Determinants of Transfers Fees: Evidence from the Five Major European Football Leagues

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Abstract:

In terms of transfer fees paid for professional players, football is a steadily growing multi-billion-dollar market. While some determinants of the market value of players have been empirically researched, such as player demographics, characteristics and performance, the effects of advisors, outfitters and social media popularity have not yet been extensively analyzed. I use a unique dataset of 389 football player transfers in the 2018/19 summer transfer window of the five major European football leagues to identify determinants of transfer fees and conduct analyses on the sub-groups of transfer fee, continent and playing position. My findings show that effects on transfer fees differ across sub-samples and besides factors that have already been identified by the literature, social media, advisors and outfitters (can) have significant effects on transfer fees and therefore player market value.

Keywords:

Soccer; Sports; Social Media; Market Value

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Introduction

Football (or soccer in the US) clubs are becoming increasingly commercialized, as revenues are growing due to the popularity of the sport. Clubs are transitioning into companies with shareholders and board structures and fans are transitioning into customers from the perspective of the clubs (Amir & Livne, 2005). Profits are tied to results in the form of league or cup success, which is highly dependent on the players employed by a club. Therefore, the choice of players employed holds strong relevance for the management of a football club (Pawlowski et al., 2010). At a club level, the major cost of a transfer comprises (1) (wage) payment to the player and advisors and (2) a transfer fee in case the player is under contract with another club. Information on salary and contract length often lacks public availability, which is why academic research has mostly focused on player performance as a determinant of transfer fees.

Data analysis in football dates back to Reep and Benjamin (1968) and Reep et al. (1971) evaluating the performance statistics of football players, finding that ball circulation (i.e. playing long passes) represents a tool for scoring goals and winning games. While clubs have implemented statistics for evaluating player performance (e.g. Zhu et al., 2015; Murtagh, 2015), the extent to which football clubs effectively implement data analysis today to evaluate transfer fees or the market values of players remains unclear. The academic literature (e.g. Müller et al., 2017) has shown that data analysis can produce reliable results and therefore may be a fitting substitute or replacement for the crowd-sourced determination of market value.

This paper analyzes 389 individual transfers from the summer transfer window of the 2018/19 season into the five major European leagues, namely the Premier League (England), Primera Division (Spain), Bundesliga (Germany), Serie A (Italy) and Ligue 1 (France). It contributes to the literature studying transfer fees or market values in football by (1) providing an analysis of the specific 2018/19 summer transfer period, (2) providing in-depth insights into discrepancies between different samples of transfer fee size, continent of birth or playing position and (3) introducing new potential characteristics that could hold explanatory power regarding transfer fees.

Literature and Hypotheses Development

Before agreeing to a player transfer, the two involved clubs need to agree on a price. Carmichael and Thomas (1993) describe this process as a classic bargaining scenario, which is why bargaining theory – and especially the Nash bargaining models (Nash, 1950; Nash 1953), - provide a framework for analyzing the transfer market. In detail, the *Nash bargaining solution* (NBS) assumes that the fee maximizes the product of utility surcharge. Literature has shown that other options acting as a second option in case of the failure of a transfer affect the outcome of bargaining if one party prefers this particular outcome to the NBS (Shaked & Stutton, 1984). Additionally, a higher state of utility of an involved party results in a more favorable view of the outcome (Nash, 1953). This implies that a higher status quo of utility for a club will result in a higher (selling) or lower (buying) price. The risk aversion of a party has an effect on the outcome of bargaining, as Kihlstrom et al. (1981) show that a higher degree of risk aversion results in a less favorable outcome.

Transfer fees in football represent an indicator of the market value of players, which is why they act as highly relevant resource for buying and selling clubs for future transfers. While transfer fees do not conceptually compare, they are comparable (He et al., 2015), which is why this study tries to explain both transfer fees and market values, although only transfer fees are empirically tested. Football leagues across European jurisdictions are separate entities that have their own set of riles and processes but are part of UEFA, an organization that organizes competitions across different leagues, such as the Champions League. As leagues are separate entities, available funds differ, as profits from revenue streams like TV contracts differ in size and how they are distributed across teams in the respective league. Thus, differences in spending behavior can be assumed. Studies have specifically looked at transfers in specific leagues, like the Bundesliga (Frick & Lehmann, 2001; Eschweiler & Vieth, 2004; Feess et al., 2004) or English leagues (Carmichael et al., 1999; Dobson & Gerrard; Reilly & Witte, 1995).

Determinants of transfer fees (e.g. Speight & Thomas, 1997; Carmichael & Thomas, 1993; Carmichael et al., 1999; Dobson et al., 2000; Feess et al., 2003; Frick, 2007; Medcalfe, 2008; Ruijg & van Ophem, 2015; Geurts, 2016 Müller et al., 2017), or market values for football players have been examined in the empirical literature. Usually, research aiming to explain transfer fees focuses on four different sets of variable categories, comprising (1) buying and (2) selling club characteristics, player characteristics and control variables (Dobson et al., 2000).

Buying and selling club characteristics provide a tool to assess the bargaining power of respective clubs. While Carmichael and Thomas (1993) state that selling clubs possess a higher degree of bargaining power, various variables such as stadium attendance (Carmichael & Thomas, 1993), historic league rankings (Dobson et al., 2000) or financial metrics (Frick, 2007) can be used to measure such ratios. The academic literature has identified several player characteristics that explain market value or the transfer fees in professional football. These can be divided into (1) player characteristics in terms of demographics and physical attributes, (2) player performance in terms of on-pitch performance and (3) player popularity through external sources like social media or news.

Player Characteristics

Age has been identified as a determinant of market value in various studies, as it represents a proxy for experience and potential (Carmichael & Thomas, 1993). The empirical literature commonly uses the quadratic term for age to account for non-linear relationships and has found a negative correlation between the variable and transfer fees (e.g. Carmichael et al., 1999; Dobson et al., 2000; Eschweiler & Vieth, 2004; Feess et al., 2004; Müller et al., 2017). Researchers have additionally analyzed the regular variable age as a determinant of transfer fees, regularly finding a positive effect (e.g. Speight & Thomas, 1997; Carmichael et al., 1999; Frick & Lehmann, 2001; Dobson et al., 2000). The height of football players has shown to have a significant positive effect on transfer values, which may be explained by increased heading abilities, which eases the player's ability to prevent or score goals (Bryson et al., 2013; Fry et al., 2014).

Players can be either right-, left- or two-footed. The characteristic of footedness has been studied in the literature on player valuation, finding that two-footedness has a positive effect on market value as it represents an advantageous skill and flexibility (Bryson et al., 2013; Herm et al., 2014).

The playing position of players can roughly be divided into the four groups of goalkeepers, defenders, midfielders and forwards but allows for more granular perspective by dividing defenders into the categories of central defenders and full-backs and midfielders into defensive and offensive ones. Eschweiler and Vieth (2004) show a negative correlation between the position of a goalkeeper and transfer fees for a sample of 254 transfers in the German Bundesliga between 1997 and 2003, while defenders, midfielders and forwards showed a positive effect. The position of forwards positively correlates in a different study on transfers in the Bundesliga (Feess et al., 2004) and English football leagues (Reilly & Witt, 1995; Frick, 2007). Attacking players generate a higher degree of attention – for instance, through goal scoring or spectacular dribbling – which makes them more visible to the crowd (He et al., 2015). Additionally, goalkeepers lack flexibility in relation to their playing position, which results in a significant negative effect on their wages compared with other positions (Frick, 2007).

Characteristics like the nationality in terms of country or continent of birth have also been identified as drivers of value for professional football players. For South Americans, positive effects on transfer fees have been identified in the literature (Frick & Lehmann, 2001; Feess et al., 2004), while being born in North America or Asia has shown negative effects (Frick & Lehmann, 2001).

Player Performance

Playing time can be represented as the number of minutes that a player spends on the pitch or the number of appearances made. Appearances can then again be divided into games as a starter or substitute and bundled as career or season statistics. The literature has identified a positive effect of playing time on market value 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, 2014; Müller et al., 2017).

Scoring abilities include characteristics like goal scoring, assists (the pass before the goal) and shots also provide a tool to measure market values of football players, as they directly measure players' performance (Carmichael et al., 1999). Dobson et al. (2000) show that the number of goals scored in the season before a transfer has a significant positive effect on transfer fees for semi-professional English football transfers between 1988 and 1997. Carmichael et al. (1999) identify that the number of goals in both league and cup matches positively correlates with transfer fees for a sample of 240 transfers in relation to 1,789 non-transfers in the English football leagues in 1993/94. Additional metrics like career goal scoring rate (Dobson & Gerrard, 1999) or current season scoring (Reilly & Witt, 1995) also provide similar results. Similar findings can be found for the assists of players, showing a positive effect on wages (Lehmann & Schulze; Franck & Nüesch, 2012) and transfer fees (Müller et al., 2017).

While goal scoring and assists represent the most commonly-used measures of player performance in the empirical literature, additional characteristics can be used. Franck and Nüesch (2012) evaluate the category of dueling, which they operationalize through the number of clearances, interceptions and blocked shots of players. Herm et al. (2014) operationalize the overall category of dueling as clearances, blocks and interceptions. Fouls (He et al., 2015), red and yellow cards (Kiefer, 2014) or dribbles (Medcalfe, 2008) represent additional performance measures that have been tested by the literature. Müller et al. (2017) find significant effects for passes, successful passes, aerial duels, tackles and yellow cards, while also testing interceptions, clearances, fouls and red cards.

Player Popularity

Independent of actual performance statistics, the popularity of a player provides football clubs with indicators on how a particular player may have an effect on jersey or ticket sales. The academic theory on superstardom suggests that the emergence of so-called superstars only partly depends on the actual talent in terms of influencing the outcome of a sports competition (Rosen, 1981), whereas additional effects such as popularity also hold relevance (Adler, 1985).

