, in the salaries model estimated by the fixed effects estimator.

```
Model 1: restricted model
Model 2: LOGSALGROSS ~ Age + Age2 + PlayingTime + RATINGS + LeagueLastSeason +
    InternationalStatus + ACMilan + Ajaccio + Alaves + Almeria +
    Amiens + Angers + Arsenal + AstonVilla + Atalanta + Athletic +
    AtleticoMadrid + Augsburg + Barcelona + Bastia + Bayer +
    Bayern + Benevento + Bologna + Bordeaux + Dortmund + Bournemouth +
    Braunschweiger + Brescia + Brest + Brighton + Burnley + Caen +
    Cagliari + Cardiff + Carpi + Catania + CeltaVigo + Cesena +
    Chelsea + Chievo + Cordoba + Crotone + CrystalPalace + Darmstadt +
    Deportivo + Dijon + Dusseldorf + Eibar + Eintracht + Elche +
    Empoli + Espanyol + Everton + Evian + Fiorentina + Freiburg +
    Frosinone + Fulham + Gazelec + Genoa + Getafe + Girona +
    Granada + Guingamp + Hamburg + Hannover + Hellas + Hertha +
    Hoffenheim + Huddersfield + Huesca + Hull + Ingolstadt +
    Inter + Juventus + Koln + LasPalmas + Lazio + Lecce + Leganes +
    Leicester + Leipzig + Levante + Lille + Liverpool + Livorno +
    Lorient + Lyon + Mainz + Malaga + Mallorca + ManCity + ManUtd +
    Marseille + Metz + Middlesbrough + Monaco + Monchengladbach +
    Montpellier + Nancy + Nantes + Napoles + Newcastle + Nice +
    Nimes + Norwich + Nurnberg + Osasuna + Paderborn + Palermo +
    Parma + Pescara + PSG + QPR + Rayo + RealBetis + RealMadrid +
    RealSociedad + Reims + Rennes + Siena + Roma + Sampdoria +
    Sassuolo + Schalke + Sevilla + Sheffield + Sochaux + Southampton +
    SPAL + SportingGinjon + StEtienne + Stoke + Strasbourg +
    Stuttgart + Sunderland + Swansea + Torino + Tottenham + Toulouse +
    Troyes + Udinese + UnionBerlin + Valencia + Valenciennes +
    Valladolid + Villarreal + Watford + Werder + WestBrom + WestHam +
    Wolfsburg

  Res.Df  Df  Chisq Pr(>Chisq)
1   7776
2   7633 143 1673.2  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Appendix 13: robust version of the F-test, used to test the joint significance of the team dummy variables, in the market values model, estimated by the fixed effects estimator.

```
Model 1: restricted model
Model 2: LOGVM ~ Age + Age2 + PlayingTime + RATINGS + LeagueLastSeason +
    InternationalStatus + ACMilan + Ajaccio + Alaves + Almeria +
    Amiens + Angers + Arsenal + AstonVilla + Atalanta + Athletic +
    AtleticoMadrid + Augsburg + Barcelona + Bastia + Bayer +
    Bayern + Benevento + Bologna + Bordeaux + Dortmund + Bournemouth +
    Braunschweiger + Brescia + Brest + Brighton + Burnley + Caen +
    Cagliari + Cardiff + Carpi + Catania + CeltaVigo + Cesena +
    Chelsea + Chievo + Cordoba + Crotone + CrystalPalace + Darmstadt +
    Deportivo + Dijon + Dusseldorf + Eibar + Eintracht + Elche +
    Empoli + Espanyol + Everton + Evian + Fiorentina + Freiburg +
    Frosinone + Fulham + Gazelec + Genoa + Getafe + Girona +
    Granada + Guingamp + Hamburg + Hannover + Hellas + Hertha +
    Hoffenheim + Huddersfield + Huesca + Hull + Ingolstadt +
    Inter + Juventus + Koln + LasPalmas + Lazio + Lecce + Leganes +
    Leicester + Leipzig + Levante + Lille + Liverpool + Livorno +
    Lorient + Lyon + Mainz + Malaga + Mallorca + ManCity + ManUtd +
    Marseille + Metz + Middlesbrough + Monaco + Monchengladbach +
    Montpellier + Nancy + Nantes + Napoles + Newcastle + Nice +
    Nimes + Norwich + Nurnberg + Osasuna + Paderborn + Palermo +
    Parma + Pescara + PSG + QPR + Rayo + RealBetis + RealMadrid +
    RealSociedad + Reims + Rennes + Siena + Roma + Sampdoria +
    Sassuolo + Schalke + Sevilla + Sheffield + Sochaux + Southampton +
    SPAL + SportingGinjon + StEtienne + Stoke + Strasbourg +
    Stuttgart + Sunderland + Swansea + Torino + Tottenham + Toulouse +
    Troyes + Udinese + UnionBerlin + Valencia + Valenciennes +
    Valladolid + Villarreal + Watford + Werder + WestBrom + WestHam +
    Wolfsburg

  Res.Df  Df  Chisq Pr(>Chisq)
1   7776
2   7633 143 636.35  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Appendix 14: robust version of the F-test, used to test the joint significance of the team dummy variables, in the salaries model, estimated by the random effects estimator.

