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The Big 5 leagues: The determinants of football transfer fees

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Abstract

This study aims to identify which determinants have a significant effect on football transfer fees, in the 2019/2020 summer transfer market, and for the European Big 5 leagues, using a sample of 436 individual transfers. Following Ante´s work (2019), the analysis is conducted through stepwise regression with backwards elimination with an elimination measure of p >= .2. The study identifies players' and performance characteristics, contract duration, the domestic league players are transferred to, and playing position as the determinants of transfer fees which have a positive or negative effect. Minutes Played, Goals, Through Balls, Contract Duration, Premier League and Strikers are some of the main determinants which show a positive effect on transfer fees. On the other hand, Age (squared), Fouls, Clearances and Central Defender present a negative impact. Furthermore, differences across the sub-samples concerning the Big 5 leagues, transfer size and playing position can be identified which suggests that the overall results, that is, the results from the full sample might not be the right path in terms of statistical analysis for determinants of transfer fees.

JEL Classification: C21; J41; J44; Z21; Z23; Z28.

Keywords: sports Economics; European football; transfer fees; market value.

Sumário

Este estudo pretende identificar os determinantes que têm um efeito significativo nos valores de transferência de jogadores de futebol, no mercado de transferências do verão de 2019/2020, e para as 5 principais ligas Europeias, utilizando uma amostra de 436 transferências. Dando continuidade ao trabalho de Ante (2019), a análise é conduzida através de regressões stepwise com eliminação para trás com uma medida de eliminação de $p >= 0.2$. O artigo identifica características dos jogadores, performance, duração de contrato, ligas para onde o jogador é transferido e posições em campo como determinantes do valor de transferência, que podem ter um efeito positivo ou negativo. Minutos Jogados, Golos, Passes em Profundidade, Duração de Contrato, Liga Inglesa e Ponta de Lança são alguns dos determinantes que afetam positivamente o valor de transferência. Por outro lado, Idade (ao quadrado), Faltas, Alívios e Defesa Central apresentam um efeito negativo. Além disso, são identificadas diferenças ao longo dos subgrupos relativos às 5 principais ligas Europeias, valor de transferência e posição em campo, o que sugere que os resultados relativos à amostra total podem não ser o caminho a seguir em termos de análise estatística relativamente aos determinantes do valor de transferência.

Classificação JEL: C21; J41; J44; Z21; Z23; Z28.

Palavras-chave: Economia do desporto; futebol; valor de transferências; valor de mercado.

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1. Introduction

Football has unquestionably become the most popular sport in the world (Matheson, 2017) as the 2018 FIFA World Cup Russia phenom corroborates. According to 2018 FIFA World Cup Russia - Global Broadcast and Audience Summary, the competition had 3.572 billion viewers, that is, more than half of the world´s population. Also, 1.12 billion people watched live the final. This sport´s popularity can also be seen in the amount of countries and regions where it is played, since it is played in more than 200 countries and it appears to be the most popular sport in Europe, South America, Africa and even Asia.

Furthermore, according to FIFA Big Count 2006, there are 270 million people active in football. The male and female footballers represent 265 million and, if referees and officials are included, we get to 270 million people involved in football. It represents a 10% increase over the first survey that used the same criteria in the year 2000 and, if only analyzing the women´s figures, an increase by over 50% is observed. Hence, a significant growth in these figures would be expected if a similar survey occurred nowadays.

The industry´s growth in terms of popularity and people involved in the sport was logically followed by a market value growth, that is, it resulted in an increase in the revenues and in the costs, especially due to higher wages and transfer fees. Thus, it is crucial to find an equilibrium between the financial and sporting performance due to the strong correlation of both (Baroncelli & Lago, 2006). In other words, profits depend on results on the pitch and those results depend on available financial resources. A main topic of discussion considers whether football clubs follow the win maximization model or the profit maximization model, but studies on the subject tend to converge to the same conclusion as in Garcia-del-Barrio and Szymanski (2009), that is, European football clubs tend to follow the win maximization model. Therefore, clubs aim to purchase and retain talented players to be successful. Inevitably, especially in the 5 major football leagues, also known as the 'big five' leagues (*English Premier League, La Liga, Bundesliga, Serie A* and *Ligue 1*), transfer fees and players' salaries experienced a significant increase based on the increase in the revenues and the win maximization model followed by most.

Researchers in Economics start to turn to sports to test several theories and, around 1970, the football industry started to gather attention and some academics turned their attention to it. However, until recently, researchers have focused on other sports like American football, basketball, baseball, and hockey. European football has been behind other sports when it comes to research due to several reasons such as lack of information about players wages and

"…excessive restrictions on player mobility the 'market' for football players had virtually nothing in common with the general labor market until the mid 1990s" (Frick, 2007, p. 424-425). Also, Frick (2007) acknowledges that professional team sports offer a unique opportunity for labor market research and states it as one of the reasons academics are turning to the football industry. Following that thought, "There is no research setting other than sports where we know the name, face, and life history of every production worker and supervisor in the industry. Total compensation packages and performance statistics for each individual are widely available, and we have a complete data set of worker–employer matches over the career of each production worker and supervisor in the industry…Moreover, professional sports leagues have experienced major changes in labor market rules and structure…creating interesting natural experiments that offer opportunities for analysis." (Kahn, 2000, p. 75). Hence, Frick (2007) states that the availability of detailed information on player salaries, transfer fees and contract lengths combined with the dramatic changes in the regulatory regime governing the football players´ now international labor market sums up the reasons that led to an increasing number of researchers to focus on the football industry.

Therefore, many academics have indeed focused their attention on the football industry, namely, the determinants of transfer fees. The empirical literature has been focused on buyer and seller characteristics, players characteristics and, recently, on players popularity. The thesis adds to the literature further analysis concerning indicators such as contract duration and playing positions which have not been the focus of previous research. And, following the Ante's work (2019), it also provides new insights concerning effects for particular sub-groups in terms of transfer fee size, the league the player was transferred to and playing position. Furthermore, this study adds to the literature the analysis of a particular transfer period and, to the best of my knowledge, different perspectives regarding the division of the sub-populations analyzed.

The results show that players characteristics, performance characteristics, contract duration, the domestic league players are transferred to and playing position can be identified as the main determinants of transfer fees. Furthermore, the paper states the importance of pursuing new methods of analysis such as more specific datasets or more insightful variables which depend on the data collected and available. For example, goals and age are perfect examples of variables which do not add to the literature the value aimed. And, goals expected or errors leading to goals against might be more interesting variables to analyze. The challenge might be to collect that data since it is not as easy to access as the more common variables present in the literature.

The thesis is structured in the following way. The literature review is presented in section 2. Then, section 3 exposes the hypotheses of this analysis. In section 4, the empirical approach of the study is defined, presenting the dataset and the econometric methodology. Section 5 covers results and discussion. Section 6 concludes the study.

2. Literature Review

2.1. European Football Market

The football industry has shown an unprecedent growth. According to Deloitte's Annual Review of Football Finance (2020), in 2018/2019, European football market revenue equaled €28.9 billion, a 2% growth compared to the previous season. The market has grown every year since 2001, excluding the UEFA and FIFA's international tournaments' biennial impact. Also, the 18/19 season saw an increase, to record levels, in the revenues of the 'big five' leagues. The new €700m broadcast arrangement from UEFA club competitions for the cycle 2018/2019 to 2020/2021, played a crucial role in the European market growth with clubs from the 'big five' leagues receiving most of it. However, this additional prize money distribution did not solve the revenue gaps between leagues and clubs, since 70% of it went to clubs from the 'big five' leagues. Thus, their share of the European football market ascended to 59%. Since, this distribution depends mostly on the results in UEFA club competitions (Appendix A), in which the better and more powerful teams are from the 'big five' leagues, it is easy to understand how it did not solve the problem. Moreover, with the increase of the distribution amount from UEFA clubs competitions, clubs depend even more on it to be competitive and to be able to purchase and retain talent.

European football has been a huge success in terms of generating revenue growth and has become such a complex market characterized by several ways to raise money. As figure 2.1 illustrates, in the 2018/2019 season, broadcasting takes the leads in relation to the 'big five' leagues clubs' revenues, with commercial and matchday revenues also playing an important role.

Furthermore, the revenue gap between English Premier League clubs and, La Liga and Bundesliga's clubs was extended further. Premier League clubs record revenues over £5 billion led to an increase in the disparity between the big clubs and the rest of the league, with the average revenue of the 'big six' clubs now at £500m, over three times that of the remaining clubs. For the second season in a row, wage cost growth outpaced revenue growth which resulted in a wages to revenue ratio of 61%.

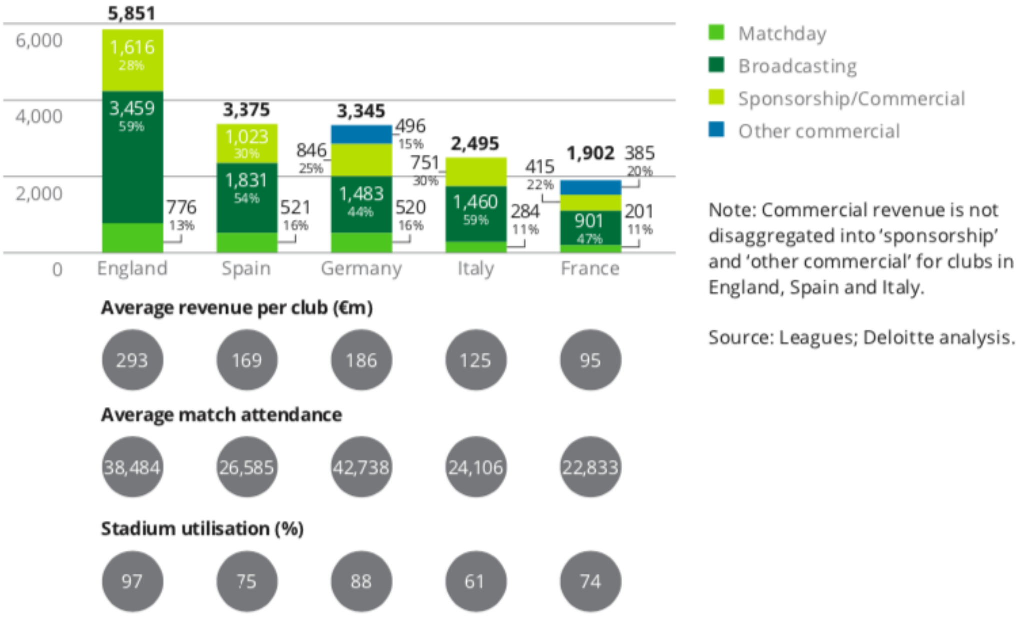

Figure 2. 1: 'Big five' European league clubs' revenue – 2018/19 (€m), Deloitte's Annual Review of Football Finance (2020)

Following this behavior, Deloitte´s review also highlights the consequences of the increasing demand for talent; it states that "It is clear that even before the onset of the COVID-19 pandemic there was some evidence of weakening cost control and profitability among Premier League clubs."(Annual Review of Football Finance, 2020, p. 3). In 2019/2020 a reduction in profitability was already expected, as it happened in 2018/2019. Higher wages and transfer fees are becoming dangerous for clubs´ finances. In 2018/2019, both Serie A and Ligue 1' clubs recorded operating losses as well as half of the Premier League's clubs. Therefore, this data supports the results of the discussions concerning whether football clubs follow the win maximization model, clubs strategy focused on sporting results that can be subject to a break-even constraint (Sloane, 1971), or the profit maximization model, clubs strategy focused on profits. Studies on the subject, as mentioned before, tend to converge to the same conclusion as Garcia-del-Barrio and Szymanski (2009) when they analyzed Spanish and English teams, that is, European football clubs tend to follow the win maximization model. Moreover, according to Deloitte's Annual Review of Football Finance 2020, in four out of the last seven seasons, a record-breaking wages to revenue ratio (107%) illustrates the EFL Championship clubs´ lack of control. And the reason is the uncontrolled pursuit of promotion to the English Premier League, the most popular league in the world and unquestionably the richest league. Deloitte's review emphasizes that "In no other industry would such a metric be viable, and whilst football benefits from the desire of many to fund those losses, the impact of the pandemic on club owners' broader finances and business interests brings the question of long-term sustainability into sharper focus than ever." (Annual Review of Football Finance, 2020, p. 3).