Garcia del Barrio and Pujol (2007) evaluated a sample of the Spanish football league and found both performance and popularity – measured by Google search hits – to be determinants of market value for football players. Franck and Nüesch (2008) argue that it is difficult to determine the real market value of star players in the Bundesliga through observable talent measures and such determination is better achieved via the use of external expert evaluation, which reveals hidden characteristics. Popularity has an effect on transfer fees. In a later study, they test player popularity that does not relate to the actual performance and identify that both talent and popularity have positive effects on the market value of football players in the Bundesliga (Franck & Nüesch, 2012). Kiefer (2014) used the number of likes on the social media channel Facebook as a measure of player popularity to test whether performance in the Euro 2012 tournament had an effect on player popularity. The study of Müller et al. (2017) uses press citations, Wikipedia page views, Google search trends, Reddit posts and YouTube videos as popularity measures, identifying positive effects on market value for all measures aside from Google search trends.

Hypotheses

Based on the literature on the determinants of market value and transfer fees in the context of professional football, I build five hypotheses for the different categories of player characteristics, player performance, player popularity, player positions and league characteristics. Accordingly, I expect that the size of transfer fees:

- **(Hypothesis 1)** can be explained by player characteristics, which I operationalize as age (squared), height, weight, footedness (*right, left, both*) and continent of birth (*Europe, South America, Africa, Asia*).
- **(Hypothesis 2)** can be explained by performance characteristics, which I operationalize as through balls (i.e. passes that lead to a direct goal scoring opportunity), longs balls, clearances, assists, being fouled, offsides, crosses, goals, shots, passing percentage, red cards, yellow cards, poor control, aerial duels won, fouls, tackles, offside decisions won, minutes played, successful dribbles, dispossessions, blocked shots, key passes and interceptions.
- **(Hypothesis 3)** can be explained by popularity, which I operationalize as a social media score calculated as the sum of the natural logarithms of Instagram and Twitter followers and Facebook likes.
- **(Hypothesis 4)** differs based on the domestic league, namely between the Premier League (England), Primera Division (Spain), Bundesliga (Germany), Serie A (Italy) and Ligue 1 (France).
- **(Hypothesis 5)** can be explained by playing positions, which I operationalize as central defender, full-back, defensive midfielder, offensive midfielder and forward.

Data and Methodology

The dataset for this paper comprises 389 individual transfers from the summer transfer window of the 2018/19 season into the five major European leagues, namely the Premier League (England), Primera Division (Spain), Bundesliga (Germany), Serie A (Italy) and Ligue 1 (France). The sample only includes outfield players, i.e. no goalkeepers. The data on player transfers and the underlying fee was collected from transfermarkt.de. The reported fee on transfermarkt.de does not necessarily fully represent the fee paid for the player, as fees are not always accurately reported publicly and additional fees (e.g. for advisors) are sometimes included and sometimes excluded. Nonetheless, transfermarkt.de represents the best source of information and has been used for similar studies in the past. Additionally, I was able to collect demographics like height, age or nationality from the site, as well as other side characteristics, like the existence of advisors, outfitters or social media accounts. Data on social media was directly collected from the players' social media accounts. Performance data for this study was collected from whoscored.com.

All collected variables, their meaning and the source of information are explained in table 6 in the appendix. The variables can be divided into the three groups of (1) player characteristics and demographics, (2) performance and (3) external effects, comprising social media, outfitters and advisors.

This paper relies on the transfer fee paid in Euros for a player as the dependent variable, i.e. the measure of market value. The variable is highly skewed, which is why I use the natural logarithm, in line with existing research on transfer fees or market values (Carmichael & Thomas, 1993; Müller et al., 2017).

For the factor of age, I use the quadratic term to allow for non-linear relationships in the model. This is also in line with existing literature where negative effects on player value have been identified for the squared term of age (Lehmann & Schulze, 2008).

I also use the sum of the natural logarithms for Instagram, Twitter and Facebook followers to calculate the s*ocial media* variable. Accordingly, I build a single proxy for social media activity and account for the highly-skewed variables. The Atkinson index (Atkinson, 1975) provides a tool that enables varying the sensitivity of inequality in different parts of a distribution. The index involves a sensitivity parameter (ε) that can range from 0 to infinity, which allows introducing social judgment weights concerning different points of the distribution scale. Here, I use the value 1 for ε. The Atkinson index ranges from 0 to 1, where 0 represents a state of equal distribution. I identify a very high inequality of distribution for all social media channels, finding Atkinson index values of 0.9 (Instagram), 0.94 (Twitter) and 0.96 (Facebook). Small numbers of players dispose of a comparatively very strong social media presence. In order to account for the skewness of the variables, I used the logged terms for multivariate analysis.

Results

Descriptive Results

The overall descriptive statistics for the dataset are presented in table 6 in the appendix. The following statistics provide additional descriptive insights that were derived from the dataset. The first part involves statistics on overall fees, player characteristics, positions and social media. The second part involves statistics on player performance. The dataset only involves players who were transferred during the period under consideration. Therefore, the results cannot be generalized for football players or the analyzed sub-groups. Results are presented for the overall sample, as well as for subsamples of continents of birth, domestic leagues, size of transfer fees and playing positions.

Table 1 provides an overview of specific descriptive statistics for the full sample and sub-samples of continents, leagues, transfer fee levels and playing positions.

The average transfer for a player amounts to a sum of €9.14 million. The average player is 25.62 years old, 1.81 meters tall and weighs 75.35 kg. 87.7% (341) of all transferred players have an Instagram account, with an average of 844,434 followers, 63.2% (246) of players used Twitter (517,740 average followers) and 50.1% (195) used Facebook (884,691 profile likes). 35.5% of all players have an outfitter, like Nike (96) or Adidas (30), and 83.8% have an advisor whose information was publicly accessible.

Table 1. Descriptive results on the dataset and sub-samples

The table shows descriptive results for the dataset, as well as sub-samples for continent of origin, leagues, size of transfer fee and playing positions. Data is rounded to two decimal places (except minutes). Dummy variables are indicated by a (d) and are shown as percentages. Transfer fees and social media metrics are shown as millions (m).

		Continents				League					Transfer fees (€ million)				Positions				
	Overall	Europe	South America	Africa	Asia	Premier League	Primera Division	Bundesliga	Serie A	League 1	<1	1 - 5	5 - 15	> 15	Central Defenders	Fullbacks	Defensive Midfielders	Offensive Midfielders	Forwards
n	389	268	57	50	11	72	80	68	104	65	101	121	95	72	72	68	87	97	65
Transfer fee (€m)	9.15	8.52	13.50	8.48	6.71	15.70	9.28	5.67	8.28	6.78	0.22	3.20	9.58	31.10	7.91	6.31	9.75	13.00	6.92
Age	25.62	25.70	25.11	25.60	25.91	24.72	26.24	24.72	26.56	25.29	27.64	25.47	24.75	24.18	25.92	25.68	26.34	24.56	25.85
Height	181.46	181.50	180.84	181.82	181.45	181.08	179.90	182.04	182.93	180.82	181.04	181.36	182.02	181.46	187.17	178.88	181.74	177.31	183.65
Weight	75.34	75.27	75.47	75.66	74.64	74.94	74.13	76.10	76.38	74.83	75.52	75.43	75.56	74.65	80.89	73.16	74.78	71.34	78.20
Outfitter (d)	35.5%	36.2%	22.8%	38.0%	63.6%	33.3%	32.5%	60.3%	31.7%	21.5%	35.6%	27.3%	36.8%	47.2%	33.3%	26.5%	37.9%	45.4%	29.2%
Advisor (d)	83.8%	82.8%	78.9%	90.0%	100.0%	84.7%	78.8%	98.5%	86.5%	69.2%	79.2%	86.8%	84.2%	84.7%	80.6%	80.9%	85.1%	84.5%	87.7%
Instagram (e)	87.7%	88.8%	89.5%	80.0%	81.8%	93.1%	87.5%	86.8%	91.3%	76.9%	82.2%	86.0%	88.4%	97.2%	86.1%	91.2%	86.2%	89.7%	84.6%
Twitter (d)	63.2%	64.2%	57.9%	58.0%	81.8%	77.8%	72.5%	51.5%	58.7%	55.4%	63.4%	51.2%	70.5%	73.6%	65.3%	66.2%	64.4%	63.9%	55.4%
Facebook (d)	50.1%	51.9%	36.8%	60.0%	27.3%	54.2%	45.0%	63.2%	44.2%	47.7%	43.6%	48.8%	48.4%	63.9%	51.4%	48.5%	47.1%	52.6%	50.8%
Instagram (mil)	0.84	0.94	0.83	0.40	0.36	0.51	0.49	0.12	1.90	0.65	0.23	0.15	0.31	3.25	0.23	0.24	0.39	2.47	0.25
Twitter (mil)	0.52	0.57	0.46	0.24	0.32	0.27	0.30	0.11	1.41	0.13	0.24	0.13	0.18	1.73	0.10	0.18	0.30	1.48	0.16
Facebook (mil)	0.88	1.08	0.41	0.28	0.94	0.33	0.37	0.12	2.97	0.14	0.46	0.09	0.18	3.00	0.11	0.17	0.42	2.71	0.22
Through balls	0.06	0.07	0.04	0.03	0.13	0.06	0.08	0.12	0.03	0.03	0.03	0.08	0.07	0.08	0.07	0.01	0.11	0.07	0.04
Long balls	1.82	1.82	1.94	1.71	1.42	1.93	2.08	1.61	1.92	1.43	1.92	1.57	1.70	2.25	3.46	1.69	2.41	1.09	0.43
Clearances	1.59	1.58	1.76	1.53	0.97	1.72	1.54	1.44	1.83	1.27	1.59	1.63	1.71	1.36	4.41	1.93	1.13	0.40	0.50
Assists	2.06	2.13	1.96	1.79	2.64	2.78	2.00	2.18	1.70	1.79	1.50	1.87	1.90	3.39	0.53	2.04	1.63	3.69	1.91
Fouled	1.09	1.03	1.26	1.09	1.61	1.17	1.10	1.01	1.04	1.13	0.90	1.06	1.10	1.37	0.69	0.93	1.19	1.34	1.15
Offsides	0.18	0.18	0.16	0.24	0.18	0.16	0.17	0.22	0.17	0.20	0.13	0.22	0.19	0.20	0.04	0.09	0.05	0.26	0.49
Goals	3.03	2.95	3.07	3.00	5.36	3.68	2.60	3.53	2.58	3.06	1.87	2.83	3.11	4.90	1.04	0.76	1.86	4.79	6.55
Shots	1.09	1.05	1.14	1.13	1.65	1.09	0.97	1.24	1.04	1.16	0.83	1.14	1.04	1.45	0.44	0.56	0.93	1.66	1.74
Pass%	78.18	78.68	77.32	76.96	76.81	79.38	78.69	75.04	79.89	76.75	79.43	75.58	77.58	81.56	82.09	77.83	82.52	76.15	71.41
Red	0.15	0.13	0.09	0.24	0.36	0.18	0.21	0.04	0.14	0.14	0.16	0.14	0.13	0.17	0.22	0.18	0.17	0.09	0.08
Yellow	3.58	3.66	3.56	3.07	3.64	4.15	4.23	3.09	3.35	3.02	3.38	3.44	3.82	3.78	3.89	3.72	4.97	2.60	2.69
Bad controls	1.20	1.11	1.35	1.51	1.35	1.29	1.09	1.11	1.13	1.45	0.94	1.30	1.25	1.35	0.44	0.98	1.00	1.75	1.74
Aerials won	1.28	1.19	1.52	1.36	1.67	1.36	1.18	1.33	1.35	1.17	1.10	1.27	1.47	1.31	2.09	1.00	1.46	0.57	1.50
Fouls	1.09	1.05	1.17	1.15	1.09	1.08	1.13	1.13	1.07	1.03	0.96	1.12	1.12	1.16	1.01	0.96	1.38	0.92	1.16
Tackles	1.43	1.40	1.56	1.49	1.22	1.56	1.56	1.32	1.30	1.45	1.39	1.36	1.48	1.55	1.58	1.80	1.92	1.19	0.59
Offsides won	0.17	0.16	0.19	0.19	0.07	0.18	0.19	0.14	0.18	0.13	0.17	0.16	0.18	0.14	0.59	0.21	0.05	0.02	0.01
Minutes	1721	1742	1588	1739	1837	2020	1709	1599	1694	1575	1425	1672	1766	2160	1937	1683	1770	1665	1539
Dribbled past	0.74	0.73	0.83	0.70	0.64	0.82	0.83	0.65	0.65	0.78	0.70	0.75	0.73	0.80	0.54	0.67	1.08	0.81	0.48
Dispossessed	0.92	0.86	1.01	1.11	1.24	1.00	0.89	0.86	0.85	1.05	0.73	0.99	0.89	1.10	0.26	0.67	0.88	1.45	1.17
Blocked Shots	0.22	0.22	0.23	0.18	0.16	0.26	0.22	0.18	0.22	0.20	0.22	0.22	0.20	0.23	0.59	0.20	0.20	0.07	0.05
Key Passes	0.76	0.76	0.74	0.74	1.02	0.86	0.74	0.80	0.69	0.76	0.64	0.78	0.68	1.02	0.20	0.78	0.79	1.20	0.67
Interceptions	0.98	0.99	1.01	0.92	0.75	1.08	1.13	0.82	0.99	0.83	1.04	0.90	1.00	0.98	1.64	1.22	1.29	0.54	0.23
Own goals	0.06	0.06	0.04	0.09	0.09	0.06	0.08	0.01	0.08	0.08	0.07	0.06	0.09	0.03	0.24	0.01	0.02	0.03	0.02