```
Model 1: restricted model
Model 2: LOGSALGROSS ~ Age + Age2 + Weight + Weight2 + PlayingTime + RATINGS +
    LeagueLastSeason + InternationalStatus + Defender + Midfielder +
    Forward + CAF + CONMEBOL + CONCACAF + AFC + OFC + ACMilan +
    Ajaccio + Alaves + Almeria + Amiens + Angers + Arsenal +
    AstonVilla + Atalanta + Athletic + AtleticoMadrid + Augsburg +
    Barcelona + Bastia + Bayer + Bayern + Benevento + Bologna +
    Bordeaux + Dortmund + Bournemouth + Braunschweiger + Brescia +
    Brest + Brighton + Burnley + Caen + Cagliari + Cardiff +
    Carpi + Catania + CeltaVigo + Cesena + Chelsea + Chievo +
    Cordoba + Crotone + CrystalPalace + Darmstadt + Deportivo +
    Dijon + Dusseldorf + Eibar + Eintracht + Elche + Empoli +
    Espanyol + Everton + Evian + Fiorentina + Freiburg + Frosinone +
    Fulham + Gazelec + Genoa + Getafe + Girona + Granada + Guingamp +
    Hamburg + Hannover + Hellas + Hertha + Hoffenheim + Huddersfield +
    Huesca + Hull + Ingolstadt + Inter + Juventus + Koln + LasPalmas +
    Lazio + Lecce + Leganes + Leicester + Leipzig + Levante +
    Lille + Liverpool + Livorno + Lorient + Lyon + Mainz + Malaga +
    Mallorca + ManCity + ManUtd + Marseille + Metz + Middlesbrough +
    Monaco + Monchengladbach + Montpellier + Nancy + Nantes +
    Napoles + Newcastle + Nice + Nimes + Norwich + Nurnberg +
    Osasuna + Paderborn + Palermo + Parma + Pescara + PSG + QPR +
    Rayo + RealBetis + RealMadrid + RealSociedad + Reims + Rennes +
    Siena + Roma + Sampdoria + Sassuolo + Schalke + Sevilla +
    Sheffield + Sochaux + Southampton + SPAL + SportingGinjon +
    StEtienne + Stoke + Strasbourg + Stuttgart + Sunderland +
    Swansea + Torino + Tottenham + Toulouse + Troyes + Udinese +
    UnionBerlin + Valencia + Valenciennes + Valladolid + Villarreal +
    Watford + Werder + WestBrom + WestHam + Wolfsburg

  Res.Df  Df  Chisq Pr(>Chisq)
1  11806
2  11659 147 970.67  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Appendix 15: robust version of the F-test, used to test the joint significance of the team dummy variables, in the market values model, estimated by the random effects estimator.