According to Baroncelli and Lago (2006), the equilibrium between financial and sporting performance is what defines a very well managed club. Moreover, Lago et al (2004) state that there is a Virtuous Circle between sportive results and financial resources. The circle works in various ways depending on the status of the club (big/leading clubs vs small clubs). In the case of big clubs, the great financial resources triggers the circle. The next step is to purchase talented players to create a competitive team and then, reach good sporting results. Consequentially, an increase in revenue occurs through matchday revenue, broadcasting revenue, sponsorship/commercial revenue. This increase, supposedly, reinforces the financial resources and restarts the circle. However, Baroncelli and Lago (2006) emphasize that this is a very dangerous path since many clubs tend to anticipate future revenues to create winning teams and only extremely solid teams seem capable of holding out. On the other hand, clubs that are not as financially solid as the most powerful ones, would risk their financial stability in case of sporting results failure. Furthermore, they illustrate it very well: "Fiorentina became bankrupt and was relegated to Serie C2, Lazio came close to bankruptcy and saved itself by selling all of its best players, Parma effected a substantial overhaul of its structure and started off again with a group of young players, and Roma made no important purchases for almost 2 years." (Baroncelli & Lago, 2006, p. 22). On the other hand, small clubs start by purchasing young and talented players at the lowest price possible and then, the club helps develop and highlight the best of the players to achieve the sporting results aimed. Consequentially, there is an increase in revenue, especially, through the sale of some talented players. This increase in revenue can be used to restart the circle by purchasing new players and to pay off shareholders.

Therefore, all the information presented above illustrates the need to regulate the market, not only to protect the clubs from bankruptcy but also to level the game between the more powerful clubs and the rest. The introduction, in 2009, of UEFA´s project known as Financial Fair Play stands out as the first step to protect the game from the uncontrolled pursuit of glory and to minimize competitive imbalance. Its main objectives are: to improve the economic and financial capability of the clubs, increasing their transparency and credibility; to place the necessary importance on the protection of creditors and to ensure that clubs settle their liabilities with employees, social/tax authorities and other clubs punctually; to introduce more discipline and rationality in club football finances; to encourage clubs to operate on the basis of their own revenues; to encourage responsible spending for the long-term benefit of football; to protect the long-term viability and sustainability of European club football. However, as reality shows, the

Financial Fair Play (FFP) has several lacunae and some researchers present evidence that leads to the following conclusion: “Overall, our results are consistent with the view that FFP tends to make European football leagues less equilibrated and to freeze current hierarchies. It fits into this picture that according to some authors FFP rules may be violating European Union antitrust laws (e.g., Kaplan, 2015).” (Birkhäuser et al, 2017, p. 31).

2.2. The Transfer Market

The process of acquiring a player depends on the characteristics of both the buying and the selling club. Moreover, Frick (2007) states that “The more successful the buying and/or the selling club is (either in economic or in sporting terms), the higher the transfer fee that the two clubs agree upon.” (p. 431). This process can be described as a classic bargaining scenario (Carmichael & Thomas, 1993).

The Bosman ruling enabled the modern automatic free transfer. It dictates that a player is permitted to leave their club at the end of the contract, without the need to command a transfer fee. The rule was introduced in 1995 after the consolidation of 3 separate legal cases, all involving the Belgian midfielder Jean-Marc Bosman. Before the ruling was introduced, clubs were under no constraints to let players leave at the end of their contracts without a transfer fee, though they could choose to allow them to leave on a free transfer. Bosman´s contract with RFC Liege had expired and he was keen to move to Dunkirk. RFC Liege however asked for a transfer fee, more than what Dunkirk was willing to offer and the move fell apart. The Belgian club then cut Bosman’s wages by 75% and refused to sell him. Unable to move Bosman took the club, the Belgian FA and eventually UEFA to court, before the court declared that the rule restricted the free movement of workers as insured by the Treaty of the European Union, thus the creation of the Bosman ruling. The ruling significantly changed the landscape of football, giving more power to the players. This resulted in three outcomes: greatly increased players’ wages; the rise of modern player agents; and enhanced domestic dominance of the wealthier clubs. With players now able to move without transfer fees, the only way for suiting clubs to entice the best talent was through offering more attractive salaries. A popular example of this is Sol Campbell’s move to Arsenal. At Arsenal, in 2001, Campbell earned £100,000 per week. A decade earlier no one was even earning £10,000. Moreover, in 2010, Carlos Tévez became the first to earn £1 million per month, that is, £286,000 per week. With the increased wages, came the agents. There was significantly more interest for agents and other middlemen, who was suddenly involved in every aspect of player’s transfers and management, with much larger income as their reward. Finally, the ruling also reinforced the wealth disparity between clubs.

Clubs that were able to offer the best wages inevitably collected the greatest hands. Small clubs suddenly had a severely reduced ability to retain their best players as talent flooded to top. The Bosman ruling stands out as the turning point in the history of football. In a positive sense, it enabled greater freedom for workers but in a negative sense, it unintentionally morphed football into its current status, in which the clubs with the deepest pockets have an even greater chance of winning.

In 2019, according to FIFA´s Global Transfer Market Report 2019 - Men, 18,042 international transfers occurred all around the world, increasing 9.1% compared to the previous year, which represents the largest year-on-year increase recorded since the use of the International Transfer Matching System (ITMS) became mandatory in 2010 and represents – for the eighth consecutive year – a new record. However, permanent club-to-club transfers only represented 11.6% of all transfers. Also, the report identifies loan-related transfer as a significant share: loans (13.5%), loan extensions (0.8%), loan to permanent transfers (1.2%) and transfers of players returning from loans (8.6%). Still, as expected every year, players out of contract represent the largest share, that is, 64.3% of all transfers completed in 2019. The Bosman ruling had a clear impact on these results. Even though hiring players out of contract, with no transfer fee involved, appears to be cheaper, that is not necessarily true. Players out of contract usually ask for a signing bonus to sign for a new club. This data is usually not disclosed but unofficial information within points to high sums and, according to Frick (2007), anecdotal evidence suggests that the amounts involved are comparable with transfer fees paid for similar players under contract at the time they move to other club.

According to FIFA´s Global Transfer Market Report 2019 – Men, transfer fees also had an unprecedent growth, reaching the amount of $7.35 billion in international transfers in 2019 which represents a 5.8% increase from 2018. This amount resulted only from 14.9% of all international transfers, since the remaining 85.1% did not include a transfer fee. Moreover, 84.3% was declared as fixed transfer fees, 14.5% as conditional fees, and 1.2% as release (buy-out) fees. In 2019, the average fee equaled $2.7 million which represents a 6.5% decrease from 2018. The report states the higher number of transfer fees as the main reason for the total transfer fees increase. Also, it is important to mention that FIFA recognize six confederations (AFC, CAF, CONCACAF, CONMEBOL, OFC, and UEFA) and UEFA, as expected, was the most active on the transfer market in 2019. European clubs were involved in 76.2% of the total value of transfer fees, which totaled the amount of $5.6 billion. Furthermore, the transfer not involving a European club only represent 5.3% of the total value of transfer fees.

The ‘big five’ leagues, as usual, were the ones who spent the most in 2019. These leagues concentrate the financially most powerful football clubs on the planet. According to FIFA´s Big 5 Report – Transfer Window Analysis Summer 2019 – Men´s Football, from June 1st to September 2nd, Big 5 clubs expenditure on transfer fees totaled $4.38 billion, which represents a 8.3% increase from the same period in 2018. However, clubs from the ‘big five’ leagues were responsible for 94.6%. *Premier League, La Liga, Bundesliga, Serie* A and *Ligue 1* were responsible for 91.6%, 95.3%, 92.0%, 98.8% and 98.1%, respectively, of their specific associations’ expenditure on international transfer fees.

In 2019, according to FIFA´s Global Transfer Market Report 2019 – Men, players involved on transfers completed had a wide age range, from 15 to 46 years old. As mentioned before, there are different types of transfers and it is important to highlight how the different types varied depending on the age of the player, as the figure 2.2 shows. Out of contract transfers were the most common type in all age groups, but it is important to mention the significant percentage variation on the different age groups, that is, out of contract transfers increase in terms of percentage from the first age group to the next and so on. In the case of players aged 36 or older, out of contract transfers represent 97.5% of all completed transfers. Permanent transfers were more common for players under 18.

Fig. 26: Type of transfer by player age (2019)

Player age	Out of contract	Permanent	Loan	Return from loan	Loan to permanent	Loan extension
<18 years old[2]	56.5%	32.6%	8.3%	0.9%	1.3%	0.4%
18-23 years old	52.5%	14.2%	19.5%	11.1%	1.6%	1.1%
24-29 years old	68.7%	10.6%	10.8%	8.1%	1.1%	0.7%
30-35 years old	86.1%	5.5%	4.2%	3.5%	0.6%	0.2%
≥36 years old	97.5%	1.7%	0.8%	0.0%	0.0%	0.0%

[2] Transfers of player under 18 only occur after approval of the respective minor application by a single judge of the FIFA Players' Status Sub-committee.

Figure 2. 2: Type of transfer by player age (2019), FIFA´s Global Transfer Market Report 2019 – Men

Furthermore, age also appears to be an important indicator regarding contract duration. As figure 2.3 shows, the contract duration decreases from the first age group to the next and so on. Also, players aged under 18 represent 36.1% of all transfer with fees which is more than double the share of any other age group. And as one may expect, players aged 36 or older only represent

2.5% of all transfers with fees. Once again, players aged under 18 correspond to the largest share, 27.0%, of all transfers in which sell-on fees were included. On the other hand, players aged 30 to 35 correspond to only 1.4% and it does not occur with players aged 36 or older. However, players aged 18 to 23 represent 51.8% ($3.8 billion) of the total expenditure on transfer fees. Players aged under 18, aged 24 to 29, aged 30-35 and aged 36 or older totaled $78.9 million, $3.058.3 million, $403.2 million, and $2.3 million, respectively. In terms of average transfer, players aged 18 to 23 and 24 to 29 equaled $2.8 million, the highest value. But players aged 30 to 35 were not far from it ($2.5 million). Players under 18 years old equaled to $1 million and in the last place, players aged 36 or older equaled $0.8 million. Thus, the data presented in this report shows how age might be a significant determinant of football transfers.

Fig. 27: Average duration of contract with the new club by player age (2019)

Player age	Avg. contract duration
<18 years old[2]	27.6 months
18-23 years old	21.7 months
24-29 years old	17.8 months
30-35 years old	13.7 months
≥36 years old	10.9 months

Figure 2. 3: Average duration of contract with the new club by player age (2019), FIFA´s Global Transfer Market Report 2019 - Men

FIFA´s Global Transfer Market Report 2019 – Men also divides the number of players transferred to other club by nationality and concludes that Brazilian was by far the most common, as figure 2.4 shows. It states that Brazilians, Argentinians and British players have been the most represented in international transfers since the introduction of ITMS in October 2010. Brazilians also represent the largest share of transfer fees, which corresponds a 12.6% of the total spending on transfer fees all around the world. However, figure 2.5 shows that French players shortened the gap to Brazilian players and got the second place. Thus, nationality presents itself as a possible transfer fee determinant.

Fig. 31: Top 10 player nationalities by number of transfers (2019). In parentheses, change from 2018

Nationality	Transfers	
Brazilian	1,988	(+13.4%)
Argentinian	946	(+6.1%)
British	801	(+15.8%)
French	726	(+8.5%)
Colombian	633	(+2.9%)
Spanish	542	(+10.8%)
Nigerian	508	(+0.2%)
Ghanaian	444	(+6.5%)
Serbian	425	(-5.1%)
Uruguayan	423	(+11.6%)

Figure 2. 4: Top 10 player nationalities by number of transfers (2019), FIFA´s Global Transfer Market Report 2019 - Men

Fig. 32: Top 10 player nationalities by value of transfers (2019). In parentheses, change from 2018

Nationality	Spending (USD million)	
Brazilian	925.0	(-19.4%)
French	826.7	(+14.4%)
Portuguese	544.5	(-5.1%)
Belgian	500.4	(+194.9%)
Spanish	460.9	(-22%)
Argentinian	397.1	(+7.5%)
Dutch	386.2	(+63.4%)
British	277.9	(+47.2%)
Croatian	230.0	(+52.3%)
Italian	153.6	(-23.8%)

Figure 2. 5: Top 10 player nationalities by value of transfers (2019), FIFA´s Global Transfer Market Report 2019 - Men

2.3. Determinants of Transfer Fees Literature

The first two sets of variables are used to evaluate the bargaining power of each club. The researchers have used variables which aim to reflect how powerful each club is in terms of financial resources or sporting results and, the literature tends to converge to the conclusion that the more powerful the buyer and selling clubs are, the higher is the transfer fee (Frick, 2007). Garcia-del-Barrio and Pujol (2020) findings support this idea by stating that "…the higher the media visibility status of the buying team, the higher the actual transfer fee paid for the player. This feature is congruent with top teams fiercely competing for a small number of very top players. This also reflects that financially powerful clubs are more capable to generate greater economic returns from the players' media visibility, thereby allowing them to pay an additional price premium." (p.17). Moreover, Carmichael and Thomas (1993) state that the selling club bargaining power is higher. Stadium attendance (Carmichael & Thomas, 1993) and clubs domestic league position (Dobson et al., 2000) are also examples of variables used in these analyses. On the other hand, contract duration might be another determinant of the bargaining power of each club and as a result, a determinant of transfer fees. Theoretically, the higher the number of remaining days on a player's contract, the higher the bargaining power of the selling club and vice versa. Additionally, researchers have found evidence of a positive correlation between contract duration and transfer fees (Feess et al., 2004; Geurts, 2016; Garcia-del-Barrio & Pujol, 2020).