Performance-wise, the average transferred player scored 3.03 goals in the season prior to the transfer and provided 2.06 assists, while collecting 3.58 yellow and 0.15 red cards. He played an average of 1,721 minutes, which accounts to slightly over nineteen full games and obtained a passing percentage of 78.18. On a per-game level, players recorded 1.09 shots, 1.09 fouls while also being fouled 1.09 times, 0.74 successful dribbles, 0.98 interceptions and 0.92 dispossessions. The variable dispossession relates to the players being dispossessed themselves. Offsides per game amount to 0.18 versus 0.17 won.

The number of transfers is not evenly distributed across players from different continents, which seem obvious given that all of the studied leagues are located in Europe. 268 (68.9%) of transfers were European players, followed by 14.7% of South Americans, 12.9% from Africa and 2.8% from Asia (11) The average transfer fee for players from South America is the highest with €13.5 million, followed by Europe (€8.5m), Africa (€8.5m) and Asia (€6.7m). Players from South America are also comparatively younger on average (25.11) than players from other continents. This may be a signal that age has a positive effect on transfer fees for South American players, as young talents possess a high market value. Age, height and weight are relatively equally distributed for players across different continents. Social media statistics differ across continents, as players from Europe have an average of more than 938k Instagram followers, compared with 832k for South America, 395k for Africa and 356k for Asia. For Twitter and Facebook, a similar ratio can be identified.

At a league-specific level, the Premier League has the highest average transfer fees with €15.7m, followed by the Primera Division (€9.8m), Serie A (€8.2m), Ligue 1 (€6.7m) and the Bundesliga with an average fee of €5.6m. With averages of both 24.72, clubs in the Premier League and the Bundesliga signed the youngest players, whereas their counterparts in both the Primera Division (26.24) and Serie A (26.56) signed considerably older players. The Bundesliga has the highest share of outfitters (60.3%) and advisors (98.5%), while Ligue 1 has the smallest ratio for both variables (21.5% outfitters, 69.2% advisors). Nonetheless, the metrics were collected from transfermarkt.de, a site that originated in Germany and may also provide the highest data quality for the German Bundesliga.

The existence of social media in terms of Instagram also differs across the five leagues. While 93.1% of Premier League players have an Instagram account, only 76.9% of Ligue 1 players do so. For Twitter, the Premier League also leads with 77.8% versus the Bundesliga as comparatively lowest league with a share of 51.5%. This ratio lies in contrast for Facebook, whereby 63.2% of Bundesliga players own a Facebook account, while only 54.2% of Premier Players do so. Serie A has the lowest ratio with 44.2%. Based on absolute social media follower numbers, Serie A shows a huge lead compared with other leagues. Nonetheless, average social media and transfer fees statistics are especially influenced by specific large transfers, like Cristiano Ronaldo (€117m fee, 194m Instagram followers, 75m Twitter followers, 122m Facebook Likes), reflecting the major reason why the average social media statistics for the Serie A are much higher compared with the other leagues. As described above, I use logarithmized variables to account for this high skewness.

By dividing the full sample into different categories based on transfer fee size, the first potential effects that drive transfer fees can be identified. 101 (26%) of all transfers amounted to a fee of up to €1m, while the average fee for this group is €0.22 million. 31.1% (121) of players were transferred for a fee between €1 million and €5 million, with an average fee of €3.2 million. The group for fees between €5 million and €15 million (95; 24.4%) had an average fee of €9.6 million, while the sample contains 72 transfers above €15 million, with an average fee of €31.1 million. The groups show a trend towards a negative effect of age on transfer fees, as the group below €1 million had an average age of 27.64 and this average decreases with higher fees to 24.18 in the group with the highest transfer fees. Weight and height are relatively evenly distributed.

The €15m+ group has by far the highest absolute numbers of social media followers as well as the highest degree of channels. For the other three groups, a trend in the relative use of Instagram channels can also be identified. Nonetheless, the number of followers does not show this trend, as the <€1m group has a comparatively higher average number of followers across all channels than the €1-5m group and in part the €5-15m group. Consequently, rather obvious average statistics like goals (<€1: 1.87; >€15: 4.9), assists (<€1: 1.5; >€15: 3.39) or minutes played (<€1: 1425; >€15: 2160) that have been identified as clear indicators of market value by the literature show a clear trend across different groups of transfer fee size.

Correlations

Correlations and variance inflation factors for most variables are displayed in table 2. All correlations rank below the critical level of 0.7 (Mukaka, 2012). Some variables show significant correlations, which can potentially be explained by the limited number of observations of the dataset. Nonetheless, based on the levels of the variance inflation factors (VIF) – which are all below 4 and well below a critical value of 10 – multicollinearity should not (but may) have a relevant effect for the dataset and the multivariate results. In order to ensure that this is not an issue, I will additionally test the VIF scores for all multivariate results.

Table 2: Correlation matrix and variance inflation factors

The table shows correlations for chosen variables and their variance inflation factor (VIF). A star (*) indicates significance at the .01 level.

	Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)	VIF
(1)	Transfer Fee	1.00																														
(2)	Age^2	-0.38*	1.00																													1.19
(3)	Height	0.06	0.09	1.00																												3.29
(4)	Weight	-0.01	0.15*	0.67*	1.00																											2.94
(5)	Social Media	0.10	0.02	-0.04	-0.04	1.00																										1.21
(6)	Outfitter	-0.04	0.08	-0.01	0.02	0.25*	1.00																									1.19
(7)	Advisor	0.05	-0.01	0.02	0.05	0.07	0.08	1.00																								1.08
(8)	Through balls	0.06	-0.04	0.00	0.05	0.02	0.12	0.03	1.00																							1.11
(9)	Long balls	-0.02	0.13	0.18*	0.16*	0.05	0.06	-0.07	-0.07	1.00																						2.43
(10)	Clearances	0.01	0.10	0.44	0.40*	-0.03	-0.05	-0.11	0.01	0.58*	1.00																					3.77
(11)	Assists	0.13*	-0.09	-0.30*	-0.31*	0.20*	-0.02	-0.01	0.03	-0.11	-0.31*	1.00																				2.87
(12)	Fouled	0.13	-0.16*	-0.25*	-0.21*	0.01	0.03	-0.01	-0.01	-0.01	-0.23*	0.33*	1.00																			1.84
(13)	Offsides	0.06	0.05	-0.05	0.03	0.05	0.01	0.04	-0.04	-0.38*	-0.33*	0.20*	0.18*	1.00																		2.18
(14)	Goals	0.13	-0.03	-0.09	-0.04	0.16*	0.00	0.04	0.02	-0.22*	-0.30*	0.52*	0.34*	0.53*	1.00																	3.65
(15)	Shots	0.13	-0.12	-0.16*	-0.12	0.13	0.05	0.06	0.00	-0.27*	-0.42*	0.47*	0.43*	0.58*	0.79*	1.00																4.10
(16)	Pass%	-0.03	0.00	0.02	0.00	0.18*	0.05	-0.08	0.07	0.32*	0.17*	0.03	-0.07	-0.32*	-0.13	-0.15*	1.00															1.53
(17)	Red	0.05	-0.01	0.06	0.00	-0.01	0.04	-0.09	-0.02	0.14*	0.13*	-0.04	0.04	-0.11	-0.09	-0.09	-0.04	1.00														1.12
(18)	Yellow	0.03	0.08	0.01	0.02	0.03	-0.09	-0.04	-0.01	0.35*	0.19*	0.10	0.27*	-0.13	0.11	0.01	0.08	0.15*	1.00													2.56
(19)	Bad controls	0.14*	-0.19*	-0.34*	-0.29*	0.00	-0.05	0.05	-0.02	-0.39*	-0.49*	0.46*	0.49*	0.54*	0.53*	0.64*	-0.32*	-0.07	-0.05	1.00												3.90
(20)	Aerials won	0.09	0.12	0.54*	0.45*	-0.07	0.01	0.00	-0.03	0.30*	0.50*	-0.26*	0.03	0.01	0.00	-0.04	-0.07	0.09	0.24*	-0.12	1.00											2.28
(21)	Fouls	0.16*	-0.01	0.10	0.07	0.00	-0.04	0.05	-0.04	0.16*	0.03*	-0.02	0.33*	0.08	0.14*	0.19*	-0.19*	0.17*	0.49*	0.14*	0.36*	1.00										2.15
(22)	Tackles	0.05	-0.04	-0.07	-0.03	-0.01	-0.03	0.04	0.02	0.40*	0.26*	-0.06	0.15*	-0.32*	-0.21*	-0.23*	-0.04	0.13*	0.34*	-0.10	0.13*	0.42*	1.00									2.75
(23)	Offsides won	-0.02	0.06	0.36*	0.38*	0.01	0.00	-0.09	0.01	0.47*	0.68*	-0.30*	-0.21*	-0.23*	-0.28*	-0.40*	0.07	0.12	0.10	-0.43*	0.30*	-0.02	0.22*	1.00								2.32
(24)	Minutes	0.15*	0.00	0.01	0.01	0.08	-0.06	0.02	0.10	0.31*	0.22*	0.45*	0.33*	0.02	0.41*	0.24*	0.10	0.09	0.62*	0.18*	0.27*	0.31*	0.24*	0.11	1.00							3.32
(25)	Dribbled past	0.05	-0.02	-0.21*	-0.27*	0.01	0.01	0.02	0.04	0.20*	-0.13	0.16*	0.28*	-0.10	0.08	0.13	-0.04	0.05	0.28*	0.22*	-0.06	0.30*	0.51*	-0.18*	0.22*	1.00						1.97
(26)	Dispossessed	0.14*	-0.20*	-0.38	-0.33	0.03	0.01	0.04	0.02	-0.32*	-0.54*	0.48*	0.52*	0.37*	0.48*	0.57*	-0.26*	0.01	-0.07	0.78*	-0.23*	0.16*	-0.05	-0.45*	0.15*	0.30*	1.00					3.68
(27)	Blocked Shots	-0.03	0.10	0.38*	0.35*	0.02	-0.05	0.00	0.02	0.52*	0.69*	-0.32*	-0.19*	-0.31*	-0.30*	-0.37*	0.16	0.10	0.15*	-0.44*	0.43*	0.06	0.28*	0.65*	0.14*	-0.03	-0.46*	1.00				1.19
(28)	Key Passes	0.10	-0.08	-0.45*	-0.42*	0.16*	0.10	0.05	0.02	-0.07	-0.44*	0.70*	0.44*	0.20*	0.42*	0.51*	-0.04	-0.05	0.04	0.54*	-0.33*	0.08	0.05	-0.40*	0.28*	0.32*	0.60*	-0.41*	1.00			3.21
(29)	Interceptions	-0.04	0.07	0.19*	0.13	-0.01	0.00	-0.02	0.03	0.60*	0.59*	-0.22*	-0.02	-0.41*	-0.33*	-0.39*	0.19*	0.18*	0.34*	-0.37*	0.33*	0.20*	0.61*	0.44*	0.21Ü	0.30*	-0.35*	0.59*	-0.21*	1.00		2.99
(30)	Own goals	-0.02	0.10	0.14*	0.21*	-0.06	-0.08	-0.07	-0.03	0.20*	0.30*	-0.11	-0.05	-0.04	-0.08	-0.13*	-0.08	0.03	0.09	-0.13	0.10	0.01	0.19*	0.33*	0.14*	-0.03	-0.14*	0.31*	-0.13*	0.17*	1.00	1.27

Multivariate Results

Table 3. Results from stepwise regressions with backwards elimination predicting transfer fees

The table shows the final results from backwards regressions for the full sample of football transfers and four sub-samples for transfer fees up to 1 million, 1- 5 million, 5 -15 million and above 15 million Euros. The dependent variable is the log of the transfer fee. Coefficients and P>|t| are presented for each model. At the bottom of the table, the mean variance inflation factor (VIF), R^2, R^2 (adjusted) and the number of observations is shown. The stepwise regression model is executed with the logic of p >= .2, which means that for each model all variables are regressed and the factor with the highest p >= .2 is eliminated. The model is then run again and again another factor is excluded. This logic is repeated until a state of p <= .2 for all remaining factors occurs, which represents the final model. The following variables that did not end up in any final model are excluded: *Primera Division, Africa, both feet, left foot, outfitter, crosses, bad controls, tackles, offsides won, dribbled past, key passes*

Variable	All Obs.		<1m€		1€m – 5m€		5€m – 15m€		> 15m€	
	Coeff.	P>|t|	Coeff.	P>|t|	Coeff.	P>|t|	Coeff.	P>|t|	Coeff.	P>|t|
Premier League	1.438	0.054	-4.113	0.046	-		-		-	
Bundesliga	-		-		-		-0.220	0.004	-	
League 1	-		4.270	0.002	-		-		-	
Serie A	-		-		-		-0.195	0.004	-	
South America	2.554	0.001	5.324	0.015	-		0.221	0.017	0.262	0.024
Europe	-		-		-		0.100	0.185	-	
Asia	-		-		0.444	0.022	-		-0.617	0.020
Central Defender	-		2.570	0.185	-		-		0.758	0.003
Defensive Midfielder	-		2.710	0.056	-		-0.363	0.000	-	
Offensive Midfielder	-		-		-		-		-0.401	0.009
Forward	-		-		-		-		-0.816	0.000
Age2	-0.011	0.000	-0.005	0.024	-0.001	0.003	-		-	
Height	0.098	0.029	-		-		-		0.015	0.133
Weight	-		-		-		0.018	0.001	-0.026	0.015
Right foot	-		-1.561	0.146	-		-0.162	0.010	-	
Social Media	0.045	0.075	-		0.007	0.038	-		-	
Advisor	-		-		-		0.179	0.031	0.031	0.113
Through balls	-		-		-		0.140	0.046	0.929	0.047
Long balls	-		-		0.068	0.074	-		-	
Clearances	-		-		-0.091	0.036	-0.079	0.004	-0.161	0.025
Assists	-		0.597	0.052	-		-0.031	0.046	-	
Fouled	-		-		-		-		0.085	0.160
Offsides	-		-5.691	0.099	-		-		1.062	0.000
Goals	-		-		-		0.010	10.165	-	
Shots	-		-3.991	0.000	-		-		-	
Pass%	-		-		-		0.014	0.000	-	
Red	-		2.311	0.087	-0.168	0.098	-0.159	0.060	-	
Yellow	-0.265	0.063	-0.458	0.037	-0.035	0.020	-0.013	0.186	0.032	0.070
Aerials won	-		-		0.110	0.011	-		-	
Fouls	1.566	0.014	3.741	0.007	-		-		-	
Minutes	0.001	0.002	-		0.000	0.080	0.000	0.002	0.000	0.023
Dispossessed	-		-		-		-0.209	0.003	-	
Blocked Shots	-		-6.752	0.015	0.474	0.097	-		-	
Interceptions	-0.704	0.097	-		-		0.127	0.029	-	
Own goals	-		-		-0.194	0.147	-		-	
Mean VIF	1.30		1.67		1.90		1.85		2.61	
R^2 (adj. R^2)	0.24 (0.22)		0.46 (0.37)		0.30 (0.23)		0.48 (0.36)		0.58 (0.47)	
n	389		101		121		95		72	

In order to build a model that successfully extracts the relevant variables that have a significant effect on transfer fees – or rather market value of football players – I use stepwise regressions with backwards elimination. In this method, I start with a regression model that involves all existing variables and eliminate the variable with the lowest explanatory value. The regression is run again and variables are eliminated in a step-wise manner until all variables possess a specific level of explanatory value. For this paper, I choose use an elimination measure of $p >= .2$ based on the recommendation for models with more than 25 predictors of Wang et al. (2007).