```
Model 1: restricted model
Model 2: LOGVM ~ Age + Age2 + Weight + Weight2 + PlayingTime + RATINGS +
    LeagueLastSeason + InternationalStatus + Defender + Midfielder +
    Forward + CAF + CONMEBOL + CONCACAF + AFC + OFC + ACMilan +
    Ajaccio + Alaves + Almeria + Amiens + Angers + Arsenal +
    AstonVilla + Atalanta + Athletic + AtleticoMadrid + Augsburg +
    Barcelona + Bastia + Bayer + Bayern + Benevento + Bologna +
    Bordeaux + Dortmund + Bournemouth + Braunschweiger + Brescia +
    Brest + Brighton + Burnley + Caen + Cagliari + Cardiff +
    Carpi + Catania + CeltaVigo + Cesena + Chelsea + Chievo +
    Cordoba + Crotone + CrystalPalace + Darmstadt + Deportivo +
    Dijon + Dusseldorf + Eibar + Eintracht + Elche + Empoli +
    Espanyol + Everton + Evian + Fiorentina + Freiburg + Frosinone +
    Fulham + Gazelec + Genoa + Getafe + Girona + Granada + Guingamp +
    Hamburg + Hannover + Hellas + Hertha + Hoffenheim + Huddersfield +
    Huesca + Hull + Ingolstadt + Inter + Juventus + Koln + LasPalmas +
    Lazio + Lecce + Leganes + Leicester + Leipzig + Levante +
    Lille + Liverpool + Livorno + Lorient + Lyon + Mainz + Malaga +
    Mallorca + ManCity + ManUtd + Marseille + Metz + Middlesbrough +
    Monaco + Monchengladbach + Montpellier + Nancy + Nantes +
    Napoles + Newcastle + Nice + Nimes + Norwich + Nurnberg +
    Osasuna + Paderborn + Palermo + Parma + Pescara + PSG + QPR +
    Rayo + RealBetis + RealMadrid + RealSociedad + Reims + Rennes +
    Siena + Roma + Sampdoria + Sassuolo + Schalke + Sevilla +
    Sheffield + Sochaux + Southampton + SPAL + SportingGinjon +
    StEtienne + Stoke + Strasbourg + Stuttgart + Sunderland +
    Swansea + Torino + Tottenham + Toulouse + Troyes + Udinese +
    UnionBerlin + Valencia + Valenciennes + Valladolid + Villarreal +
    Watford + Werder + WestBrom + WestHam + Wolfsburg

  Res.Df  Df  Chisq Pr(>Chisq)
1  11806
2  11659 147 751.61  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Appendix 16: Robust version of the F-test, used to test the joint significance of a player's position, in the salaries model, estimated by the pooled OLS.

```
Linear hypothesis test

Hypothesis:
Defender = 0
Midfielder = 0
Forward = 0

Model 1: restricted model
Model 2: LOGSALGROSS ~ Age + Age2 + Weight + Weight2 + PlayingTime + RATINGS +
    LeagueLastSeason + InternationalStatus + Defender + Midfielder +
    Forward + CAF + CONMEBOL + CONCACAF + AFC + OFC + ACMilan +
    Ajaccio + Alaves + Almeria + Amiens + Angers + Arsenal +
    AstonVilla + Atalanta + Athletic + AtleticoMadrid + Augsburg +
    Barcelona + Bastia + Bayer + Bayern + Benevento + Bologna +
    Bordeaux + Dortmund + Bournemouth + Braunschweiger + Brescia +
    Brest + Brighton + Burnley + Caen + Cagliari + Cardiff +
    Carpi + Catania + CeltaVigo + Cesena + Chelsea + Chievo +
    Cordoba + Crotone + CrystalPalace + Darmstadt + Deportivo +
    Dijon + Dusseldorf + Eibar + Eintracht + Elche + Empoli +
    Espanyol + Everton + Evian + Fiorentina + Freiburg + Frosinone +
    Fulham + Gazelec + Genoa + Getafe + Girona + Granada + Guingamp +
    Hamburg + Hannover + Hellas + Hertha + Hoffenheim + Huddersfield +
    Huesca + Hull + Ingolstadt + Inter + Juventus + Koln + LasPalmas +
    Lazio + Lecce + Leganes + Leicester + Leipzig + Levante +
    Lille + Liverpool + Livorno + Lorient + Lyon + Mainz + Malaga +
    Mallorca + ManCity + ManUtd + Marseille + Metz + Middlesbrough +
    Monaco + Monchengladbach + Montpellier + Nancy + Nantes +
    Napoles + Newcastle + Nice + Nimes + Norwich + Nurnberg +
    Osasuna + Paderborn + Palermo + Parma + Pescara + PSG + QPR +
    Rayo + RealBetis + RealMadrid + RealSociedad + Reims + Rennes +
    Siena + Roma + Sampdoria + Sassuolo + Schalke + Sevilla +
    Sheffield + Sochaux + Southampton + SPAL + SportingGinjon +
    StEtienne + Stoke + Strasbourg + Stuttgart + Sunderland +
    Swansea + Torino + Tottenham + Toulouse + Troyes + Udinese +
    UnionBerlin + Valencia + Valenciennes + Valladolid + Villarreal +
    Watford + Werder + WestBrom + WestHam + Wolfsburg

  Res.Df Df  Chisq Pr(>Chisq)
1  11662
2  11659  3 751.28  < 2.2e-16 ***
```

Appendix 17: Robust version of the F-test, used to test the joint significance of a player's position, in the market values model, estimated by the pooled OLS.