The set of variables related to player characteristics can be divided into: player characteristics in terms of demographics and physical attributes; player performance in terms of on-pitch performance; and player popularity through external sources like social media or news (Ante, 2019).

First, regarding player characteristics in terms of demographics and physical attributes, the literature has found a positive correlation between the variable age and transfer fees (Carmichael et al., 1999; Frick & Lehmann, 2001; Dobson et al., 2000). Furthermore, to account for non-linear relationships, the empirical literature tends to use the quadratic term for the variable age and has identified a negative correlation between age (squared) and transfer fees (Carmichael et al., 1999; Dobson et al., 2000; Eschweiler & Vieth, 2004; Feess et al., 2004; Müller et al., 2017; Ante, 2019). These results can be explained by the fact that, in sports, a player's career is characterized by a peak in terms of physical conditions and performance results. Literature has also identified a positive influence of height and footedness on transfer fees, which might be explained by the advantage in aerial duels and the advantage in terms of skill and unpredictability respectively (Bryson et al., 2013; Fry et al., 2014; Ante, 2019). Additionally, weight has shown a significant effect on transfer fees, negative or positive depending on the groups analyzed (Ante, 2019).

Playing position can be divided in four major groups: goalkeepers, defenders, midfielders, and forwards. Goalkeepers have a negative influence on transfer fees, while defenders, midfielders and forwards showed a positive effect (Eschweiler & Vieth, 2004). Goalkeepers being transferred for high sums is a very rare phenomenon (Sahakian et al., 2020). Moreover, forwards also revealed a positive correlation in other studies (Reilly & Witt, 1995; Feess et al., 2004; Frick, 2007; Ante 2019). Although, this type of division is very simplistic since a player´s role on the field is much more complex and diverse than what that division illustrates.

Nationality has also been a variable studied in the literature and it has shown significant results. The literature has found a positive correlation between South Americans and transfer fees (Frick & Lehmann, 2001; Feess et al., 2004; Ante, 2019). On the other hand, North Americans or Asians have a negative effect on transfer fees (Frick & Lehmann, 2001; Ante, 2019). However, Ante (2019) emphasizes the differences in the results concerning the variable nationality across the different leagues.

In terms of performance characteristics, the literature have found a positive effect on transfer fees for domestic league games (Carmichael & Thomas, 1993; Garcia-del-Barrio &

Pujol, 2007), career games (Feess et at., 2004; Franck & Nüesch, 2012), substitute appearances (Bryson et al., 2013) and minutes played (Ruijg & van Ophem, 2015; Müller et al., 2017; Ante, 2019). Moreover, the literature has identified a positive correlation between goals scored in the previous season and transfer fees (Carmichael et al., 1999; Dobson et al., 2000). Additionally, assists also show a positive effect on transfer fees (Müller et al., 2017). Recently, researchers have focused on several different measures of player performance and they have been expanding the literature in terms of data performance analysis, as previously studies used to focus on the variables concerning goal scoring and assists. Müller et al. (2017) identified a significant correlation between many variables (passes, successful passes, aerial duels, tackles, and yellow cards) and transfer fees. Moreover, Ante (2019) found significant effects of yellow cards, fouls, minutes played and interceptions on transfer fees but tested several others (e.g. bad controls, aerials won, offsides, shots, long balls, tackles, red cards).

Lastly, player popularity is a variable more and more important as the years go by as mentioned before, the European football market has witnessed an unprecedent growth and the increase in revenues that followed had an effect on transfer fees. Currently, a player can generate revenue by drawing masses to the stadium but also through broadcasting, commercial revenue, and merchandising. The controversial topic concerning players' image right deals effectively illustrates how the popularity of a player might be determinant. Researchers have identified significant effects of popularity on transfer fees (Garcia-del-Barrio & Pujol, 2007; Franck & Nüesch, 2012; Müller et al., 2017; Ante, 2019). Furthermore, Garcia-del-Barrio and Pujol (2020) use an index of media visibility (the main explanatory variable) to capture both in-field and off-field talent of soccer players which aids in explaining the market value of a player. They state in the paper that "direct sport performance indicators are already captured by means of the media visibility ratings and, therefore, there is no need for them to be explicitly included in the explanatory model". In the paper, they identify having global star players in the team as a determinant of economic returns. Moreover, "…the influence of players' media visibility as statistically relevant not just in absolute values but also in relative terms: we find a positive effect associated to increasing the relative share of the players' media status inside the roster of the selling club. In fact, along with individual media visibility scores, there is a statistically significant and positive relationship between the transfer fee actually paid and the share of media visibility that the player concentrates relative to the overall figure of his squad." (Garcia-del-Barrio & Pujol, 2020, p. 17).

Additional information on some of the studies, after Frick (2007), mentioned above is presented in table 2.1.

To sum up, researchers have been focusing their attention on the football industry and the topic regarding football players' transfers is gathering more and more attention year after year. Therefore, many academics have turned their attentions to the determinants of transfer fees. Buyer and seller characteristics, and player's characteristics stand out as the determinants more included in those analysis. However, nowadays popularity seems to be gathering most of the attention and several studies have been conducted in recent years. Thus, the quantity of the studies and the quality of the analysis and its conclusions are the reasons why popularity is left out of this paper's analysis. Furthermore, contract duration and, especially, playing positions require further analysis. To the best of my knowledge, analysis on playing positions tend to structure the variable in a simplistic way by dividing it in 4/5 playing positions. This paper aims to present a new perspective on it by dividing it in 7 playing positions as well as to conduct analysis on one of the biggest dataset regarding potential explanatory variables. Therefore, following the work of Ante (2019), this paper also aims to identify effects for particular sub-groups in terms of transfer fee size, playing position and the league the player was transferred to. It adds to the literature the analysis of a particular transfer period and, to the best of my knowledge, different perspectives regarding the division of the sub-populations analyzed.

Table 2. 1 – The determinants of popularity and transfer fees

Author(s)/Year of publication	**Data**	**Dependent Variable/ Estimation Model**	**Significant Findings**
Franck & Nüesch (2012)	1370 players from the first German soccer league for more than half an hour during the seasons 2001/2002-2004/2005	Log of Press citations (number of articles mentioning the player's name); OLS regression	**Positive:** goals; assists; shots off target; clearances, blocks and interceptions; saves to shots ratio of the goalkeeper; red cards; yellow cards.
Ruijg & van Ophem (2015)	373 transfers in the English Premier League in the season 2011–2012	Log of transfer fee; OLS regression, Heckman selection	**OLS:** minutes played (+); age (squared) (-); %golden sub (+). **Heckman:** age (squared) (-); height (+); minutes played (+);

		model and ordered probit model	red cards (+); %golden sub (+); %substitute (-); number of matches played (+). **Ordered probit:** age(squared) (+); not being a goalkeeper (+); minutes played (+); goals (+); red and yellow cards (-); %golden substitute (-).
Geurts (2016)	406 football player transfers from the Big 5 European leagues in the 2015/2016 summer transfer window	Log of transfer fee; OLS regression	**Positive:** contract duration; goals; assists; performance (normalised position-specific performance measure). **Negative:** minutes played.
Müller et al. (2017)	4,217 players from the Big 5 European leagues in the seasons 2009/2010-2014/2015	Log of market value; multilevel regression analysis	**Positive:** previous market value; minutes played; goals, assists; passes; successful passes; dribbles; aerial duels; popularity. **Negative:** age (squared); tackles; yellow cards.
Ante (2019)	389 football player transfers from the Big 5 European leagues in the 2018/19 summer transfer window	Log of transfer fee; stepwise regressions with backwards elimination - analyses on the sub-groups of transfer fee, continent and playing position	**Positive:** height; footedness; South Americans; minutes played; fouls; popularity; Premier League; forwards. **Negative:** age(squared); yellow cards; interceptions; North Americans and Asians.

Garcia-del-Barrio and Pujol (2020)	1083 football player transfers from several leagues in the seasons 2010/2011-2014/2015	Log of transfer fee; OLS regression – pooled model and separate regressions for each season	**Positive:** individual media visibility, media visibility share of the player within his team, contract duration, status of the hiring team, the domestic league of the hiring team. **Negative:** years of experience (squared), player's age at the end of the contract.

3. Hypothesis

The following hypothesis comprise the potential determinants to explain transfer fees which are based on the literature and the current context of the football industry:

- **Hypothesis 1** – transfer fees can be explained by player characteristics, such as age (squared[1]), height, weight, footedness (right, left, both).
- **Hypothesis 2** - transfer fees can be explained by performance characteristics, such as minutes played, goals, assists, penalties scored, yellow cards, red cards, tackles, interceptions, fouls, offsides won, clearances, dribbled, blocks, own goal, shots, key passes, dribbles, fouled, offsides, dispossessed, bad controls, passes, pass%, longs balls and through balls.
- **Hypothesis 3** - transfer fees can be explained by contract duration, that is, the number of days left for the end of the contract when the transfer occurs.
- **Hypothesis 4** - differences in transfer fees based on the domestic league players are transferred to (English Premier League, La Liga, Bundesliga, Serie A and Ligue 1 – Big 5 leagues).
- **Hypothesis 5** – transfer fees can be explained by playing positions, which I characterized as central defender, full-back, defensive midfielder, central midfielder, offensive midfielder, forward and striker.

[1] The empirical literature, to account for non-linear relationships, tends to use the quadratic term for the variable age.

4. Data and Methodology

In this section the data and the method are described. The analysis is comprised of 436 individual European football transfers at a particular period, the summer transfer window of the 2019/2020 season, into the Big 5 European leagues, namely, *English Premier League* (England), *La Liga* (Spain), *Bundesliga* (Germany), *Serie A* (Italy) and *Ligue 1* (France). However, the size of the sample is not identical for all the variables which will be described further ahead.

4.1. Data

In this sub-section the data is presented in detail and the dependent and independent variables are described. to account for non-linear relationships, the empirical literature tends to use the quadratic term for the variable age

The data on transfer fees, the dependent variable, was collected from *transfermarkt.com* which is recognized as, unquestionably, the best source concerning transfer fees. However, it is important to state that the data on transfer fees presented on *transfermarkt.com* does not necessarily represent the real amount paid for a player's transfer. Transfer fees paid do not always become public and even when they do, the accuracy of the data is dubious as the role of additional fees is not always explained properly.

The data on the player's characteristics was also collected from *transfermarkt.com* (Age, Footedness, Playing Position, Contract Duration and Domestic League) and *infogol.net* (Height and Weight). The reason for using two sources is the mistakes detected concerning the data on the variables Height and Weight presented on *transfermarkt.com* by comparing it with data on European leagues official sources (e.g. *premierleague.com*). Moreover, data for 27 players regarding contract duration from *transfermarkt.com* was unaccounted and hence the average contract duration by player age[2] was used as an alternative for those 27 players, according to FIFA´s Global Transfer Market Report 2019 – Men. The reason why this data might be a proper replacement for the missing data is the fact it indicates the number of days which the club aims to secure the player so it is expected that for the respective age the contract duration will tend to the values that figure 2.3 indicates.

Performance data was collected from *whoscored.com* since it presents an extensive database concerning several performance indicators and it appears to be the one which presents

[2] The average contract duration offered to players purchased in 2019 by player age.

the higher number of performance indicators. Additionally, the source has already been used in previous studies.

The dependent variable is the transfer fee (log). Additional information on the variables analyzed is presented in table 4.1.

Table 4. 1 - Summary statistics, variable definitions and sources

Observations (N); Mean; Standard Deviation (SD), Minimum (Min) and maximum (Max) - for all the variables in the dataset. Furthermore, all variables are described and their source is presented. The source (1) stands for *transfermarkt.com*, (2) for *infogol.net* and (3) *whoscored.com*.