The multivariate results shown in table 3 comprise the final results of stepwise regressions with backwards elimination with the log of transfer fee as the dependent variable. Overall, five models are tested: the full sample of football transfers and four sub-samples for transfer fees up to €1 million, €1 million-€5 million, €5 million-€15 million and above €15 million. Variance inflation factors do not signal potential problems of multicollinearity. As the dependent variable has a logarithmic scale, estimated coefficients can be interpreted as percent changes. The height and age of players can be identified as significant determinants of transfer fees, given that height has a positive (.098; $p < .05$) and age a negative (-.265; $p < .1$) impact. Player who are transferred to the English Premier League generate a higher fee compared with the other four observed leagues (1.428; $p < .1$). Social media has a positive but rather low significant impact on transfer fees (.045; $p < .1$), while players from South America show a highly significant positive effect (2.554; $p < .001$. The playing position of defensive midfield shows a highly significant but low negative effect (-0.011; $p < .001$) Three performance indicators remain in the final model: interceptions have a negative but hardly significant effect (-.704; $p < .1$); fouls show a significant positive impact, which means that an increase of one more average foul per game of a player would lead to an increase of 156% in the respective transfer fee ($p < .05$); and minutes played shows a highly significant positive impact, whereby every additional playing minute increases the transfer fee of a player by 0.1% ($p < .01$). Yellow cards have a negative coefficient.

League-Specific Results

Table 4 shows the results from five individual step-wise regressions with backwards elimination predicting transfer fees. The dependent variable is the log of transfer fee and the sub-samples tested in the models comprise players who were transferred into each of the European football leagues stated above the model column. The models show adjusted R^2 between 0.21 (Bundesliga) and 0.56 (Ligue 1), suggesting high differences in explanatory power at the model level. VIF values range between 1.5 and 2.16, suggesting no multicollinearity.

No significant effects of player heritage (i.e. continents) are found for the Premier League (adj. r^2 0.27), the Bundesliga and Serie A (adj. R^2 0.27). The Primera Division shows a negative effect for African (-5.703; $p < .05$) and European (-3.932; $p < .01$) players. The same – but less significant – results can be identified for Ligue 1, where the actual impact shifts between Africa (-3.712; $p < .1$) and Europe (-5.483 $p < .05$). Additionally, the Primera Division shows the highest negative effect across all continent effects for players from Asia (-9.806; $p < .1$).

For specific playing positions, all but the Spanish league show variables in their final model. Central defenders have a positive effect in England (3.639; $p < .05$), Germany (4.173; $p < .1$) and France (4.708; $p < .1$). A positive effect for defensive midfielders can be observed for the Premier League (5.065; $p < .01$) and Serie A (5.016; $p < .01$). Additionally, forwards show a positive effect in Serie A (4.305; $p < .05$).

Table 4. Results from stepwise regressions with backwards elimination predicting transfer fees across European leagues

The table shows the final results from backwards regressions for the full sample of football transfers and the sub-samples consisting of the five main European football leagues. The dependent variable is the log of the transfer fee. Constant is included but not shown in the table. Coefficients and P>|t| are presented for each model. At the bottom of the table, the mean variance inflation factor (VIF), R^2, R^2 (adjusted) and the number of observations is shown. The stepwise regression model is executed with the logic of $p >= .2$, which means that for each model all variables are regressed and the factor with the highest $p >= .2$ is eliminated. The model is then run again and again another factor is excluded. This logic is repeated until a state of $p <= .2$ for all remaining factors occurs, which represents the final model. The following variables that did not end up in any final model are excluded: *South America, fullback, offensive mid, height, both feet, advisor, fouled, shots, pass%, aerials won, key passes* and *own goals.*

Variable	Premier League		Bundesliga		Primera Division		League 1		Serie A	
	Coeff.	P>|t|	Coeff.	P>|t|	Coeff.	P>|t|	Coeff.	P>|t|	Coeff.	P>|t|
Africa	-		-		-5.703	0.023	-3.712	0.096	-	
Europe	-		-		-3.932	0.007	-5.483	0.014	-	
Asia	-		-		-9.806	0.017	-		-	
Central defender	3.639	0.031	4.173	0.080	-		4.708	0.059	-	
Defensive midfielder	5.065	0.005	-		-		-		5.016	0.001
Forward	-		-		-		-		4.305	0.032
Age^2	-0.013	0.001	-		-0.011	0.002	-0.007	0.029	-0.013	0.000
Weight	-		-0.250	0.073	0.320	0.005	-		-	
Right foot	-3.781	0.002	2.915	0.062	-		-		-	
Social media	-		-		-		0.315	0.000	-	
Outfitter	-		-2.547	0.097	2.912	0.043	-2.609	0.122	-	
Through balls	-17.154	0.029	-		-		27.368	0.010	-	
Long balls	-		-		-0.676	0.163	-		-	
Clearances	-		-		-		-		1.319	0.001
Assists	0.484	0.100	-		-		-		0.901	0.002
Offsides	-		6.833	0.021	-		-11.880	0.001	4.408	0.070
Goals	0.460	0.003	-0.091	0.062	-		-		-	
Red	-		5.228	0.111	-		2.614	0.135	-	
Yellow	-0.517	0.013	-		-		-		-	
Bad controls	-		-		-		1.451	0.109	-	
Fouls	3.895	0.011	-		-		2.282	0.089	-	
Tackles	-		-		-		1.065	0.160	-	
Offsides won	-		-		-		5.945	0.065	-	
Minutes	-		0.002	0.065	0.002	0.020	-		-	
Dribbled past	1.846	0.188	3.915	0.061	-3.055	0.039	-3.183	0.054	-	
Dispossessed	-2.609	0.027	-		1.619	0.153	-		-	
Blocked shots	-		-		-		-14.227	0.000	-	
Interceptions	-1.6881	0.127	-		-		-		-	
Mean VIF	1.92		1.55		1.4		2.16		1.5	
R^2 (adj. R^2)	0.39 (0.27)		0.32 (0.21)		0.44 (0.36)		0.67 (0.56)		0.32 (0.27)	
N	72		68		80		65		104	

For the category of physical attributes, age (squared) has a significantly negative effect on transfer fees in all leagues aside from the Bundesliga. The effects are the highest in the Premier League (-.013; $p < 0.01$) and Serie A (-0.013; $p < .001$). A higher weight of a transferred players has a negative effect for the Bundesliga (-.250; $p < .1$) and a positive effect for the Spanish league (-.011; $p < .01$). Footedness (here, the right foot) has a negative effect in the Premier League and a positive one in the Bundesliga.

Social media is only represented in one final model, namely Ligue 1. The results show a highly significant positive effect (.315; $p < .001$). Negative but hardly significant effects of outfitters can be identified in the Bundesliga (-2.547; $p < .1$) and Ligue 1 (-2.609; $p < .2$), while the effect shows a positive and significant coefficient for the Primera Division (2.912; $p < .05$).

Seventeen different performance indicators end up across the five different models, whereby Ligue 1 shows the highest number of individual indicators, with nine (England: 8; Germany: 5; Spain: 4; Italy: 3). Through balls show a negative effect for the Premier League (-17.154; $p < .05$) and a positive for Ligue 1 (27.368; $p < .05$). Significant effects for clearances (1.319; $p < .005$) and assists (.484; $p < 0.5$) only end up in the Italian final model, while offsides show positive coefficients for the Bundesliga (6.833; $p < .05$) and Serie A (4.408; $p < .1$) and a negative one for Ligue 1 (-11.880; $p < .005$). Goal scoring only has a positive effect in the Premier League (.460; $p < .005$) and astonishingly shows a negative but hardly significant coefficient for the Bundesliga (-.091; $p < 0.1$). Yellow cards have a negative effect in the Premier League (-.517; $p < 0.05$), while no significant findings on red cards could be identified, although red cards are represented in two final models. Fouls show a positive significant impact in the English (3.895; $p < .05$) and French (2.282; $p < .1$) leagues. Minutes played has positive effects for the German Bundesliga (.002; $p < .1$) and the Spanish league (.002; $p < .05$) in their final models. The dribbled past variable is the only factor that is represented in four of the five final models, although only the Primera Division (-3.055; $p < .05$) shows significant results. Finally, blocked shots show a highly significant and positive effect in Ligue 1 (-14.227; $p < .001$).

Position-specific Results

Table 5 shows the results from five individual step-wise regressions with backwards elimination predicting transfer fees. The models are calculated on sub-samples comprising the five different playing positions. The models show an adjusted R^2 between 0.26 (offensive midfielder) and 0.56 (forwards), suggesting strong differences in explanatory power at the model level. VIF values range between 1.19 and 2.89, suggesting potential problems with multicollinearity for the sample of defensive midfielders.

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

The table shows the final results from backwards regressions for the full sample of football transfers and the sub-samples consisting of the five major playing positions (*full-backs, central defenders, defensive midfielders, offensive midfielders* and *forwards*). The dependent variable is the log of the transfer fee. Constant is included but not shown in the table. Coefficients and P>|t| are presented for each model. At the bottom of the table, the mean variance inflation factor (VIF), R^2, R^2 (adjusted) and the number of observations is shown. The stepwise regression model is executed with the logic of p >= .2, which means that for each model all variables are regressed and the factor with the highest p >= .2 is eliminated. The model is then run again and again another factor is excluded. This logic is repeated until a state of p <= .2 for all remaining factors occurs, which represents the final model. The following variables that did not end up in any final model are excluded: *Primera Division, Serie A, both feet, clearances, through balls.*