```
Linear hypothesis test

Hypothesis:
Defender = 0
Midfielder = 0
Forward = 0

Model 1: restricted model
Model 2: LOGVM ~ Age + Age2 + Weight + Weight2 + PlayingTime + RATINGS +
    LeagueLastSeason + InternationalStatus + Defender + Midfielder +
    Forward + CAF + CONMEBOL + CONCACAF + AFC + OFC + ACMilan +
    Ajaccio + Alaves + Almeria + Amiens + Angers + Arsenal +
    AstonVilla + Atalanta + Athletic + AtleticoMadrid + Augsburg +
    Barcelona + Bastia + Bayer + Bayern + Benevento + Bologna +
    Bordeaux + Dortmund + Bournemouth + Braunschweiger + Brescia +
    Brest + Brighton + Burnley + Caen + Cagliari + Cardiff +
    Carpi + Catania + CeltaVigo + Cesena + Chelsea + Chievo +
    Cordoba + Crotone + CrystalPalace + Darmstadt + Deportivo +
    Dijon + Dusseldorf + Eibar + Eintracht + Elche + Empoli +
    Espanyol + Everton + Evian + Fiorentina + Freiburg + Frosinone +
    Fulham + Gazelec + Genoa + Getafe + Girona + Granada + Guingamp +
    Hamburg + Hannover + Hellas + Hertha + Hoffenheim + Huddersfield +
    Huesca + Hull + Ingolstadt + Inter + Juventus + Koln + LasPalmas +
    Lazio + Lecce + Leganes + Leicester + Leipzig + Levante +
    Lille + Liverpool + Livorno + Lorient + Lyon + Mainz + Malaga +
    Mallorca + ManCity + ManUtd + Marseille + Metz + Middlesbrough +
    Monaco + Monchengladbach + Montpellier + Nancy + Nantes +
    Napoles + Newcastle + Nice + Nimes + Norwich + Nurnberg +
    Osasuna + Paderborn + Palermo + Parma + Pescara + PSG + QPR +
    Rayo + RealBetis + RealMadrid + RealSociedad + Reims + Rennes +
    Siena + Roma + Sampdoria + Sassuolo + Schalke + Sevilla +
    Sheffield + Sochaux + Southampton + SPAL + SportingGinjon +
    StEtienne + Stoke + Strasbourg + Stuttgart + Sunderland +
    Swansea + Torino + Tottenham + Toulouse + Troyes + Udinese +
    UnionBerlin + Valencia + Valenciennes + Valladolid + Villarreal +
    Watford + Werder + WestBrom + WestHam + Wolfsburg

  Res.Df Df  Chisq Pr(>Chisq)
1  11662
2  11659  3 834.36  < 2.2e-16 ***
```

Appendix 18: Robust version of the F-test, used to test the joint significance of a player's position, in the salaries model, estimated by the random effects estimator.