Variable	N	Mean	SD	Min	Max	Description	Source
Transfer Fee (log)	436	1.70	1.33	-2.38	4.85	Log of the reported transfer fee in million EUR	1
Premier League	436	0.16	0.37	0	1	Dummy: Player transferred into Premier League	1
La Liga	436	0.20	0.40	0	1	Dummy: Player transferred into La Liga	1
Bundesliga	436	0.17	0.37	0	1	Dummy: Player transferred into Bundesliga	1
Serie A	436	0.27	0.45	0	1	Dummy: Player transferred into Serie A	1
Ligue 1	436	0.19	0.16	0	1	Dummy: Player transferred into Ligue 1	1
Central Defender	436	0.18	0.39	0	1	Dummy: Players main field position is central defender	1
Full-back	436	0.18	0.38	0	1	Dummy: Players main field position is full-back	1
Defensive Midfielder	436	0.06	0.24	0	1	Dummy: Players main field position is defensive midfielder	1
Central Midfielder	436	0.14	0.34	0	1	Dummy: Players main field position is central midfielder	1
Offensive Midfielder	436	0.09	0.28	0	1	Dummy: Players main field position is offensive midfielder	1
Forward	436	0.18	0.39	0	1	Dummy: Players main field position is forward	1
Striker	436	0.18	0.38	0	1	Dummy: Players main field position is striker	1
Contract Duration	436	747.48	355.94	145	1820	Time remaining (days left) on a player's contract with the selling team	1
Age2	436	582.69	174.39	289	1225	Age of the player at the time of transfer	1
Height	436	1.82	0.06	1.67	1.98	Height of the player in meters	2
Weight	436	75.50	6.48	59	100	Weight of the player in kg	2
Two-footed	436	0.03	0.16	0	1	Dummy: Player is two-footed	1
Right-footed	436	0.70	0.46	0	1	Dummy: Player is right-footed	1
Left-footed	436	0.27	0.45	0	1	Dummy: Player is left-footed	1
Minutes	436	2218.55	1042.65	16	5496	Minutes played in the season prior to the transfer	3
Goals	436	4.63	6.20	0	37	Goals scored in the season prior to the transfer	3
Penalties Scored	436	0.47	1.31	0	9	Penalties scored in the season prior to the transfer	1
Assists	436	2.86	3.26	0	23	Total of assists in the season prior to the transfer	3
Yellow Cards	436	4.38	3.17	0	18	Total of yellow cards in the season prior to the transfer	3
Red Cards	436	0.21	0.45	0	2	Total of red cards in the season prior to the transfer	3

Tackles	311	1.36	0.79	0	4.3	Tackles per game in the season prior to the transfer	3
Interceptions	311	0.86	0.59	0	2.8	Interceptions per game in the season prior to the transfer	3
Fouls	311	1.03	0.45	0.1	2.6	Fouls per game in the season prior to the transfer	3
Offsides Won	311	1.49	0.25	0	1.2	Offsides won per game in the season prior to the transfer	3
Clearances	311	1.48	1.52	0	6	Clearances per game in the season prior to the transfer	3
Dribbled	311	0.67	0.42	0	2.3	Dribbled past per game in the season prior to the transfer	3
Blocks	311	0.23	0.27	0	1.1	Blocked shots per game in the season prior to the transfer	3
Own Goal	311	0.06	0.25	0	2	Total of own goals in the season prior to the transfer	3
Shots	311	1.16	0.83	0	4.2	Shots per game in the season prior to the transfer	3
Key Passes	311	0.83	0.59	0	2.9	Key passes per game in the season prior to the transfer	3
Dribbles	311	0.87	0.69	0	4.2	Dribbles per game in the season prior to the transfer	3
Fouled	311	1.02	0.59	0	3	Fouled per game in the season prior to the transfer	3
Offsides	311	0.17	0.23	0	1.2	Offsides per game in the season prior to the transfer	3
Dispossessed	311	0.93	0.64	0	3.1	Dispossessed per game in the season prior to the transfer	3
Bad Controls	311	1.35	0.82	0	3.8	Bad controls per game in the season prior to the transfer	3
Passes	311	31.68	14.95	2.7	79.8	Passes per game in the season prior to the transfer	3
Pass%	311	78.67	7.70	43.8	100	Pass success percentage in the season prior to the transfer	3
Long Balls	311	1.73	1.46	0	7.1	Long balls per game in the season prior to the transfer	3
Through Balls	311	0.04	0.07	0	0.4	Through balls per game in the season prior to the transfer	3

4.2. Methodology

Following Ante´s work (2019), the analysis is conducted through stepwise regression with backwards elimination with an elimination measure of a p-value $p >= .2$, that is, for each model all remaining variables are regressed and the variable with the highest $p >= .2$ is eliminated. This logic is repeated until a step of $p <= .2$ for all remaining variables, which represents the final model. The elimination measure used is based on the recommendation for models with more than 25 predictors (Wang et al., 2007). It is strongly recommended to use a measure of elimination between 0.15 and 0.20 (Chowdhury & Turin, 2020) due to issues of potential strong collinearity.

In terms of correlations (Appendix D), some variables show significant correlations and a possible explanation for that is the fact some variables might influence others, for example, a player who makes a lot of tackles has a greater risk of getting booked (receive a yellow/red card) than one that does not. Furthermore, the limited size of the dataset might have an influence on it as well.

The models are also tested for multicollinearity and heteroskedasticity. In multiple regression, the variance inflation factor (VIF) is used as an indicator of multicollinearity. Researchers still argue about the critical value for the VIF test. Some claim that the critical value is 10 (Hair et al., 1995) or 5 (Ringle et al., 2015). However, others state that if the VIF value is above 4 then there is a problem with multicollinearity (Hair et al., 2010). Therefore, this analysis aims to maintain those values below 4 if possible and never above 5. Moreover, the vce(robust) option in Stata is used to solve heteroskedasticity issues and correct the OLS standard errors in those cases (Appendix C show the cases where it occurred). Lastly, the RESET test is also used and it does not raise any problem for the models except for the following ones: Transfer fee < 2.5m€ and Transfer fee > 15m€. Both sub-populations rejected the null hypothesis for the RESET test, that is, the estimated model is not correctly specified which is a limitation of the analysis regarding both sub-populations.

Overall, 17 models are tested with the log of transfer fee as the dependent variable: the full sample of football transfers; four sub-samples for transfer fees up to €2.5 million, from €2.5 million to €7.5 million, from €7.5 million to €15 million and above €15 million; five sub-samples comprising players who were transferred into each of the Big 5 leagues; and seven sub-samples comprising each playing position. However, the number of observations is not the same for every variable so by estimating the model with all the variables some of the data is lost. To prevent that loss, both the model with all the variables presented before and the model with only the variables with the highest number of observations are tested. Furthermore, the model concerning all the variables appears to be the best model so this paper will focus on it.

5. Results

This section presents the descriptive statistics and estimation results. Further interpretation of the coefficients will be discussed in section 6.

5.1. Descriptive Statistics

In this subsection, the descriptive statistics concerning the mean are presented for the entire dataset and for each sub-sample analyzed as the table 5.2 shows. These results cannot be generalized in any case since it only comprises football players who were transferred during the period under analysis.

However, before going into that analysis it might be interesting to observe some other statistics, namely, the league´s transfer flux in/out at the period under analysis. Table 5.1 shows the Big 5 leagues preferences in terms of the leagues in which they acquire new players. First, it is clear that clubs from Serie A were the ones which acquired more players, representing 27,3% of the total amount of football players transferred to the Big 5 leagues. Moreover, Premier League, La Liga, Bundesliga, Serie A and Ligue 1 clubs acquired almost half of the new players (48%, 48%, 46%, 49%, and 47%, respectively) from clubs from the same football association, which includes lower divisions. A reason for that might be that the clubs want players who have become acquainted with the country´s football culture, as well as players who already proved themselves in that particular competitive environment. It is also interesting to observe that Ligue 1 is the one who sells more to the Big 5 which might be due to the gap in revenues and the financial power between Ligue 1 and the rest of the Big 5 leagues.

Table 5. 1 – League´s transfer flux in/out from the period under analysis.

		Buyer					
		Premier League	**La Liga**	**Bundesliga**	**Serie A**	**Ligue 1**	**Total**
Seller	**Premier League**	14	7	5	6	4	36 **(8,3%)**
	La Liga	4	25	3	6	7	45 **(10,3%)**
	Bundesliga	3	2	23	1	2	31 **(7,1%)**
	Serie A	4	2	0	35	7	48 **(11%)**

	Ligue 1	9	9	6	3	26	53 **(12,1%)**
	Championship	20	2	0	1	1	24 **(5,5%)**
	La Liga 2	1	18	0	1	1	21 **(4,8%)**
	2. Bundesliga	0	0	10	1	2	13 **(3%)**
	Serie B	0	2	0	23	0	25 **(5,7%)**
	Ligue 2	0	2	1	2	14	19 **(4,4%)**
	Other Leagues	16	20	24	40	21	121 **(27,8%)**
	Total	71 **(16,3%)**	89 **(20,4%)**	72 **(16,5%)**	119 **(27,3%)**	85 **(19,5%)**	436 **(100%)**

Next, table 5.2 shows an average transfer fee equal to € 11.74m and the average player is 23.89 years old, 1.82 meters tall, weighs 75.5 kg and has a contract duration of 747 days left.

In terms of performance, on average a player was on the pitch for 2218.55 minutes and scored 4.63 goals while assisting 2.86 times in the season prior to the transfer. He was booked 4.38 yellow and 0.21 red cards while recording 1.36 tackles, 0.86 interceptions, 1.03 fouls, 1.49 offsides won, 1.48 clearances, 0.23 blocks and 0.06 own goals. Also, on average a player recorded 31.68 passes and got a successful pass percentage of 78.67.

Moving to the sub-samples concerning the leagues the player is transferred to, the Premier League has the highest average transfer fee (€21.12m), followed by La Liga (€14.14m), Bundesliga (€9.60m), Serie A (€8.57m) and Ligue 1 (€7.63m). These results are very interesting as they follow the Big 5 leagues hierarchy in terms of revenues (Deloitte's Annual Review of Football Finance, 2020) which might help to explain those numbers. Premier League has also the highest average contract duration with 829.37 days, while Ligue 1 is again at the bottom of the list with 710.75 days. In terms of age, Bundesliga hired younger players than the rest (23.07), whereas La Liga signed the oldest players (24.96). Performance-wise, Premier League (2564.58) and La Liga (2370.81) have considerably higher figures concerning minutes played.

In terms of playing position, Defensive Midfielder and Offensive Midfielder represent only 6% and 9%, respectively, of the total amount of transfers analyzed which might be due to the fact both variables represent very specific playing positions while the rest comprises a greater range of possibilities. Moreover, Forwards have the highest average transfer fee (€15.57m), followed by Strikers with (€11.93m) which might be explained by the fact that both have a higher direct goal contributions (goals + assists) than the rest.

Furthermore, in terms of transfer fee size, most transfer fees are below €2.5m with 128 transfers which represents 29% of all transfers analyzed, followed by transfer fees between €2.5m and €7.5m (114). The transfer fees over €15m (105) were more common than the ones between €7.5m and €15m (89). Also, transfers over €15m have, obviously, the highest average transfer fee with €33.09m. The results show a positive effect of contract duration with 559.10, 723.71, 760.29, 992.09, respectively, on transfer fees which might be explained by the fact clubs want to retain their greatest assets as much as possible, and having longer contract durations gives the seller club a greater bargaining power and the more powerful the buyer and selling clubs are, the higher is the transfer fee (Frick, 2007; Garcia-del-Barrio and Pujol, 2020). On the other hand, Age has a negative effect on transfer fees which goes from 23.28 for transfers over €15m to 24.64 for transfer below €2.5m. In terms of performance, several performance indicators such as minutes played, goals, assists, penalties scored and passes have a considerable positive effect on transfer fees. Expensive players usually present better performance statistics, also because their role on the field entails greater responsibility. Therefore, this positive effect on transfer fees might be explained by that.

Table 5. 2 – Descriptive Statistics on the full sample and sub-samples analyzed.

		Leagues					Playing Position							Transfer Fee (million euros)			
Variables	Full Sample	Premier League	La Liga	Bundesliga	Serie A	Ligue 1	CD	FB	DM	CM	OM	FW	ST	<2.5	2.5 – 7.5	7.5 – 15	>15
n	436	71	89	72	119	85	79	77	26	60	38	79	77	128	114	89	105
Transfer Fee (€m)	11.74	21.12	14.14	9.60	8.57	7.63	10.34	10.23	11.45	11.62	9.74	15.57	11.93	1.40	4.48	10.72	33.09
Contract Duration	747.48	829.37	724.33	739.10	747.26	710.75	764.00	739.71	688.50	768.75	688.26	771.57	746.17	559.10	723.71	760.29	992.09
Age	23.89	23.33	24.96	23.07	23.87	23.94	24.15	24.18	23.73	23.45	23.89	23.53	24.06	24.64	24.05	23.30	23.28
Height	1.82	1.82	1.80	1.82	1.84	1.80	1.87	1.80	1.84	1.81	1.79	1.77	1.83	1.82	1.82	1.81	1.82
Weight	75.50	75.49	73.87	76.67	76.65	74.64	80.19	73.96	75.73	74.97	72.18	71.73	78.08	75.25	75.54	75.49	75.78
Minutes Played	2219	2565	2371	2056	2078	2105	2508	2209	2140	2076	2192	2177	2124	1901	2167	2299	2593
Goals	4.63	5.56	5.47	5.19	3.56	3.99	1.47	1.01	1.65	2.5	3.79	7.62	11.51	3.09	3.74	4.96	7.21
Penalties Scored	0.47	0.61	0.57	0.50	0.39	0.35	0	0	0.19	0.25	0.32	0.82	1.43	0.28	0.35	0.55	0.78
Assists	2.86	3.92	3.03	3.26	2.19	2.38	0.48	3.05	1.35	2.37	4.53	4.78	3.19	1.94	2.53	3.08	4.15
Yellow Cards	4.38	3.76	4.98	4.04	4.70	4.13	5.03	4.35	5.96	5.43	4.16	3.31	3.61	4.06	4.61	4.39	4.52
Red Cards	0.21	0.14	0.19	0.15	0.28	0.24	0.29	0.21	0.23	0.22	0.13	0.20	0.16	0.19	0.23	0.27	0.16

Table 5.2 (cont.) – Descriptive Statistics on the full sample and sub-samples analyzed.