	Fullbacks		Central Defenders		Defensive Midfielders		Offensive Midfielders		Forwards	
	Coeff.	P>|t|	Coeff.	P>|t|	Coeff.	P>|t|	Coeff.	P>|t|	Coeff.	P>|t|
Premier League	3.999	0.026	2.387	0.069	-		2.051	0.179	-	
Bundesliga	-3.752	0.063	-		-		-		-2.503	0.114
League 1	-		-		-		-		-5.631	0.000
South America	-10.932	0.072	-		12.138	0.002	-		-	
Africa	-17.557	0.009	-		10.055	0.010	-		-	
Europe	-14.130	0.020	-2.794	0.023	8.048	0.019	-2.040	0.13	-	
Asia	-		-		-		-7.480	0.02	-	
Age^2	-0.023	0.000	-0.017	0.000	-0.012	0.000	-0.006	0.076	-0.008	0.006
Height	0.324	0.051	-		-		0.234	0.024	0.316	0.073
Weight	0.414	0.024	-		-		-		-0.284	0.047
Right foot	-		-1.899	0.105	-		-		6.844	0.003
Left foot	-		-		2.170	0.138	-		3.863	0.094
Social Media	-		0.072	0.134	0.078	0.127	-		-0.108	0.049
Outfitter	3.966	0.013	-1.591	0.163	-3.093	0.010	-		-	
Advisor	-		-		5.044	0.001	-		2.833	0.088
Long balls	-2.678	0.005	-		-0.918	0.031	-		-16.142	0.015
Assists	-		-		-		0.540	0.014	-	
Fouled	-		3.351	0.009	-		-		-1.439	0.124
Offsides	-6.843	0.116	-		-		-		-2.829	0.104
Goals	-		-1.106	0.018	-0.866	0.009	0.214	0.121	-	
Shots	-5.543	0.045	-		-		-		-	
Pass%	-0.248	0.056	-		0.162	0.172	-0.117	0.045	0.178	0.046
Red	-		-		-		-		8.517	0.002
Yellow	-		-		-0.734	0.003	-		-	
Bad controls	-		-		-4.343	0.005	-		-	
Aerials won	2.606	0.035	-		1.067	0.080	-		2.494	0.000
Fouls	2.886	0.190	-		3.207	0.011	-		-	
Tackles	-		-		-		-		-4.209	0.047
Offsides won	-		-		-		20.021	0.107	-	
Minutes	0.002	0.012	0.002	0.001	0.001	0.119	-		-	
Dribbled past	-3.847	0.091	-		-		-		-	
Dispossessed	-		-		2.641	0.088	-		-	
Blocked Shots	-		-		-5.628	0.054	-		-	
Key Passes	-		-		5.068	0.001	-3.879	0.025	6.914	0.000
Interceptions	2.769	0.036	-		-		-		-9.943	0.011
Own goals	-		-		9.326	0.018	-11.124	0.110	-	
Mean VIF	2.33		1.19		2.89		2.14		2.09	
R^2 (Adj. R^2)	0.65 (0.53)		0.53 (0.47)		0.56 (0.43)		0.35 (0.26)		0.68 (0.56)	
N	68		72		87		97		65	

Of the five league variables, Primera Division and Serie A did not end up in any model. The Premier League (-3.999; $p < .05$) and the Bundesliga (-3.752; $p < .1$) show negative effects for full-backs, while Ligue 1 only shows significant negative effects for forwards (-5.631; $p < .001$). The continent of South America has a negative but insignificant effect on transfer fees for the sample of full-backs (-10.932; $p < .1$) and positive effects for central defenders (3.49; $p < .05$) and defensive midfielders (12.138; $p < .005$). Likewise, full-backs show a negative effect for Africa (-17.557; $p < .01$) and Europe (-14.130; $p < .05$), while the coefficient for African (10.055; $p < .005$) and European (8.048; $p < .05$) defensive midfielders is positive. Asia shows significant negative values for offensive midfielders (-7.48; $p < .05$).

The player characteristic of age has significantly negative effects across all samples of player positions. Height shows a positive impact on transfer fees for full-backs, offensive midfielders and forwards. For full-backs, weight also significantly and positively correlates with transfer fees, while the effect is negative and significant for forwards (-.284; $p <.5$). For footedness, the only significant effect can be identified for forwards, showing a comparably higher positive effect of right-footed players (6.844; $p < .01$).

Social media shows insignificant positive results for central defenders and defensive midfielders and significant negative ones for forwards (-.108; $p < .5$). For full-backs, outfitters have a positive effect (3.966; $p < .05$), while the effect is negative for defensive midfielders (-3.093; $p < .05$). The existence of advisors shows a highly significant positive effect on defensive midfielders (5.044; $p < .005$) and a lesser and less significant positive effect on forwards (2.833; $p < 0.1$).

Overall, 23 different performance variables remain across the five different final models. The model for defensive midfielders has the highest number of individual performance measures (12; of which eight have $p < .05$), while the central defender model has the lowest number (9). No individual variable ends up in all five models and only pass percentage is represented four times (two times significant, $p < .05$).

The long balls variable indicates a significant negative effect for forwards (-16.142; $p < .05$), full-backs (-2.678; $p < .01$) and defensive midfielders (-.918; $p < .5$), showing high differences in the manifestation of negativity. The number of instances in which a player is fouled leads to mixed results across the final models, although only fouled central defenders show a significant impact on transfer fees (3.351; $p < .01$), while the negative result for forwards remains insignificant. The goals variable shows a negative and significant coefficient for central defenders (-1.116; $p < .05$) and defensive midfielders (-.866; $p < .01$). For full-backs, the number of shots per game shows a negative effect on the log of transfer fee (-5.543; $p < .05$). The pass success percentage shows significant negative results for offensive midfielders and positive ones for forwards. Red cards show a highly significant positive coefficient for forwards, while yellow cards show a negative coefficient for defensive midfielders (-.734; $p < .005$). Poor control only ends up in one final model (defensive midfielders), with a negative and significant score (-4.343; $p < .001$). Aerial duels show positive and significant effects for the two models for full-backs (2.606; $p < .05$) and forwards (2.494; $p < .001$) and shows hardly significant results for defensive midfielders

(1.067; $p < .1$). The number of fouls committed has a significantly positive effect for defensive midfielders (2.886; $p < .05$), while the coefficient of full-backs remains insignificant ($p = .19$). The number of successful tackles only remains in the final model for forwards and has a negative impact on the transfer fee prediction (-4.209; p $p < .05$). Two final models (full-backs; .002; $p < .05$ and central defenders; .002; $p < .005$) involve significant results for playing time in terms of minutes on the pitch and the three models for defensive midfielders, offensive midfielders and forwards show for a significant effect of key passes. Nonetheless, this effect is negative for offensive midfielders and positive for the other two position models. A similar variation of significant effects can be seen for interceptions, as full-backs (2.769; $p < .05$) show positive and forwards (-9.943; .05) show negative coefficients. Finally, the models for defensive midfielders has a significant positive result for own goals, while the negative effect for offensive midfielders remains insignificant.

Discussion

Overall, the results from my statistical models confirm existing findings on the determinants of transfer fees. Factors like buying and selling club characteristics or salaries have been identified as determinants for the market value of football players. Therefore, comparatively low R^2s for the regression results do not signal problems for the models themselves, as the goal of this study is not to perfectly predict transfer fees but rather to test for the relevance of specific factors.

In line with empiric literature, I identify a negative effect of age (squared) (e.g. Carmichael et al., 1999; Eschweiler & Vieth, 2004; Feess et al., 2004; Müller et al., 2017), a positive effect of height (e.g. Bryson et al., 2013; Fry et al., 2014) and footedness (Bryson et al., 2013; Herm et al., 2014) on transfer fees. In addition, I identify that the weight characteristic can provide a factor that influences transfer fees, in my statistical models for the samples of transfer fees between €5 million and €15 million (positive effect) and for the sample of > €15 million (negative effect). At a league level, weight has a negative but hardly significant effect for players being transferred into the German Bundesliga and a negative effect for players being transferred into the Spanish league. Based on specific positions, weight has a positive effect for full-backs and a negative effect for forwards.

Confirming previous empirical results (e.g. Frick & Lehmann, 2001; Feess et al., 2004), players from South America generate higher transfer fees. These finding are consistent across transfer fee sizes (all but the €1-€5 million group). Players from Asia show positive effects for the sample of fees between €1 million and €5 million and negative results for the sample of fees above €15 million. The results shown in table 4 directly illustrates differences in the determinants of transfer fees across the specific leagues. Clear differences can be identified, as effects for the continents Africa, Europe and Asia are negative for all cases where the variables remained in the final models for the Primera Division and Ligue 1, while such effects do not exist for the other three leagues. This may be an indicator that the Spanish and Italian leagues specifically look to attract players from South America, with possible explanation being cultural similarities between the countries or work permit and passport issues. For instance, many players from South America already speak Spanish, which makes it much easier to integrate them compared with leagues like the Premier League or the

Bundesliga. Accordingly, I accept hypothesis 1, given that certain player characteristics possess explanatory value for transfer fees.

Performance characteristics show clear effects on transfer fees and differ across different regression models. In the full model, only yellow cards (-), fouls (+), minutes played (+) and interceptions (-) remain as determinants of transfer fees in the final model specifications. These explanatory variables have also (in part) been identified as relevant for transfer fees in previous studies (e.g. Carmichael & Thomas, 1993; Garcia del Barrio & Pujol, 2007; He et al., 2015; Müller et al., 2017). The number of minutes played shows consistent positive results across different transfer fees, the German and Spanish leagues and all three defensive positions.

It is somewhat surprising that the number of goals scored over the previous season does not show significant positive results for the full sample but only for the models of the Premier League (+), Bundesliga (+), central defenders (-) and defensive midfielders (-). Similar results are identified for assists, as only the models for fees up to €1 million, between €5 million and €15 million (-), Serie A (+) and offensive midfielders (+) end up with significant results for this variable. Effects of performance differ across the respective sizes of transfer fees or market values of players, leagues and positions. Defensive characteristics like aerials, fouls or interceptions provide explanatory value for defensive positions, while rather offensive variables like goals, shots or assists remain inconclusive on the position-specific models. This indicates that "overall" results may be the wrong statistical direction, as cross-sample effects clearly provide differences. Performance acts as a predictor of transfer fees, although the relevant predictors differ based on the sample of players. Therefore, I accept hypothesis 2.

In line with previous studies (e.g. Garcia del Barrio & Pujol, 2007; Frank & Nüesch, 2012; Müller et al., 2017), I am able to identify popularity as a predictive variable of transfer fee size and therefore accept hypothesis 3. Nonetheless, these effects cannot be measured for all regression models aside from the full sample. Only the sub-groups of transfer fees between €1 million and €5 million, the Italian league, central defenders and defensive midfielders showed positive significant results. The model containing forwards produced significant positive results. This may be an indicator that forwards' effects of popularity (Adler, 1985) could already be priced in and buying clubs do not interpret high popularity in terms of social media followers as a quality signal.