```
Linear hypothesis test

Hypothesis:
Defender = 0
Midfielder = 0
Forward = 0

Model 1: restricted model
Model 2: LOGSALGROSS ~ Age + Age2 + Weight + Weight2 + PlayingTime + RATINGS +
    LeagueLastSeason + InternationalStatus + Defender + Midfielder +
    Forward + CAF + CONMEBOL + CONCACAF + AFC + OFC + ACMilan +
    Ajaccio + Alaves + Almeria + Amiens + Angers + Arsenal +
    AstonVilla + Atalanta + Athletic + AtleticoMadrid + Augsburg +
    Barcelona + Bastia + Bayer + Bayern + Benevento + Bologna +
    Bordeaux + Dortmund + Bournemouth + Braunschweiger + Brescia +
    Brest + Brighton + Burnley + Caen + Cagliari + Cardiff +
    Carpi + Catania + CeltaVigo + Cesena + Chelsea + Chievo +
    Cordoba + Crotone + CrystalPalace + Darmstadt + Deportivo +
    Dijon + Dusseldorf + Eibar + Eintracht + Elche + Empoli +
    Espanyol + Everton + Evian + Fiorentina + Freiburg + Frosinone +
    Fulham + Gazelec + Genoa + Getafe + Girona + Granada + Guingamp +
    Hamburg + Hannover + Hellas + Hertha + Hoffenheim + Huddersfield +
    Huesca + Hull + Ingolstadt + Inter + Juventus + Koln + LasPalmas +
    Lazio + Lecce + Leganes + Leicester + Leipzig + Levante +
    Lille + Liverpool + Livorno + Lorient + Lyon + Mainz + Malaga +
    Mallorca + ManCity + ManUtd + Marseille + Metz + Middlesbrough +
    Monaco + Monchengladbach + Montpellier + Nancy + Nantes +
    Napoles + Newcastle + Nice + Nimes + Norwich + Nurnberg +
    Osasuna + Paderborn + Palermo + Parma + Pescara + PSG + QPR +
    Rayo + RealBetis + RealMadrid + RealSociedad + Reims + Rennes +
    Siena + Roma + Sampdoria + Sassuolo + Schalke + Sevilla +
    Sheffield + Sochaux + Southampton + SPAL + SportingGinjon +
    StEtienne + Stoke + Strasbourg + Stuttgart + Sunderland +
    Swansea + Torino + Tottenham + Toulouse + Troyes + Udinese +
    UnionBerlin + Valencia + Valenciennes + Valladolid + Villarreal +
    Watford + Werder + WestBrom + WestHam + Wolfsburg

  Res.Df Df  Chisq Pr(>Chisq)
1  11662
2  11659  3 64.584  6.158e-14 ***
```

Appendix 19: Robust version of the F-test, used to test the joint significance of a player's position, in the market values model, estimated by the random effects estimator.

```
Linear hypothesis test

Hypothesis:
Defender = 0
Midfielder = 0
Forward = 0

Model 1: restricted model
Model 2: LOGVM ~ Age + Age2 + Weight + Weight2 + PlayingTime + RATINGS +
    LeagueLastSeason + InternationalStatus + Defender + Midfielder +
    Forward + CAF + CONMEBOL + CONCACAF + AFC + OFC + ACMilan +
    Ajaccio + Alaves + Almeria + Amiens + Angers + Arsenal +
    AstonVilla + Atalanta + Athletic + AtleticoMadrid + Augsburg +
    Barcelona + Bastia + Bayer + Bayern + Benevento + Bologna +
    Bordeaux + Dortmund + Bournemouth + Braunschweiger + Brescia +
    Brest + Brighton + Burnley + Caen + Cagliari + Cardiff +
    Carpi + Catania + CeltaVigo + Cesena + Chelsea + Chievo +
    Cordoba + Crotone + CrystalPalace + Darmstadt + Deportivo +
    Dijon + Dusseldorf + Eibar + Eintracht + Elche + Empoli +
    Espanyol + Everton + Evian + Fiorentina + Freiburg + Frosinone +
    Fulham + Gazelec + Genoa + Getafe + Girona + Granada + Guingamp +
    Hamburg + Hannover + Hellas + Hertha + Hoffenheim + Huddersfield +
    Huesca + Hull + Ingolstadt + Inter + Juventus + Koln + LasPalmas +
    Lazio + Lecce + Leganes + Leicester + Leipzig + Levante +
    Lille + Liverpool + Livorno + Lorient + Lyon + Mainz + Malaga +
    Mallorca + ManCity + ManUtd + Marseille + Metz + Middlesbrough +
    Monaco + Monchengladbach + Montpellier + Nancy + Nantes +
    Napoles + Newcastle + Nice + Nimes + Norwich + Nurnberg +
    Osasuna + Paderborn + Palermo + Parma + Pescara + PSG + QPR +
    Rayo + RealBetis + RealMadrid + RealSociedad + Reims + Rennes +
    Siena + Roma + Sampdoria + Sassuolo + Schalke + Sevilla +
    Sheffield + Sochaux + Southampton + SPAL + SportingGinjon +
    StEtienne + Stoke + Strasbourg + Stuttgart + Sunderland +
    Swansea + Torino + Tottenham + Toulouse + Troyes + Udinese +
    UnionBerlin + Valencia + Valenciennes + Valladolid + Villarreal +
    Watford + Werder + WestBrom + WestHam + Wolfsburg

  Res.Df Df Chisq Pr(>Chisq)
1  11662
2  11659  3  91.9  < 2.2e-16 ***
```

Appendix 20: Robust version of the F-test, used to test the joint significance of the nationality group to which each player belongs, in the salaries model, estimated by the pooled OLS.