		Leagues					Playing Position							Transfer Fee (million euros)			
Variable	Full Sample	Premier League	La Liga	Bundesliga	Serie A	Ligue 1	CD	FB	DM	CM	OM	FW	ST	<2.5	2.5 - 7.5	7.5 - 15	>15
n	311	61	66	53	75	56	55	52	17	49	29	56	53	65	75	72	99
Tackles	1.36	1.30	1.23	1.38	1.40	1.50	1.44	1.95	2.23	1.71	1.39	0.90	0.56	1.40	1.38	1.37	1.31
Interceptions	0.86	0.87	0.75	0.82	0.93	0.94	1.47	1.20	1.36	0.91	0.67	0.44	0.25	0.86	0.89	0.81	0.88
Fouls	1.03	0.93	1.06	1.01	1.06	1.11	0.91	1.05	1.26	1.16	1.10	0.88	1.09	1.03	1.08	1.03	1.00
Offsides Won	0.15	0.13	0.14	0.14	0.17	0.16	0.54	0.21	0.07	0.04	0.07	0.01	0.01	0.15	0.17	0.13	0.14
Clearances	1.48	1.49	1.45	1.39	1.60	1.40	4.07	2.05	1.42	0.84	0.62	0.32	0.52	1.71	1.59	1.29	1.37
Dribbled	0.67	0.63	0.63	0.60	0.70	0.75	0.44	0.69	1.08	1.00	0.78	0.64	0.40	0.61	0.73	0.68	0.65
Blocks	0.23	0.23	0.19	0.22	0.27	0.23	0.66	0.24	0.31	0.17	0.12	0.04	0.06	0.26	0.26	0.19	0.22
Own Goal	0.06	0.07	0.05	0.06	0.07	0.05	0.15	0.12	0.06	0.04	0.03	0	0	0.06	0.05	0.10	0.03
Shots	1.16	1.22	1.24	1.25	1.00	1.12	0.50	0.58	0.84	0.99	1.20	1.70	2.07	0.87	0.97	1.28	1.41
Key Passes	0.83	0.88	0.87	0.85	0.74	0.82	0.24	0.92	0.75	0.83	1.16	1.16	0.84	0.63	0.74	0.88	0.99
Dribbles	0.87	0.96	0.84	0.98	0.71	0.91	0.34	0.86	0.62	1.00	1.10	1.39	0.70	0.62	0.70	0.99	1.07
Fouled	1.02	1.06	1.11	0.95	0.98	1.03	0.71	1.05	0.92	1.05	1.09	1.34	0.98	0.89	0.88	1.10	1.17
Offsides	0.17	0.15	0.23	0.17	0.12	0.15	0.03	0.08	0.03	0.05	0.15	0.28	0.44	0.11	0.15	0.17	0.21
Disposessed	0.93	1.09	0.92	0.91	0.81	0.96	0.23	0.65	0.78	0.98	1.23	1.41	1.26	0.68	0.83	1.00	1.12
Bad Controls	1.35	1.48	1.37	1.34	1.21	1.40	0.52	1.04	0.99	1.24	1.51	2.01	1.96	1.08	1.31	1.45	1.50
Passes	31.68	32.85	32.04	29.92	31.05	32.48	44.38	36.84	43.17	37.12	31.02	21.14	16.22	28.75	29.53	30.80	35.87
Pass%	78.67	78.86	78.37	76.59	79.52	79.66	81.93	79.07	83.67	83.10	80.27	75.86	71.31	77.47	77.57	78.72	80.26
Long Balls	1.73	1.76	1.83	1.57	1.58	1.93	3.54	1.67	2.72	2.06	1.41	0.75	0.49	1.78	1.75	1.53	1.81
Throug h Balls	0.04	0.04	0.05	0.05	0.03	0.04	0.02	0.02	0.02	0.05	0.07	0.07	0.05	0.03	0.02	0.05	0.06

5.2. Estimation Results

The evidence presented in table 5.3 comprise the final results from stepwise regressions with backwards elimination with an elimination measure of $p >= .2$ and the log of transfer fee as the dependent variable. The models include the full sample and the sub-samples concerning transfer size.

The coefficients presented can be understood as percentage variations as the dependent variable has a logarithmic scale. Moreover, multicollinearity problems are not pointed by the VIF test.

Concerning the full sample analysis, looking at the domestic leagues variables, Premier League is the only one which presents itself as a significant determinant at a 10% level of transfer fees with a positive effect (0.491; $p < 0.01$). La Liga is also present on the model for the full sample but with a p-value of 11% and a coefficient of 0.194. Moreover, Bundesliga (0.281; $p < 0.01$) and La Liga (0.145; $p < 0.05$) have a significant positive effect on transfer fees between 2.5m€ and 7.5m€, and between 7.5m€ and 15m€, respectively. For the full sample, all the rest remaining constant, a transfer fee to the Premier League is on average 49% greater than to the Bundesliga, Serie A and Ligue 1, and about 30% greater than to the La Liga.

Playing positions variables can only be identified as significant determinants across transfer size. Striker shows a hardly significant impact (0.625; $p < 0.05$) and Central Defender shows a significant negative effect (-0.349; $p < 0.05$) on transfer fees below 2.5m€ and between 2.5m€ and 7.5m€, respectively. Furthermore, across the fees between 7.5m€ and 15m€, Defensive Midfielder shows a positive influence but at a lower significance level (0.246; $p < 0.1$).

Contract duration can be identified as a significant determinant for the full sample and two sub-samples but the positive effect is extremely low despite being highly significant ($p < 0.01$). The reason for those results might be the unit of measure being days, further research should focus on analyzing it with a different unit if measure such as months or years. Age (squared) shows a highly significant negative impact (-0.001; $p < 0.01$)) on transfer fees while Height and Weight only present significant results across transfer size. Moreover, Two-footed shows a highly significant positive effect (0.971; $p < 0.01$) on transfer fees below 2.5m€, that is, ceteris paribus, being two-footed increases the transfer fee by 97,1% for that transfer size. On the other hand, Right-footed has a significant negative impact (-0.124; $p < 0.05$).

In terms of performance indicators, Yellow Cards show a significant positive effect (0.053; $p < 0.05$) for the full sample. However, it shows a significant negative effect on other sub-samples. Furthermore, the following variables have presented statistically significant effects on transfer fees for the full sample: Minutes Played (+) ; Goals (+); Fouls (-); Clearances (-); Offsides (+); Passes (+); Pass% (+); and Through Balls (+).

Table 5. 3– Results from stepwise regressions with backwards elimination predicting transfer fees for the full sample and across transfer fee size[3]

Variables	**All obs.**		**<2.5m€**		**2.5m€ - 7.5m€**		**7.5m€ - 15m€**		**>15m€**	
	Coef.	**P > |t|**	**Coef.**	**P > |t|**	**Coef.**	**P > |t|**	**Coef.**	**P > |t|**	**Coef.**	**P > |t|**
Premier League	0.491	0.000	-	-	-	-	-	-	0.147	0.136
La Liga	0.194	0.110	-	-	0.119	0.120	0.145	0.016	0.160	0.154
Bundesliga	-	-	-	-	0.281	0.000	-	-	-	-
Central Defender	-	-	-	-	-0.349	0.013	-	-	-	-
Full-back	-	-	-	-	-	-	-0.110	0.173	-	-
Defensive Midfielder	-	-	-	-	-	-	0.246	0.056	-	-
Striker	0.231	0.193	0.625	0.023	-	-	-	-	-	-
Contract Duration	0.001	0.000	-	-	0.000	0.005	-	-	0.000	0.001
Age2	-0.002	0.000	-0.001	0.011	-	-	-0.001	0.002	-	-
Height	1.153	0.197	2.050	0.076	1.916	0.001	-	-	-	-
Weight	-	-	-	-	-	-	-	-	0.017	0.020
Two-footed	-	-	0.971	0.000	-	-	-	-	-	-
Right-footed	-	-	-	-	-	-	-0.124	0.034	-	-
Minutes Played	0.000	0.074	0.000	0.154	0.000	0.000	-	-	0.000	0.001
Goals	0.031	0.013	-	-	-	-	-	-	-	-
Penalties Scored	-	-	-	-	-	-	0.031	0.105	-	-
Assists	-	-	-	-	-	-	0.026	0.016	-	-
Yellow Cards	0.053	0.011	-0.088	0.004	-0.045	0.000	0.013	0.194	-0.039	0.006
Red Cards	0.175	0.132	0.274	0.003	0.127	0.079	-0.133	0.015	-	-
Interceptions	-	-	-	-	-	-	-0.165	0.020	-	-
Fouls	-0.661	0.000	-	-	-	-	-	-	-	-
Offsides Won	-	-	-	-	-	-	0.382	0.034	-0.332	0.096
Clearances	-0.158	0.001	-	-	-	-	-	-	-	-
Dribbled	-	-	0.731	0.001	-	-	-	-	-	-
Blocks	-	-	-	-	0.265	0.159	-0.284	0.135	-	-
Own Goal	-0.328	0.117	-	-	-0.500	0.000	-	-	-	-
Key Passes	-	-	-	-	-	-	-	-	-0.117	0.186
Dribbles	-	-	0.538	0.015	-	-	-	-	0.017	0.108
Fouled	-	-	0.191	0.086	-	-	0.099	0.100	-	-
Offsides	0.983	0.000	2.041	0.000	0.358	0.036	-	-	0.342	0.051
Dispossessed	-	-	-0.552	0.022	-0.111	0.068	-0.129	0.025	-	-

[3] The following variables that did not end up in any final model are excluded: Serie A; Ligue 1; Central Midfielder; Offensive Midfielder; Forward; Left-footed; Tackles; Shots; and Long Balls. Table 5.3 does not mention any constant for the model but it is present for each model in analysis which is also valid for Table 5.4 and 5.5.

Bad Controls	-	-	-	-	-	-	-	-	-0.233	0.007
Passes	0.025	0.000	2.437	0.027	-	-	-	-	-	-
Pass%	2.226	0.011	-	-	1.283	0.002	-	-	-	-
Through Balls	1.723	0.011	-	-	-	-	-0.420	0.195	2.275	0.001
Mean VIF	1.84		2.09		2.12		1.98		1.87	
$R^2 (adj. R^2)$ [4]	0.6062		0.4587		0.6104 (0.5274)		0.4517 (0.3048)		0.4984	
n	311		65		75		72		99	

5.3. Domestic League Results

Table 5.4 shows the estimated models for the sub-samples concerning domestic leagues. Therefore, the following dummy variables leave the set of independent variables for this models to be the reference group of this analysis: Premier League; La Liga; Bundesliga; Serie A; and Ligue 1. The VIF test values presented do not suggest any multicollinearity problems.

The purpose of this section is to identify interesting differences or similarities between the results from the models in table 5.4 and the full sample, as well as to identify interesting differences across leagues. Moreover, the focus will be on the results with a $p < 0.01$ due to the high number of results and to focus on the most important determinants.

In terms of playing positions, Striker shows an enormous significant positive impact (1.203; $p < 0.01$) on transfer fees paid by Premier League clubs. On the other hand, Central Defender shows a highly significant negative impact on transfer fees paid by clubs from Ligue 1.

Contract duration, as is for the full sample, can be identified as a determinant of transfer fees, given the significant positive effect across every league in analysis with a $p < 0.01$. Age (squared) also presents similar results to the ones for the full sample.

In contrast with the full sample, both Height and Weight show a highly significant positive effects on transfer fees.

Furthermore, several performance indicators present interesting results. The following variables present similar results to the ones for full sample in at least one league: Minutes Played (+ | Bundesliga) ; Goals (+ | La Liga/Serie A); Yellow Cards (+ | All but Serie A); Red Cards (+ | Premier League/Bundesliga/Serie A); Fouls (- | All but La Liga); Clearances (- | Premier League); Offsides (+ | La Liga); Passes (+ | Premier League/Serie A); Pass% (+ | Bundesliga); and Through Balls (+ | All but Serie A). On the other hand, the following variables which were not identified as determinants of transfer fees for the full sample, now present significant results across the Big 5 leagues: Assists (- | La Liga); Tackles (-/+ | Bundesliga/Serie A); Interceptions (- | Serie A); Offsides Won (- | Bundesliga); Own Goal (- | Serie A); Key Passes (-/+ | Premier

[4] Only R^2 presented when a robust standard error cluster is used.

League/La Liga); Dribbles (+ | La Liga); Fouled (+ | Bundesliga); Dispossessed (+ | Premier League/Ligue 1); Bad Controls (- | La Liga); and Long Balls (- | Serie A).