The results for the overall sample indicate that players being transferred into the English Premier League generate higher transfer fees. A possible explanation for that is the TV deal that the English Premier League was able to close provides English clubs with substantial financial resources compared with the other leagues (BBC, 2018). Selling clubs set their prices knowing the perceived wealth, resulting in comparatively higher transfer fees for clubs from the Premier League. Nonetheless, these effects reverse for the sample of transfers up to €1 million. A possible explanation might be that clubs possess a level of wealth and competition, which leads to them buying players and talents for more than €1 million. The French Ligue 1 shows a significant positive effect for the sample of <€1m, which may be an indicator for a different stance, meaning that comparatively "cheap" talents or older players are transferred into Ligue 1. The Bundesliga and Serie A possess negative coefficients for the sub-sample of €5 million to €15 million, which suggests that they are less willing to spend substantial amounts of money for transfers compared with other leagues. Accordingly, I accept hypothesis 4, as determinants of transfers fees differ across and for domestic leagues.

The results in table 3 show no position-specific effects for the full sample but do so for specific funding categories. Comparatively cheap players (<€1m) show a premium for defensive players, while comparatively expensive players (>€15m) have a negative effect for offensive players. This may be an indicator that defensive players were a scarcer "product" in this specific transfer period, which led to an increase in transfer fees. Moreover, it could also mean that defending players are overall favored, as the strength of the defense comes in first place and attacking comes second. The league-specific results indicate that such effects are specifically relevant for the Premier League, Bundesliga and Ligue 1, while Serie A additionally shows positive results for forwards. The obvious explanation of this finding may be that the transfer of Christiano Ronaldo (€117m) led to a specific premium for forwards. This is not the case, as I additionally tested the model without this observation and the positive effect of forwards remained positive and significant. Given that transfer fees can be explained by playing positions, I thus accept hypothesis 5.

Overall, all hypotheses can be accepted, as I find effects for player characteristics, player performance and player popularity to be a determinant of transfer fees. Additionally, league- and country-specific differences can be identified.

The advisors and outfitters variables are used as control variables but produce significant effects. The two samples of fees between €5 million and €15 million and >€15 million show significant positive effects for advisors. A potential explanation may be that qualitative advisors focus on high-profile (high-value) clients, as advisor fees are calculated as a percentage of fees from the transfer sum. The sample for defensive midfielders also shows a strong positive effect for the existence of an advisor. The existence of an outfitter shows positive effects for the Spanish league, while results for other leagues remain inconclusive. At a position level, the existence of an outfitter has a positive effect on the transfer fee of full-backs and a negative effect on defensive midfielders.

Effects of performance, popularity or external network (advisors and outfitters) on transfer fees differ across transfer fee sizes, leagues and heritage. This indicates that "overall" or "general" results may be the wrong statistical direction for football clubs to (1) evaluate the market value for players to sell or (2) evaluate the market value for players whom the club is trying to attract. Clubs should closely evaluate effects of their specific league (or the league the player is transferred to), heritage and playing position in their statistical models.

Signaling theory (Spence, 1973) postulates that signals can alleviate asymmetric information. For example, if a seller possesses much more information about a product than a prospective buyer, sales can be increased if the seller signals the value of the product to the buyer. In order to be effective and credible, signals should be costly to imitate or sent by trusted third parties (Sanders & Boivie, 2004; Fischer & Reuber, 2007). Johnstone and Grafen (1993) argue that inferior signalers are incentivized to produce dishonest signals to attract signal receivers, as the interests of the two involved parties compete. I identify popularity in terms of social media network size as an overall determinant of transfer fees, and therefore market value. Social media only represents a cheap signal, whose value can directly be influenced; for example, by buying fake followers (Ante & Fiedler, 2019). Therefore, I identify an inefficiency in the market, as players and/or selling clubs are incentivized to misbehave and inflate the networks of the player to generate higher transfer fees. This inefficiency should diminish over time, as the market learns to disregard the signal.

The analyzed data only comprises a comparatively small dataset for one specific transfer period. Therefore, the results and especially regressions of sub-samples may suffer from (1) a lack of sample size and (2) period-specific effects that may limit the general transferability of the results. The results can potentially not be generalized but may only provide insights for determinants of transfer fees for a specific transfer period in the past.

Social media may represent a fitting mechanism to represent popularity, although the time of data collection holds strong relevance in terms of finding relevant results. Once transfer rumors occur, players start to attract social media followers from the related team, as fans want to express their encouragement or refusal of a potential transfer. Therefore, the social media variables may never fully account for pre-transfer popularity but likely still represents a fitting mechanism to measure popularity. In addition, the true size of social media networks may differ, as fake followers and likes can also be bought via cash.

My findings show clear differences in the determinants of market values based on the playing position and domestic leagues. Therefore, future research should closely evaluate samples and make use of multiple models to account for specific differences. Due to sample distribution, I was unable to analyze specific samples for continents of birth. Nonetheless, I also expect to find differences there, as the results show that players from South America are a driver of transfer fees. Future research should analyze such effects accordingly.

While popularity in terms of social media presence provides explanatory power for transfer fees, it remains unclear how much of the size of social media networks can be explained by player characteristics, performance, positions or domestic leagues. Future research should evaluate the extent to which these characteristics are able to explain popularity in term of social media or if unobserved variables (e.g. looks or ethnicity) or faked followers play a major role.

The continent of birth represents a variable that holds explanatory power on transfer fees. Researchers using larger data samples should additionally evaluate country-specific effects. My findings show a positive effect for South America on transfer fee size, although I cannot ascertain whether this effect may only be caused by Brazilians, Argentinians or possibly all countries from South America.

Effects for external advisors or partners have not been expensively analyzed by the empiric literature for football market values. My results show a positive effect for advisors and both positive and negative results for outfitters. Future research should aim to analyze this topic further.

Conclusion

This study provides a descriptive and empirical analysis of 389 individual transfers from the summer transfer window of the 2018/19 season into the five major European leagues, namely the Premier League (England), Primera Division (Spain), Bundesliga (Germany), Serie A (Italy) and Ligue 1 (France). I analyze the data using multiple regressions to identify effects for particular sub-populations in terms of transfer fee size, continent of birth and playing position. Therefore, this study adds to the literature by observing detailed effects for one particular transfer period. I identify player characteristics like age or height, player performance and player popularity in terms of social media network size as determinants of transfer fee size and thus market value. Additionally, I identify differences across all samples, which suggests that generalized models across playing positions and heritage may only provide basic information but do not possess practical use. The findings show that the existence of external advisors has a positive effect on transfer fees above €5 million and the existence of outfitters has an explanatory value. Nonetheless, this study cannot reliably clarify the extent and direction of this effect. Summarized, the use of data analysis provides a suitable took to assess transfer fees of professional football players but analysis must be done at a detailed level.

Literature

Adler, M. (1985). Stardom and talent. *The American economic review*, 75(1), 208-212.

Amir, E., & Livne, G. (2005). Accounting, valuation and duration of football player contracts. *Journal of Business Finance & Accounting*, 32(3-4), 549-586.

Ante, L., & Fiedler, I. (2019). Cheap Signals in Security Token Offerings. https://www.researchgate.net/publication/331287045_Cheap_Signals_in_Security_Token_Offerings/ Accessed 16 March 2019.

Atkinson, A. B. (1975). *The economics of inequality*. Clarendon Press, Oxford University Press, London.

BBC (2018). Premier League TV rights: Five of seven live packages sold for £4.464bn. https://www.bbc.com/sport/football/43002985/ Accessed 10 March 2019.

Brandes, L., Franck, E., & Nüesch, S. (2008). Local heroes and superstars: An empirical analysis of star attraction in German soccer. *Journal of Sports Economics*, 9(3), 266-286.

Bryson, A., Frick, B., & Simmons, R. (2013). The returns to scarce talent: Footedness and player remuneration in European soccer. *Journal of Sports Economics*, 14(6), 606-628.

Carmichael, F., & Thomas, D. (1993). Bargaining in the transfer market: theory and evidence. *Applied Economics*, 25(12), 1467-1476.

Carmichael, F., Forrest, D., & Simmons, R. (1999). The labour market in association football: who gets transferred and for how much?. *Bulletin of Economic Research*, 51(2), 125-150.

Dobson, S., & Gerrard, B. (1999). The determination of player transfer fees in English professional soccer. *Journal of Sport Management*, 13(4), 259-279.

Dobson, S., Gerrard, B., & Howe, S. (2000). The determination of transfer fees in English nonleague football. *Applied Economics*, 32(9), 1145-1152.

Eschweiler, M., & Vieth, M. (2004). Preisdeterminanten bei Spielertransfers in der Fußball-Bundesliga. *Die Betriebswirtschaft*, 64(6), 671.

Feess, E., & Muehlheusser, G. (2003). The impact of transfer fees on professional sports: an analysis of the new transfer system for European football. *Scandinavian Journal of Economics*, 105(1), 139-154.

Fischer, E., & Reuber, R. (2007). The good, the bad, and the unfamiliar: The challenges of reputation formation facing new firms. *Entrepreneurship Theory and Practice*, 31(1), 53-75.

Franck, E., & Nüesch, S (2008). Mechanisms of Superstar Formation in German—Empirical Evidence. *European Sport Management Quarterly*, 8, 2008, 145–164.

Franck, E., & Nüesch, S. (2012). Talent and/or popularity: what does it take to be a superstar?. Economic Inquiry, 50(1), 202-216.

Frick, B. (2007). The Football Players' Labor Market: Empirical Evidence from the Major European Leagues. *Scottish Journal of Political Economy*, 54(3), 422-446.

Frick, B., & Lehmann, E. (2001). *Die Kosten der externen Rekrutierung qualifizierten personals: Empirische Evidenz aus dem professionellen Fußball. Entlohnung, Arbeitsorganisation und personalpolitische Regulierung.* Munchen: Rainer Hampp Verlag, 243-63.

Fry, T. R., Galanos, G., & Posso, A. (2014). Let's get Messi? Top-scorer productivity in the European Champions League. *Scottish Journal of Political Economy*, 61(3), 261-279.