```
Hypothesis:
CAF = 0
CONMEBOL = 0
CONCACAF = 0
AFC = 0
OFC = 0

Model 1: restricted model
Model 2: LOGSALGROSS ~ Age + Age2 + Weight + Weight2 + PlayingTime + RATINGS +
    LeagueLastSeason + InternationalStatus + Defender + Midfielder +
    Forward + CAF + CONMEBOL + CONCACAF + AFC + OFC + ACMilan +
    Ajaccio + Alaves + Almeria + Amiens + Angers + Arsenal +
    AstonVilla + Atalanta + Athletic + AtleticoMadrid + Augsburg +
    Barcelona + Bastia + Bayer + Bayern + Benevento + Bologna +
    Bordeaux + Dortmund + Bournemouth + Braunschweiger + Brescia +
    Brest + Brighton + Burnley + Caen + Cagliari + Cardiff +
    Carpi + Catania + CeltaVigo + Cesena + Chelsea + Chievo +
    Cordoba + Crotone + CrystalPalace + Darmstadt + Deportivo +
    Dijon + Dusseldorf + Eibar + Eintracht + Elche + Empoli +
    Espanyol + Everton + Evian + Fiorentina + Freiburg + Frosinone +
    Fulham + Gazelec + Genoa + Getafe + Girona + Granada + Guingamp +
    Hamburg + Hannover + Hellas + Hertha + Hoffenheim + Huddersfield +
    Huesca + Hull + Ingolstadt + Inter + Juventus + Koln + LasPalmas +
    Lazio + Lecce + Leganes + Leicester + Leipzig + Levante +
    Lille + Liverpool + Livorno + Lorient + Lyon + Mainz + Malaga +
    Mallorca + ManCity + ManUtd + Marseille + Metz + Middlesbrough +
    Monaco + Monchengladbach + Montpellier + Nancy + Nantes +
    Napoles + Newcastle + Nice + Nimes + Norwich + Nurnberg +
    Osasuna + Paderborn + Palermo + Parma + Pescara + PSG + QPR +
    Rayo + RealBetis + RealMadrid + RealSociedad + Reims + Rennes +
    Siena + Roma + Sampdoria + Sassuolo + Schalke + Sevilla +
    Sheffield + Sochaux + Southampton + SPAL + SportingGinjon +
    StEtienne + Stoke + Strasbourg + Stuttgart + Sunderland +
    Swansea + Torino + Tottenham + Toulouse + Troyes + Udinese +
    UnionBerlin + Valencia + Valenciennes + Valladolid + Villarreal +
    Watford + Werder + WestBrom + WestHam + Wolfsburg

  Res.Df Df  Chisq Pr(>Chisq)
1  11664
2  11659  5 153.93  < 2.2e-16 ***
```

Appendix 21: Robust version of the F-test, used to test the joint significance of the nationality group to which each player belongs, in the market values model, estimated by the pooled OLS.