Table 5. 4 – Results from stepwise regressions with backwards elimination predicting transfer fees across the Big 5 leagues[5]

Variables	**Premier League**		**La Liga**		**Bundesliga**		**Serie A**		**Ligue 1**	
	Coef.	**P > |t|**	**Coef.**	**P > |t|**	**Coef.**	**P > |t|**	**Coef.**	**P > |t|**	**Coef.**	**P > |t|**
Central Defender	-	-	-	-	-	-	-	-	-1.022	0.002
Full-back	0.666	0.013	-0.581	0.025	-	-	-0.458	0.087	-0.687	0.016
Defensive Midfielder	0.608	0.058	-	-	-	-	-	-	-	-
Central Midfielder	-	-	-0.760	0.023	-0.598	0.149	-	-	-	-
Offensive Midfielder	-	-	-	-	-	-	-	-	-0.902	0.042
Forward	0.689	0.030	-	-	-	-	-	-	-0.476	0.077
Striker	1.203	0.001	-	-	-	-	-	-	-	-
Contract Duration	0.001	0.000	0.002	0.000	0.001	0.000	0.001	0.000	0.001	0.000
Age2	-0.001	0.064	-0.001	0.031	-	-	-0.002	0.000	-0.001	0.038
Height	5.840	0.005	4.324	0.008	-	-	-	-	4.281	0.026
Weight	-0.030	0.061	-	-	-	-	0.059	0.002	-	-
Left-footed	-	-	-	-	-	-	0.400	0.103	-	-
Minutes Played			0.000	0.154	0.000	0.033	-	-	-	-
Goals			0.075	0.000	-	-	0.079	0.001	-	-
Penalties Scored	-0.072	0.190	-	-	-	-	-	-	-	-
Assists	-	-	-0.141	0.008	-	-	-	-	-	-
Yellow Cards	0.157	0.000	0.070	0.020	0.119	0.040	-	-	0.143	0.002
Red Cards	0.680	0.009	-	-	0.515	0.005	0.586	0.002	0.421	0.141
Tackles	-	-	-	-	-0.431	0.034	0.381	0.070	-	-
Interceptions	-	-	-	-	-	-	-0.547	0.082	-	-
Fouls	-1.018	0.000	-	-	-1.444	0.001	-0.581	0.035	-1.017	0.000
Offsides Won	-	-	-	-	-1.221	0.030	-	-	-	-
Clearances	-0.345	0.001	-	-	-	-	-0.143	0.153	-	-
Dribbled	-	-	0.418	0.120	0.531	0.168	-	-	-	-
Own Goal			-	-	-	-	-0.817	0.050	-	-
Key Passes	-1.013	0.000	0.622	0.013	-	-	-	-	-	-
Dribbles	-	-	1.189	0.000	0.360	0.148	-	-	-	-
Fouled	-	-	-	-	0.844	0.018	-	-	-	-
Offsides			1.184	0.013	-	-	-	-	-	-
Dispossessed	0.761	0.000	-	-	-	-	-	-	0.454	0.011
Bad Controls	-	-	-1.311	0.000	-	-	-	-	-	-
Passes	0.029	0.005	-	-	-	-	0.049	0.000	-	-
Pass%			-	-	5.571	0.000	2.469	0.116	-	-
Long Balls	-	-	-	-	-	-	-0.328	0.021	-	-
Through Balls	4.950	0.000	4.460	0.002	3.895	0.027	-	-	3.489	0.011
Mean VIF	2.53		2.60		2.24		2.35		1.60	
$\boldsymbol{R^2}(\boldsymbol{adj.R^2})$	0.7997 (0.7206)		0.8262 (0.7786)		0.6475 (0.5300)		0.7416 (0.6759)		0.6673 (0.5841)	

[5] The following variables that did not end up in any final model are excluded: Two-footed; Right-footed; Blocks; and Shots.

n	61	66	53	75	61

5.4. Playing Positions Results

Table 5.5 shows the estimated models for the sub-samples concerning playing positions. Therefore, the following dummy variables leave the set of independent variables for this models to be the reference group of this analysis: Central Defender; Full-Back; Defensive Midfielder; Central Midfielder; Offensive Midfielder; Forward; and Striker. The VIF test values presented do not suggest multicollinearity problems.

The purpose of this section is to identify interesting differences or similarities between the results from the models in table 5.5 and the full sample, as well as to identify interesting differences across playing positions. Moreover, the focus will be on the results with a $p < 0.01$. However, it is important to state that there are no results for two (Defensive Midfielder with N=19 and Offensive Midfielder with N=29) of the seven playing positions the paper aimed to analyze due to the small size of the sample.

Across playing positions, all leagues except Bundesliga can be identified as determinants of transfer fees. Both Premier League (0.843) and La Liga (0.922) show a highly significant effect for the sub-sample Central Defender, while Premier League (1.811), Serie A (1.056) and Ligue 1 (0.850) show a highly significant effect for the sub-sample Striker.

Contract duration and Age (squared) continue to present similar results to the ones from the full sample. In contrast with the full sample, Left-footed shows highly significant positive effects on transfer fees.

Performance-wise, 21 variables can be identified as determinants of transfer fees. The following variables present similar results for at least one sub-sample to the ones from the full sample: Minutes Played (+ | Full-Back) ; Goals (+ | Central Defender/Forward/Striker); Yellow Cards (+ | Central Defender/Central Midfielder); Red Cards (+ | Central Defender); Fouls (- | All but Striker); Clearances (- | Full-Back); Offsides (+ | Full-Back/Striker); Passes (+ | Central Defender/Central Midfielder); Pass% (+ | Forward); and Through Balls (+ | Forward).

Table 5. 5 – Results from stepwise regressions with backwards elimination predicting transfer fees across playing positions[6]

[6] The model could not be tested for the following sub-samples due to lack of observations: Defensive Midfielder; and Offensive Midfielder. The following variables that did not end up in any final model are excluded: Bundesliga; Weight; Two-footed; Right-footed; Penalties Scored; Blocks; and Bad Controls.

Variables	**Central Defender**		**Full-Back**		**Central Midfielder**		**Forward**		**Striker**	
	Coef.	**P > |t|**	**Coef.**	**P > |t|**	**Coef.**	**P > |t|**	**Coef.**	**P > |t|**	**Coef.**	**P > |t|**
Premier League	0.843	0.002	-	-	0.500	0.099	-	-	1.811	0.000
La Liga	0.922	0.000	-	-	-	-	0.429	0.019	-	-
Serie A	-	-	-	-	0.332	0.172	-	-	1.056	0.000
Ligue 1	-	-	-	-	-	-	-	-	0.850	0.003
Contract Duration	0.001	0.001	0.001	0.000	0.001	0.003	0.001	0.009	0.001	0.003
Age2	-0.001	0.009	-0.003	0.000	-	-	-0.004	0.000	-	-
Height	-	-	3.435	0.158	-	-	-	-	-	-
Left-footed	0.732	0.004	-0.428	0.040	-	-	-	-	-	-
Minutes Played	0.000	0.133	0.000	0.040	-	-	-	-	-	-
Goals	0.285	0.000	-	-	-	-	0.093	0.000	0.086	0.000
Assists	0.434	0.002	-0.127	0.028	-	-	0.067	0.091	-0.098	0.044
Yellow Cards	0.090	0.053	-	-	0.170	0.001	-	-	-	-
Red Cards	0.421	0.031	-	-	-	-	-	-	-	-
Tackles	-	-	-	-	-	-	0.533	0.020	-	-
Interceptions	0.493	0.018	0.678	0.015	-0.600	0.033	-	-	-	-
Fouls	-1.419	0.000	-0.554	0.072	-1.600	0.000	-0.792	0.003	-	-
Offsides Won	-	-	-	-	1.582	0.053	-	-	-	-
Clearances	-	-	-0.344	0.019	-	-	0.563	0.178	-	-
Dribbled	-	-	-0.646	0.058	0.830	0.003	-	-	-	-
Own Goal	-0.578	0.018	-	-	-	-	-	-	-	-
Shots	-	-	0.455	0.134	-	-	-	-	-	-
Key Passes	-2.079	0.011	-	-	-	-	0.408	0.069	-1.488	0.000
Dribbles	-	-	-	-	-	-	-	-	0.668	0.011
Fouled	-	-	-0.554	0.019	-	-	-	-	-	-
Offsides	-	-	5.660	0.000	-	-	0.496	0.177	1.162	0.006
Dispossessed	-	-	-	-	0.645	0.011	-	-	-	-
Passes	0.051	0.000	-	-	0.040	0.000	-	-	-	-
Pass%	-	-	-	-	-	-	4.864	0.000	-	-
Long Balls	-0.282	0.006	0.609	0.003	-0.261	0.004	-0.462	0.007	-	-
Through Balls	-	-	-	-	-	-	-	-	3.372	0.073
Mean VIF	2.04		1.84		1.93		2.24		1.92	
$\mathbf{R^2(adj. R^2)}$	0.8633 (0.8057)		0.8565 (0.8022)		0.7400 (0.6627)		0.8540 (0.8133)		0.7386 (0.6763)	
n	55		52		49		56		53	

5.5. Discussion

The results of the study meet all the expectations because not only corroborates previous studies and results from the literature, but it also conveys new insights. The values concerning R^2 (adj. R^2) are encouraging since most of them are quite significant and high. For example, if compared to a similar analysis by Ante (2019) concerning results from stepwise regressions with backwards elimination predicting transfer fees across the Big 5 leagues, it is possible to observe the R^2 (adj. R^2) for Premier League, La Liga, Bundesliga, Serie A and Ligue 1 are 0.39 (0.27); 0.44 (0.36); 0.32 (0.21); 0.32 (0.27) and 0.67 (0.56), respectively. Nevertheless, the aim of the study is to test for the relevance of each factor on transfer fees and not so much to perfectly predict/fit it.

Firstly, I identify player's characteristics as determinants of transfer fees, that is, this paper's hypothesis 1 can be validated. In line with the literature, Age (squared) shows a highly significant negative impact (Carmichael et al., 1999; Dobson et al., 2000; Eschweiler & Vieth, 2004; Feess et al., 2004; Müller et al., 2017; Ante, 2019) which might be explained by the fact that, in sports, a player's career is characterized by a peak in terms of physical conditions and performance results, which is followed by a decline stage. Also, Age (squared) results are consistent for most of the sub-groups analyzed as well. Moreover, Height and footedness show a positive effect on transfer fees which, as stated before, might be due to potential advantages in terms of aerial duels and, skill and unpredictability, respectively (Bryson et al., 2013; Fry et al., 2014; Ante, 2019). Weight presents similar results to Ante´s work (2019) in the sense that shows significant effects on transfer fees, which are negative or positive depending on the sub-groups analyzed.

Secondly, several performance indicators show a significant impact on transfer fees. However, the impact, sometimes, differs through different sub-groups. I identify as determinants of transfer fee, for the full sample, the following variables: Minutes Played (+) ; Goals (+); Yellow Cards (+); Fouls (-); Clearances (-); Offsides (+); Passes (+); Pass% (+); and Through Balls (+). In line with the literature, Minutes Played shows a positive influence on transfer fees (Ruijg & van Ophem, 2015; Müller et al., 2017; Ante, 2019) and a reason for that might be the fact the indicator Minutes Played can show how much a team can rely on a player to be available to play several minutes throughout an entire season. Goals also shows a positive influence on transfer fees (Carmichael et al., 1999; Dobson et al., 2000) for the full sample and for the sub-groups La Liga, Serie A, Central Defender, Forward and Striker. Goals results are in line with what is expected in theory, especially, for the full sample because goals define games and, in particular, because players popularity depends a lot on goals scored and popularity also plays an important role on transfer fees (Garcia-del-Barrio & Pujol, 2020), and for the attacking playing positions (Forward and Striker) as well since one of their main purposes is to score goals. Moreover, Yellow Cards can be identified as a determinant of transfer fees and it shows a positive impact, which is in line with Franck and Nüesch' work (2012), for the full sample, Central Defender, Central Midfielder and across all leagues except for Serie A. On the other hand, it shows a negative impact across transfer size except for the fees between 7.5m€ and 15m€ (Ruijg & van Ophem, 2015; Müller et al., 2017; Ante, 2019). The different results might be explained, in theory, by the way the results can be interpreted, that is, teams might value more aggressive players that fight for the ball and engage in duels which easily leads to fouls and potential yellow cards or it can also be the case teams do not appreciate players who get booked regularly since it might indicate that the player can compromise the team with his risky actions. Furthermore, there are a few surprising results such as Assists and Key Passes having a negative influence for Strikers or Dispossessed having a positive effect for Central Midfielders which defy logic, to the best of my knowledge. Hence, performance indicators influence transfer fees in different ways depending on the sub-group analyzed. In addition, performance indicators that, in theory, were supposed to show significant results for specific sub-groups did not present the expected results (e.g. clearances are supposed to be a determinant for Central Defenders but the results do not show it). Following that thought, I agree with Ante (2019) as he states " (…) "overall" results might be the wrong statistical direction, as cross-sample effects clearly provide differences". However, some performance variables show consistent results across all samples: Minutes Played (+) ; Goals (+); Yellow Cards (+); Red Cards (+); Fouls (-); Clearances (-); Offsides (+); Passes (+); Pass% (+); and Through Balls (+). Therefore, in my opinion, sometimes it can be difficult to define an indicator as positive or negative because sports, namely football, is not an exact science and it is subject to interpretation as different approaches on the field by different but equally successful coaches prove. In addition, football, as every sport, is in constant change and development so what can be seen as positive today may not be perceived the same way in the future which makes the prediction of the determinants of transfer fees a difficult process. Nevertheless, hypothesis 2 can be accepted because performance indicators show a significant effect on transfer fees even though it differs across sub-groups.