Geurts, J. S. (2016). Football players' transfer price determination based on performance in the Big 5 European leagues. https://run.unl.pt/bitstream/10362/18646/1/Geurts_2016.pdf/ Accessed 01 March 2019.

He, M., Cachucho, R., & Knobbe, A. J. (2015). Football Player's Performance and Market Value. *MLSA@ PKDD/ECML*, 87-95.

Herm, S., Callsen-Bracker, H. M., & Kreis, H. (2014). When the crowd evaluates soccer players' market values: Accuracy and evaluation attributes of an online community. *Sport Management Review*, 17(4), 484-492.

Johnstone, R. A., & Grafen, A. (1993). Dishonesty and the handicap principle. *Animal Behaviour*, 46(4), 759-764.

Kiefer, S. (2014). The impact of the Euro 2012 on popularity and market value of football players. *International Journal of Sport Finance*, 9(2), 95-111.

Kihlstrom, R. E., Roth, A. E., & Schmeidler, D. (1981). Risk Aversion and Solutions to Nash's Bargaining Problem. In O. Moeschlin and D. Pallaschke, (Eds.). *Game Theory and Mathematical Economics*. Elsevier.

Lehmann, E. E., & Schulze, G. G. (2008). What does it take to be a star? The role of performance and the media for German soccer players. *Applied Economics Quarterly*, 54(1), 59.

Lucifora, C., & Simmons, R. (2003). Superstar effects in sport: Evidence from Italian soccer. *Journal of Sports Economics*, 4, 35–55.

Medcalfe, S. (2008). English league transfer prices: is there a racial dimension? A re-examination with new data. *Applied Economics Letters*, 15(11), 865-867.

Mukaka, M. M. (2012). A guide to appropriate use of correlation coefficient in medical research. *Malawi Medical Journal*, 24(3), 69-71.

Müller, O., Simons, A., & Weinmann, M. (2017). Beyond crowd judgments: Data-driven estimation of market value in association football. Eur*opean Journal of Operational Research*, 263(2), 611-624.

Murtagh, J. (2015). Moneyball FC: how Midtjylland harnessed the power of stats to set up Euro showdown with Southampton. http://www.mirror.co.uk/sport/football/news/money ball-fc- how-midtjylland-harnessed-6282271/ Accessed 16 March 2019.

Nash Jr, J. F. (1950). The bargaining problem. *Econometrica: Journal of the Econometric Society*, 155-162.

Nash, J. (1953). Two-person cooperative games. *Econometrica: Journal of the Econometric Society*, 128-140.

Pawlowski, T., Breuer, C., & Hovemann, A. (2010). Top clubs' performance and the competitive situation in European domestic football competitions. *Journal of Sports Economics*, 11(2), 186-202.

Garcia-del-Barrio, P., & Pujol, F. (2007). Hidden monopsony rents in winner-take-all markets — sport and economic contribution of Spanish soccer players. *Managerial and Decision Economics*, 28(1), 57-70.

Reep, C., & Benjamin, B. (1968). Skill and chance in association football. *Journal of the Royal Statistical Society. Series A (General*), 131(4), 581-585.

Reep, C., Pollard, R., & Benjamin, B. (1971). Skill and chance in ball games. *Journal of the Royal Statistical Society: Series A (General)*, 134(4), 623-629.

Reilly, B., & Witt, R. (1995). English league transfer prices: is there a racial dimension?. *Applied Economics Letters*, 2(7), 220-222.

Rosen, S. (1981). The economics of superstars. *The American economic review*, 71(5), 845-858.

Ruijg, J., & van Ophem, H. (2015). Determinants of football transfers. *Applied Economics Letter*s, 22(1), 12-19.

Sanders, W. G., & Boivie, S. (2004). Sorting things out: Valuation of new firms in uncertain markets. *Strategic Management Journal*, 25(2), 167-186.

Shaked, A., & Sutton, J. (1984). Involuntary unemployment as a perfect equilibrium in a bargaining model. *Econometrica: Journal of the Econometric Society*, 1351-1364.

Speight, A., & Thomas, D. (1997). Football league transfers: a comparison of negotiated fees with arbitration settlements. *Applied Economics Letters*, 4(1), 41-44.

Spence, M. (1973). Job market signaling. The Quarterly Journal of Economics, 87(3), 355-374.

Wang, Q., Koval, J. J., Mills, C. A., & Lee, K. I. D. (2007). Determination of the selection statistics and best significance level in backward stepwise logistic regression. *Communications in Statistics-Simulation and Computation*, 37(1), 62-72.

Zhu, F., Lakhani, K. R., Schmidt, S. L., & Herman, K. (2015). TSG Hoffenheim: football in the age of analytics. *Harvard Business School Case*, 616, 10.

Appendix

Table 6. Descriptive statistics, variable definitions and sources

The table shows the descriptive statistics of the dataset. Observations (N), mean, standard deviation (SD), median (p50), minimum and maximum are presented. All variables are described and their source is shown. The source (1) stands for transfermarkt.de, (2) for whoscored.com and (3) stands for direct collection of data from the social media networks Instagram, Twitter and Facebook.

Variable	N	Mean	SD	p50	Min.	Max.	Description	Source
Transfer Fee (log)	389	12.66	6.23	15.31	0	18.72	Log of the reported transfer fee in EUR	(1)
Premier League	389	0.19	-	0	0	1	Dummy: Player transferred into Premier League	(1)
Bundesliga	389	0.17	-	0	0	1	Dummy: Player transferred into Bundesliga	(1)
Primera Division	389	0.21	-	0	0	1	Dummy: Player transferred into Primera Division	(1)
League 1	389	0.17	-	0	0	1	Dummy: Player transferred into League 1	(1)
Serie A	389	0.28	-	0	0	1	Dummy: Player transferred into Serie A	(1)
South America	389	0.15	-	0	0	1	Dummy: Player is born in South America	(1)
Africa	389	0.13	-	0	0	1	Dummy: Player is born in Africa	(1)
Europe	389	0.69	-	1	0	1	Dummy: Player is born in Europe	(1)
Asia	389	0.03	-	0	0	1	Dummy: Player is born in Asia	(1)
Central Defender	389	0.19	-	0	0	1	Dummy: Players main field position is central defender	(1)
Fullback	389	0.17	-	0	0	1	Dummy: Players main field position is fullback	(1)
Defensive Midfielder	389	0.22	-	0	0	1	Dummy: Players main field position is defensive midfielder	(1)
Offensive Midfielder	389	0.25	-	0	0	1	Dummy: Players main field position is offensive midfielder	(1)
Forward	389	0.17	-	0	0	1	Dummy: Players main field position is forwards	(1)
Age^2	389	669.93	195.51	625	256	1600	Square of the players age at the time of transfer	(1)
Height	389	181.46	6.42	182	165	199	Height of the player in cm	(1)
Weight	389	75.34	6.42	75	57	96	Weight of the player in kg	(2)
Two feet	389	0.67	-	1	0	1	Dummy: Player is two-footed	(1)
Right foot	389	0.28	-	0	0	1	Dummy: Player is right-footed	(1)
Left foot	389	0.05	-	0	0	1	Dummy: Player is left-footed	(1)
Social Media	389	21.73	11.21	21.06	0	55.59	Sum of the log of Instagram, log of Twitter and log of Facebook followers	(3)
Outfitter	389	0.35	-	0	0	1	Dummy: Player has an outfitter	(1)
Advisor	389	0.84	-	1	0	1	Dummy: Player has an advisor	(1)
Through balls	389	0.06	0.33	0.00	0	5.1	Through balls per game in the season before the transfer	(2)
Long balls	389	1.82	1.53	1.40	0	8.8	Long balls per game in the season before the transfer	(2)
Clearances	389	1.59	1.68	1	0	7.8	Clearances per game in the season before the transfer	(2)
Assists	389	2.06	2.41	1	0	12	Total number of assists in the season before the transfer	(2)
Fouled	389	1.09	0.66	1	0	4.3	Fouls committed to the player per game in the season before the transfer	(2)
Offsides	389	0.18	0.26	0.10	0	2.0	Offsides per game in the season before the transfer	(2)
Goals	389	3.03	4.13	1	0	26	Total number of goals in the season before the transfer	(2)
Shots	389	1.09	0.86	0.90	0	6.6	Shots per game in the season before the transfer	(2)
Pass%	389	78.18	9.29	79.40	0	94.8	Pass percentage in percent in the season before the transfer	(2)
Red	389	0.15	0.39	0	0	2	Number of red cards in the season before the transfer	(2)
Yellow	389	3.58	2.92	3	0	16	Number of red cards in the season before the transfer	(2)
Bad controls	389	1.20	0.78	1.10	0	4.1	Bad controls per game in the season before the transfer	(2)
Aerials won	389	1.28	1.03	1	0	6.2	Aerials won per game in the season before the transfer	(2)
Fouls	389	1.09	0.53	1	0	2.7	Fouls committed from the player per game in the season before the transfer	(2)
Tackles	389	1.43	0.87	1.30	0	9.0	Successful tackles per game in the season before the transfer	(2)
Offsides won	389	0.17	0.29	0	0	1.4	Offsides won per game in the season before the transfer	(2)
Minutes	389	1721	934	1680	0.4	4230	Total number of minutes played in the season before the transfer	(2)
Dribbled past	389	0.74	0.47	0.60	0	2.6	Successful dribbles per game in the season before the transfer	(2)
Dispossessed	389	0.92	0.64	0.80	0	3.5	Dispossessions per game in the season before the transfer	(2)
Blocked Shots	389	0.22	0.25	0.10	0	1.2	Blocked outfielder shots by the player per game in the season before the transfer	(2)
Key Passes	388	0.76	0.57	0.70	0	2.9	Key passes per game in the season before the transfer	(2)
Interceptions	389	0.98	0.73	0.90	0	4.0	Interceptions per game in the season before the transfer	(2)
Own goals	389	0.06	0.30	0	0	3	Own goals per game in the season before the transfer	(2)