```
Hypothesis:
CAF = 0
CONMEBOL = 0
CONCACAF = 0
AFC = 0
OFC = 0

Model 1: restricted model
Model 2: LOGVM ~ Age + Age2 + Weight + Weight2 + PlayingTime + RATINGS +
    LeagueLastSeason + InternationalStatus + Defender + Midfielder +
    Forward + CAF + CONMEBOL + CONCACAF + AFC + OFC + ACMilan +
    Ajaccio + Alaves + Almeria + Amiens + Angers + Arsenal +
    AstonVilla + Atalanta + Athletic + AtleticoMadrid + Augsburg +
    Barcelona + Bastia + Bayer + Bayern + Benevento + Bologna +
    Bordeaux + Dortmund + Bournemouth + Braunschweiger + Brescia +
    Brest + Brighton + Burnley + Caen + Cagliari + Cardiff +
    Carpi + Catania + CeltaVigo + Cesena + Chelsea + Chievo +
    Cordoba + Crotone + CrystalPalace + Darmstadt + Deportivo +
    Dijon + Dusseldorf + Eibar + Eintracht + Elche + Empoli +
    Espanyol + Everton + Evian + Fiorentina + Freiburg + Frosinone +
    Fulham + Gazelec + Genoa + Getafe + Girona + Granada + Guingamp +
    Hamburg + Hannover + Hellas + Hertha + Hoffenheim + Huddersfield +
    Huesca + Hull + Ingolstadt + Inter + Juventus + Koln + LasPalmas +
    Lazio + Lecce + Leganes + Leicester + Leipzig + Levante +
    Lille + Liverpool + Livorno + Lorient + Lyon + Mainz + Malaga +
    Mallorca + ManCity + ManUtd + Marseille + Metz + Middlesbrough +
    Monaco + Monchengladbach + Montpellier + Nancy + Nantes +
    Napoles + Newcastle + Nice + Nimes + Norwich + Nurnberg +
    Osasuna + Paderborn + Palermo + Parma + Pescara + PSG + QPR +
    Rayo + RealBetis + RealMadrid + RealSociedad + Reims + Rennes +
    Siena + Roma + Sampdoria + Sassuolo + Schalke + Sevilla +
    Sheffield + Sochaux + Southampton + SPAL + SportingGinjon +
    StEtienne + Stoke + Strasbourg + Stuttgart + Sunderland +
    Swansea + Torino + Tottenham + Toulouse + Troyes + Udinese +
    UnionBerlin + Valencia + Valenciennes + Valladolid + Villarreal +
    Watford + Werder + WestBrom + WestHam + Wolfsburg

  Res.Df Df  Chisq Pr(>Chisq)
1  11664
2  11659  5 248.47  < 2.2e-16 ***
```

Appendix 22: Robust version of the F-test, used to test the joint significance of the nationality group to which each player belongs, in the salaries model, estimated by the random effects estimator.

```
Hypothesis:
CAF = 0
CONMEBOL = 0
CONCACAF = 0
AFC = 0
OFC = 0

Model 1: restricted model
Model 2: LOGSALGROSS ~ Age + Age2 + Weight + Weight2 + PlayingTime + RATINGS +
    LeagueLastSeason + InternationalStatus + Defender + Midfielder +
    Forward + CAF + CONMEBOL + CONCACAF + AFC + OFC + ACMilan +
    Ajaccio + Alaves + Almeria + Amiens + Angers + Arsenal +
    AstonVilla + Atalanta + Athletic + AtleticoMadrid + Augsburg +
    Barcelona + Bastia + Bayer + Bayern + Benevento + Bologna +
    Bordeaux + Dortmund + Bournemouth + Braunschweiger + Brescia +
    Brest + Brighton + Burnley + Caen + Cagliari + Cardiff +
    Carpi + Catania + CeltaVigo + Cesena + Chelsea + Chievo +
    Cordoba + Crotone + CrystalPalace + Darmstadt + Deportivo +
    Dijon + Dusseldorf + Eibar + Eintracht + Elche + Empoli +
    Espanyol + Everton + Evian + Fiorentina + Freiburg + Frosinone +
    Fulham + Gazelec + Genoa + Getafe + Girona + Granada + Guingamp +
    Hamburg + Hannover + Hellas + Hertha + Hoffenheim + Huddersfield +