Furthermore, Contract Duration has a positive influence on transfer fees as previous studies also defend (Feess et al., 2004; Geurts, 2016; Garcia-del-Barrio & Pujol, 2020). The results explanation might be related to the fact that, in theory, the higher the number of remaining days on a player's contract, the higher the bargaining power of the selling club and vice versa. Thus, the buying team has to offer a higher fee when the player has a longer contract duration because the selling team has more time to evaluate their options and to wait for the right proposal.

In terms of the leagues players are transferred to, for the full sample, Premier League is the only which can be identified as a determinant of transfer fees. The result is the expected one since Premier League clubs are usually willing to pay higher fees which might be explained by their greater financial power (Deloitte's Annual Review of Football Finance, 2020). Therefore, the interest in a player by a Premier League club obviously inflates the selling price established because selling clubs are aware those clubs can pay higher fees. La Liga and Ligue 1 for instance show a positive impact for the fees between 7.5m€ and 15m€ and, 2.5m€ and 7.5m€, respectively. A possible explanation might be that La Liga clubs having the greatest financial power after Premier League clubs (Deloitte's Annual Review of Football Finance, 2020) which means they have the power to purchase expensive players. On the other hand, Ligue 1 does not have the financial power of the other Big 5 which might explain why they are focused on players not as expensive as the ones the other big leagues pursue. Hence, I also find evidence in favor of hypothesis 4.

Lastly, playing position can be identified as a determinant of transfer fee as well. However, results for the full sample are not significant. Striker shows a positive impact on fees below 2.5m€ and Defensive Midfielder a positive impact on fees between 7.5m€ and 15m€. This might happen because, in that specific transfer period, defensive players were a priority over offensive players or because there was a higher number of offensive players available. On the other hand, Central Defender shows a negative effect for fees between 2.5m€ and 7.5m€ which might be explained by the clubs not wanting to invest that kind of money on it. Perhaps, clubs rather do higher investments in top Central Defenders than getting an average player or they might rather invest less in defensive players which would be consistent with the statistics concerning transfer fees since the most expensive players are usually offensive players.

Therefore, all hypothesis can be accepted which shows there are several determinants of transfer fees as expected and that overall results might not be reliable since results differ across sub-samples which is understandable since in sports it is all about the context. Clubs have different goals, different resources and different cultures. Thus, clubs should always evaluate a player's market value based on the club´s specific context and on the player desired and his club's context. The football industry has become so complex with players agents emerging as a tremendous force and with the sponsors increasing their power over clubs and players due to the high amounts offered by them. To perfectly predict transfer fees or the market values of players appears to be a mirage. There are too many indicators to be considered which makes statistical analysis extremely difficult.

Furthermore, clubs' goals concerning the market and also the club´s general strategy might change during the season due to several factors. Two of the most common examples that might cause potential changes are: injuries and, especially, clubs performance on the pitch. Clubs performance on the pitch and revenues have an intimate relationship. Therefore, bad performances can make the clubs change the strategy immediately. S.L. Benfica is a good example of it as the beginning of the season 2020/2021 shows. The club strategy for the season was based on a huge investment to purchase great players and win several trophies but qualifying for the Champions League changes everything since the revenues from it are unmatched. Therefore, when Benfica failed to qualify for the Champions League the strategy changed because it was based on revenues that depended on the clubs performance and the club was forced to sell their best player to balance their finances. Following that thought, it is clear that clubs strategy and the investment on the market can be very risky and the fact the market only closes after the competition already started, which is extremely debated, makes it even more difficult for clubs to know with which players they can count on for the season. Which leads us to the next point, that is, the uncertainty of the market after the competition already started combined with teams still trying to qualify for the Champions League might result in unexpected transfers. The reason for that is because it leads to clubs leaving big decisions to the end of the market and making business when the clock is ticking inflates, or undervalues transfer fees because the selling or the buying team know the other club needs to make the deal happen. Therefore, the values of transfer fees might happen due to reasons that are impossible to measure and consider when a statistical analysis is prepared.

However, empirical literature as well as this paper show statistical analysis can produce interesting findings.

Moreover, the dataset is quite small considering that it only comprises a specific transfer period which means results might only provide relevant information regarding the transfer period under analysis. However, by comparing it with results from empirical literature it is possible to find similar results which may show it would be interesting to further analyze it to corroborate and strengthen previous results and conclusions.

In addition, I would like to highlight the importance of using multiple models and of analyzing different sub-samples due to the differences found across sub-groups to provide specific insights and observe possible differences.

6. Conclusion

The thesis offers a descriptive and empirical analysis of 436 individual transfers from a particular period, the summer transfer window of the 2019/2020 season, into the Big 5 European leagues, namely, English Premier League (England), La Liga (Spain), Bundesliga (Germany), Serie A (Italy) and Ligue 1 (France). The analysis is based on multiple stepwise regressions to identify the determinants for the full sample as well as the particular effects for specific sub-samples: transfer size, the league players are transferred to and playing position. This methodology enables the comparison between the full sample and the sub-samples analyzed which produces interesting insights, especially, to conduct further research. Hence, the thesis adds to the literature the analysis of a particular transfer period and, to the best of my knowledge, different perspectives regarding the division of the sub-populations analyzed. In addition, it supports empirical findings in previous research and analyzes some variables that have not been the focus of previous literature, such as contract duration or Through-Balls . The hypothesis concerning the indicators the study aimed to identify as significant determinants of transfer fees can be all validated. Player's characteristics, performance characteristics, contract duration, the domestic league players are transferred to and playing position can be identified as determinants of transfer fees. Moreover, differences across the specific samples can be identified which indicates overall results might not be the right path in terms of statistical analysis for determinants of transfer fees.

In terms of limitations, apart from the dataset size already mentioned, the variable Age (squared) might not represent what in theory should represent. In sports, a player's career is characterized by a peak in terms of physical conditions and performance results, followed by a decline stage. But being older can be seen as having more experience or be seen as having physical limitations. And, even concerning the physical limitations side of being older, that is only true after a certain age and until that same age the interpretation is completely different because it can be the case the player´s body is still developing and it has not yet achieved all of its potential. There are a lot of variables affecting the variable age. Therefore, the variable Age (squared) might not be reliable. I think it would be of great value for further research to focus on this variable because so far, in my opinion, the literature has not found the right solution to identify how these variable affects transfer fees. Perhaps, the analysis of sub-populations by age could be an interesting starting point. In addition, the paper does not present new insights in terms of econometric methodology and it might be one of the biggest limitations of this analysis.

Furthermore, I believe the literature has been focused on variables that are too objective and which do not represent the big picture. But, most of the times it happens because the data available does not allow a more realistic analysis. For example, goals is one of the variables more subject to analysis but it only represents half the story. It might be the case a player scored 15 goals last season but the expected goals[7] were 10 or 30 which means that he is an

[7] Expected goals (or xG) measures the quality of a chance by calculating the likelihood that it will be scored from a particular position on the pitch during a particular phase of play. This value is based on several factors from before the shot was taken. xG is measured on a scale between zero and one, where

extraordinary player who scored more than expected or his composure in front of goal might not be the best. Therefore, I defend sports analysis cannot be seen as objective as the literature shows. The right path might be to invest in more detailed datasets and to analyze new and more insightful variables. In addition, as mentioned before, the fact that the data collected on transfer fees does not necessarily represent the real amount paid for a player´s transfer might be a limitation of this analysis because it means the data concerning the dependent variable might not be accurate.

To sum up, this type of analysis offers significant and interesting insights concerning transfer fees. However, further research should focus on specific sub-samples analysis to provide specific insights and observe possible differences from the overall results in which the empirical literature mainly consists as of now. Moreover, it could be interesting to analyze a dataset that contains different transfer periods to compare the results by season or to compare the winter transfer window with the summer transfer window of the same season or through the analysis of several years.

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8. Appendix

Appendix A. How clubs' 2019/20 UEFA Champions League revenue will be shared

Share for 12 clubs participating in UEFA Champions League play-offs

A total of €30m will be paid out to clubs involved in the UEFA Champions League play-offs: clubs that are eliminated will each receive a fixed payment of €5m. The winners of the play-offs will not receive any specific payment for this round but will get payments for participating in the UEFA Champions League group stage.

Share for clubs competing in the UEFA Champions League (group stage onwards)

Forecast amounts (total €1.95bn)

The net revenue available to participating clubs will be divided into four different pillars:

• 25% will be allocated to the starting fees (€488m).
• 30% will be allocated to the performance-related fixed amounts (€585m).
• 30% will be distributed on the basis of ten-year performance-based coefficient rankings (€585m).
• 15% will be allocated to the variable amounts (market pool) (€292m).

Starting fees (€488m)

Each of the 32 clubs that qualify for the group stage can expect to receive a group stage allocation of €15.25m, split into a down payment of €14.5m and a balance payment of €0.75m.

Fixed amounts (€585m)

Group stage performance bonuses will be paid for each match: €2.7m per win and €900,000 per draw. Undistributed amounts (€900,000 per draw) will be pooled and redistributed among the clubs playing in the group stage in amounts proportionate to their number of wins.

Clubs that qualify for the knockout stage can expect to receive the following amounts:

• qualification for the round of 16: €9.5m per club
• qualification for the quarter-finals: €10.5m per club
• qualification for the semi-finals: €12m per club
• qualification for the final: €15m per club
• The UEFA Champions League winners can expect to pick up an additional €4m.
• The two clubs that qualify for the 2019 UEFA Super Cup can each expect to receive €3.5m, with the winners collecting an additional €1m.

Coefficient ranking (€585m)

A new ranking was introduced last season on the basis of performances over a ten-year period. In addition to coefficient points accumulated during this period, this ranking includes bonus points for winning the UEFA Champions League/European Champion Clubs' Cup, the UEFA Europa League/UEFA Cup and the Cup Winners' Cup. On the basis of these parameters, a ranking has been established and the total amount of €585.05m has been divided into 'coefficient shares', with each share worth €1.108m. The lowest-ranked team will receive one share (€1.108m). One share will be added to every rank and so the highest-ranked team will receive 32 shares (€35.46m).

Figure A. 1: How clubs' 2019/20 UEFA Champions League revenue will be shared, UEFA (2019)

Market pool (€292m)
The estimated available amount of €292m will be distributed in accordance with the proportional value of each TV market represented by clubs taking part in the UEFA Champions League (group stage onwards). The different market shares will be distributed to the participating clubs from each association.

The various amounts distributed from the market pool on a club-by-club basis depend on five factors:

1) the actual final amount in the market pool
2) the composition of the field of clubs participating in the 2019/20 UEFA Champions League
3) the number of clubs from any given association competing in the 2019/20 UEFA Champions League
4) the final position of each competing club in their previous season's domestic championship
5) the performance of each club in the 2019/20 UEFA Champions League

Solidarity payments

Solidarity payments for the qualifying phase of the UEFA club competitions

Under the new distribution system, €107.5m will be distributed to the clubs as follows.

UEFA Champions League – champions and league paths
Each domestic champion club that does not qualify for the UEFA Champions League or UEFA Europa League group stage will receive €260,000 in addition to the amounts due for participation in each qualifying round.

Each club participating in the qualifying rounds that does not qualify for the UEFA Champions League play-offs will receive the following amounts per round played:
• preliminary round – €230,000
• first qualifying round – €280,000
• second qualifying round – €380,000
• third qualifying round – €480,000 (only for clubs eliminated from the champions path, since clubs eliminated from the league path qualify directly for the UEFA Europa League group stage and therefore benefit from its distribution system)
• No solidarity payments will be paid in the play-offs as the clubs involved will benefit from the UEFA Champions League/UEFA Europa League centralised phase distribution.

Solidarity payments to clubs that do not qualify for the group stage of the UEFA Champions League or the UEFA Europa League

The solidarity payments to non-participating clubs via their national associations will represent 4% of the overall gross revenues of the two competitions.

A forecast total of €130m will therefore be distributed to national associations for their clubs.