    Huesca + Hull + Ingolstadt + Inter + Juventus + Koln + LasPalmas +
    Lazio + Lecce + Leganes + Leicester + Leipzig + Levante +
    Lille + Liverpool + Livorno + Lorient + Lyon + Mainz + Malaga +
    Mallorca + ManCity + ManUtd + Marseille + Metz + Middlesbrough +
    Monaco + Monchengladbach + Montpellier + Nancy + Nantes +
    Napoles + Newcastle + Nice + Nimes + Norwich + Nurnberg +
    Osasuna + Paderborn + Palermo + Parma + Pescara + PSG + QPR +
    Rayo + RealBetis + RealMadrid + RealSociedad + Reims + Rennes +
    Siena + Roma + Sampdoria + Sassuolo + Schalke + Sevilla +
    Sheffield + Sochaux + Southampton + SPAL + SportingGinjon +
    StEtienne + Stoke + Strasbourg + Stuttgart + Sunderland +
    Swansea + Torino + Tottenham + Toulouse + Troyes + Udinese +
    UnionBerlin + Valencia + Valenciennes + Valladolid + Villarreal +
    Watford + Werder + WestBrom + WestHam + Wolfsburg

  Res.Df Df  Chisq Pr(>Chisq)
1  11664
2  11659  5 25.049  0.0001363 ***
```

Appendix 23: Robust version of the F-test, used to test the joint significance of the nationality group to which each player belongs, in the market values model, estimated by the random effects estimator

```
Hypothesis:
CAF = 0
CONMEBOL = 0
CONCACAF = 0
AFC = 0
OFC = 0

Model 1: restricted model
Model 2: LOGVM ~ Age + Age2 + Weight + Weight2 + PlayingTime + RATINGS +
    LeagueLastSeason + InternationalStatus + Defender + Midfielder +
    Forward + CAF + CONMEBOL + CONCACAF + AFC + OFC + ACMilan +
    Ajaccio + Alaves + Almeria + Amiens + Angers + Arsenal +
    AstonVilla + Atalanta + Athletic + AtleticoMadrid + Augsburg +
    Barcelona + Bastia + Bayer + Bayern + Benevento + Bologna +
    Bordeaux + Dortmund + Bournemouth + Braunschweiger + Brescia +
    Brest + Brighton + Burnley + Caen + Cagliari + Cardiff +
    Carpi + Catania + CeltaVigo + Cesena + Chelsea + Chievo +
    Cordoba + Crotone + CrystalPalace + Darmstadt + Deportivo +
    Dijon + Dusseldorf + Eibar + Eintracht + Elche + Empoli +
    Espanyol + Everton + Evian + Fiorentina + Freiburg + Frosinone +
    Fulham + Gazelec + Genoa + Getafe + Girona + Granada + Guingamp +
    Hamburg + Hannover + Hellas + Hertha + Hoffenheim + Huddersfield +
    Huesca + Hull + Ingolstadt + Inter + Juventus + Koln + LasPalmas +
    Lazio + Lecce + Leganes + Leicester + Leipzig + Levante +
    Lille + Liverpool + Livorno + Lorient + Lyon + Mainz + Malaga +
    Mallorca + ManCity + ManUtd + Marseille + Metz + Middlesbrough +
    Monaco + Monchengladbach + Montpellier + Nancy + Nantes +
    Napoles + Newcastle + Nice + Nimes + Norwich + Nurnberg +
    Osasuna + Paderborn + Palermo + Parma + Pescara + PSG + QPR +
    Rayo + RealBetis + RealMadrid + RealSociedad + Reims + Rennes +
    Siena + Roma + Sampdoria + Sassuolo + Schalke + Sevilla +
    Sheffield + Sochaux + Southampton + SPAL + SportingGinjon +
    StEtienne + Stoke + Strasbourg + Stuttgart + Sunderland +
    Swansea + Torino + Tottenham + Toulouse + Troyes + Udinese +
    UnionBerlin + Valencia + Valenciennes + Valladolid + Villarreal +
    Watford + Werder + WestBrom + WestHam + Wolfsburg

  Res.Df Df  Chisq Pr(>Chisq)
1  11664
2  11659  5 56.819  5.511e-11 ***
```