Figure A. 1 (continued): How clubs' 2019/20 UEFA Champions League revenue will be shared, UEFA (2019)

Appendix B. The determinants of transfer fees in European Football

The determinants of transfer fees in European football[a]

Author(s) and year of publication	Data	Dependent variable/ estimation technique	Significant findings
Eschweiler and Vieth (2004)	254 transfers in the German Bundesliga in the seasons 1997/1998–2002/2003	Log of transfer fee in constant 1996 prices; OLS regression	Positive: log sponsoring revenues and log attendance of buying club; buying/selling club qualified for European cup competition, defender, midfielder, forward (ref.: goalie), age, FIFA-coefficient of country of origin, international caps Negative: age^2, international $caps^2$
Feess, Frick and Muehlheusser (2004)	239 transfers in the German Bundesliga in the seasons 1994/1995–1999/2000	Log of standardized transfer fee; OLS regression as well as Heckman two-step estimation (with $n = 604$)	Positive: remaining contract years, remaining contract years interacted with 'Post-*Bosman*' regime, age, career games played, international caps, forward, buying club qualified for European cup competition, player is from south America Negative: age^2, career games $played^2$, player is a semi-professional
Frick and Lehmann (2001)	1,211 (out of 1,269) transfers in the German Bundesliga in the seasons 1983/1984–1999/2000	Log of transfer fee in constant 1985 prices; OLS regression	Positive: age, career games played, career goals scored, international caps, selling club from western Europe, south America, time trend Negative: age^2, career games $played^2$, international $caps^2$, selling club from German third division, north America, Asia
Dobson, Gerrard and Howe (2000)	114 (out of 198) transfers in semi-professional (non-league) English football, 1988–1997	Log of transfer fee; OLS regression	Positive: age, goals scored previous season, average attendance of selling club in previous season, number of seats in buying club's stadium, average attendance of buying club in previous season Negative: age^2, league position of selling club in previous season, goal difference of selling club in previous season, stadium capacity of buying club
Carmichael, Forrest and Simmons (1999)	240 mover as opposed to 1,789 stayer in the English football leagues in 1993/1994	Log of transfer fee; Heckman two-step procedure to control for selection bias	Positive: age, games played for current club, games played for other clubs, goals scored in league matches, goals scored in cup matches, international caps Negative: age^2, selling club playing in second, third or fourth division
Dobson and Gerrard (1999)	1,350 english football League transfer fees (out of 2,215 moves), June 1990–August 1996	Log of transfer fee in constant 1990 prices; OLS regression	Positive: age, career games played, career goal scoring rate, games previous season, goals previous season, international caps, under 21-international caps, goal difference of buying club previous season, buying club playing in first or second division, goal difference of selling club last season Negative: age^2, number of previous clubs, career games $played^2$, league position of buying club previous season, league position of selling club previous season
Speight and Thomas (1997a)[b]	217 arbitrated settlements on disputed transfers referred to the Football League Appeals Committee, 1978/1979–1991/1992 and 187 transfers settled by negotiation during 1990/1991 season	Log of transfer fee in constant 1990 prices; OLS regression, joint estimate (all cases) as well as separate estimates (arbitrated vs. negotiated cases)	Positive: age, games played previous season, average attendance of buying club in previous season, buying team playing in first, second or third division (ref. league: fourth division), average attendance of selling club in previous season, league position of selling club, selling club playing in first or second division Negative: age^2, league position of selling club previous season squared, arbitrated settlement (dummy)
Speight and Thomas (1997b)[c]	164 arbitrated settlements of disputed transfer fees for out-of-contract players in English football league, 1985/1986–1989/1990	Log of arbitrated fee, final buyer offer and final seller offer in constant 1989 prices	Positive: age, international caps, career goals scored, number of games played in previous season, average attendance of buying club, goal difference of buying club previous season Negative: age^2, selling club's goal difference, league position of buying club previous season, buying club playing in third or fourth division
Reilly and Witt (1995)	202 transfers in the English football leagues in 1991/1992	Log of transfer fee; OLS regression	Positive: appearances last season, goals scored current season, age, forward, full international, seller is a first, second or third division club; buyer is a first, second or third division club (ref.: club is from fourth division) Negative: number of previous clubs
Carmichael and Thomas (1993)[c]	214 transfers in the English football league in the season 1990/1991	Log of transfer fee; OLS regression	Positive: average attendance of buying club in previous season, goal difference of buying club in previous season, buying club playing in first, second, or third division (ref. league: fourth division), goal difference of selling team in previous season, selling team playing in first or second division, career games played, arbitrated fee (dummy) Negative: league position of buying club in previous season squared, league position of selling club in previous season squared, player age squared

[a]For ease of presentation, significant interaction effects are not reported in column 'major findings'.
[b]Results from estimations with selling club's last offer and buying club's last offer are virtually identical and are not displayed here for sake of brevity.
[c]Table includes only results from preferred estimation.

Figure B. 1: The determinants of transfer fees in European Football, Frick (2007)

Appendix C. Methodology

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. estat hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of LogTransferFee

         chi2(1)      =     7.43
         Prob > chi2  =   0.0064
```

Figure C. 1: Overall model: heteroskedasticity test

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. estat hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of LogTransferFee

         chi2(1)      =     9.62
         Prob > chi2  =   0.0019
```

Figure C. 2: Model for transfer fee < 2.5m€: heteroskedasticity test

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. estat hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of LogTransferFee

         chi2(1)      =     4.56
         Prob > chi2  =   0.0327
```

Figure C. 3: Model for transfer fees > 15m€: heteroskedasticity test

Appendix D. Correlations

	LogTra~e	Contra~t	Age2	Heightm	Weightkg	Minutes	Goals
LogTransfe~e	1.0000						
ContractDu~t	0.4487	1.0000					
Age2	-0.1795	-0.1901	1.0000				
Heightm	-0.0108	0.0993	0.0072	1.0000			
Weightkg	0.0316	0.1037	0.1207	0.7241	1.0000		
Minutes	0.2418	0.1094	0.0656	0.0251	0.0692	1.0000	
Goals	0.2563	0.0705	-0.0129	-0.0523	0.0171	0.4062	1.0000
PenaltiesS~d	0.1467	0.0182	0.1100	0.0247	0.0014	0.2588	0.6801
Assists	0.2564	0.0697	0.0351	-0.2583	-0.1734	0.4714	0.5245
YellowCards	0.0009	-0.0103	0.0020	0.0872	0.0799	0.4577	0.0328
RedCards	-0.0127	0.0307	-0.0406	0.1046	0.1445	0.0171	-0.0460
Tackles	-0.0515	0.0089	-0.0041	-0.0139	-0.0620	0.2122	-0.3007
Intercepti~s	-0.0360	0.0842	0.0478	0.2373	0.1019	0.2731	-0.3646
Fouls	-0.0567	0.0336	-0.0369	0.1005	0.1217	0.2268	0.0829
OffsidesWon	-0.0460	0.0927	0.0661	0.3654	0.2834	0.1614	-0.2597
Clearances	-0.1000	0.0700	0.1162	0.4627	0.3590	0.2308	-0.2968
Dribbled	0.0029	-0.0511	0.0392	-0.1682	-0.1757	0.1547	-0.0376
Blocks	-0.0929	0.0618	0.1221	0.4122	0.3023	0.2407	-0.2851
OwnGoal	-0.0789	-0.0240	0.0630	0.0636	0.0447	0.1416	-0.1015
Shots	0.2862	0.0825	-0.0079	-0.0990	-0.0001	0.3018	0.7860
KeyPasses	0.2422	0.0330	0.0510	-0.3438	-0.2559	0.3972	0.3834
Dribbles	0.2837	0.0845	-0.1818	-0.2881	-0.2576	0.2320	0.2471
Fouled	0.2193	0.0996	-0.0729	-0.2030	-0.1419	0.3241	0.3020
Offsides	0.1793	0.0184	0.1005	-0.0509	0.0525	0.0917	0.5951
Dispossessed	0.2717	-0.0119	-0.1237	-0.1987	-0.1336	0.2531	0.5360
Badcontrols	0.2029	0.0281	-0.0654	-0.1881	-0.1151	0.2396	0.5554
Passes	0.1905	0.1014	0.1543	0.1699	0.1324	0.4993	-0.1923
Pass	0.1498	0.0448	-0.0782	-0.0096	-0.1044	0.0023	-0.3017
Longballs	-0.0035	0.0249	0.2038	0.2635	0.1970	0.3194	-0.2581
Throughballs	0.2437	-0.0256	0.1289	-0.1869	-0.1020	0.1993	0.3277

Figure D. 1: Correlations between all the variables in analysis except for dummies (I)

	Penalt~d	Assists	Yellow~s	RedCards	Tackles	Interc~s	Fouls
PenaltiesS~d	1.0000						
Assists	0.4067	1.0000					
YellowCards	0.0191	0.0969	1.0000				
RedCards	0.0223	0.0293	0.1896	1.0000			
Tackles	-0.1622	-0.0491	0.3522	0.0664	1.0000		
Intercepti~s	-0.2131	-0.1827	0.3151	0.1018	0.6733	1.0000	
Fouls	0.0682	0.0801	0.5506	0.1543	0.3829	0.1469	1.0000
OffsidesWon	-0.1873	-0.2663	0.1333	0.1142	0.2103	0.5334	-0.1135
Clearances	-0.1892	-0.3383	0.2046	0.1323	0.2970	0.6731	-0.0165
Dribbled	0.0329	0.1968	0.2398	0.0223	0.5706	0.2621	0.3922
Blocks	-0.1748	-0.2723	0.2318	0.1406	0.2834	0.6184	0.0389
OwnGoal	-0.0316	-0.0696	0.0682	-0.0078	0.0716	0.2725	-0.0572
Shots	0.5320	0.5752	0.0863	-0.0507	-0.3187	-0.4729	0.1798
KeyPasses	0.3354	0.7595	0.1341	-0.0452	0.0453	-0.1681	0.1648
Dribbles	0.2338	0.5109	0.0097	-0.0322	0.0467	-0.1776	0.0596
Fouled	0.2822	0.4200	0.2310	0.0446	0.1532	-0.0366	0.3256
Offsides	0.4121	0.3647	-0.0378	-0.0249	-0.3976	-0.4691	0.0871
Dispossessed	0.4080	0.5415	0.0736	-0.0150	-0.1206	-0.3970	0.2434
Badcontrols	0.3737	0.5291	0.0588	-0.0209	-0.1592	-0.4242	0.2584
Passes	-0.0653	0.0344	0.3371	0.0234	0.5571	0.6734	0.1383
Pass	-0.1368	-0.1598	0.0555	-0.0111	0.2246	0.3111	-0.0807
Longballs	-0.1028	-0.1242	0.2686	0.0335	0.3653	0.5952	0.0450
Throughballs	0.2789	0.4507	0.0140	-0.0543	-0.0856	-0.2203	0.0034

Figure D. 2: Correlations between all the variables in analysis except for dummies (II)

	Offsid~n	Cleara~s	Dribbled	Blocks	OwnGoal	Shots	KeyPas~s
OffsidesWon	1.0000						
Clearances	0.7887	1.0000					
Dribbled	-0.2191	-0.1575	1.0000				
Blocks	0.6922	0.8520	-0.0799	1.0000			
OwnGoal	0.1526	0.2556	-0.0418	0.1519	1.0000		
Shots	-0.4340	-0.4868	0.0358	-0.4237	-0.1505	1.0000	
KeyPasses	-0.3641	-0.4289	0.3259	-0.3591	-0.0825	0.5522	1.0000
Dribbles	-0.3297	-0.4149	0.1953	-0.3568	-0.1278	0.4264	0.5728
Fouled	-0.2083	-0.2315	0.2281	-0.1896	0.0191	0.4298	0.4435
Offsides	-0.2915	-0.3506	-0.1949	-0.3650	-0.1091	0.5904	0.2472
Dispossessed	-0.5141	-0.5914	0.1687	-0.5179	-0.1439	0.6760	0.5758
Badcontrols	-0.4654	-0.5484	0.1472	-0.4994	-0.1649	0.7296	0.5563
Passes	0.4482	0.5387	0.2718	0.5230	0.2051	-0.2822	0.0833
Pass	0.1873	0.1882	0.0633	0.1985	0.1248	-0.3942	-0.1186
Longballs	0.5385	0.6371	0.1422	0.6586	0.1537	-0.3444	-0.1103
Throughballs	-0.1987	-0.2633	0.1089	-0.2010	-0.1472	0.3755	0.4435

	Dribbles	Fouled	Offsides	Dispos~d	Badcon~s	Passes	Pass
Dribbles	1.0000						
Fouled	0.5027	1.0000					
Offsides	0.1323	0.2200	1.0000				
Dispossessed	0.6904	0.5305	0.4601	1.0000			
Badcontrols	0.6292	0.5139	0.5842	0.8433	1.0000		
Passes	-0.0100	0.0761	-0.4260	-0.2369	-0.3286	1.0000	
Pass	-0.0952	-0.1186	-0.4483	-0.2496	-0.4624	0.5056	1.0000
Longballs	-0.1711	-0.0830	-0.4343	-0.3948	-0.4616	0.7698	0.3592
Throughballs	0.3593	0.3314	0.2484	0.3884	0.3648	0.0847	-0.0514

	Longba~s	Throug~s
Longballs	1.0000	
Throughballs	-0.0645	1.0000

Figure D. 3: Correlations between all the variables in analysis except for dummies (III)