Analysis of Football Transfer Networks and Performance

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Abstract

This paper examines the European football transfer market with the help of the toolkit of network science. Using a unique dataset of all transfers conducted by the first-tier football teams of the top 5 European leagues from 1992/1993 to 2021/2022, a directed transfer network is constructed (clubs represent nodes and transfers are links) for each transfer window. The questions the study aim to answer is how the global characteristics of these networks evolved over time and the existence and extent of the impact of node characteristics in the transfer market networks on the later performance of the corresponding football clubs. The relevance of the study lies in the high number of transfers on the football transfer market with questionable effects on realized sport achievements. The findings of this study are useful for practitioners and sport scientists alike.

Contents

1 Introduction

Football used to be simply known as the most popular sport throughout the world, the "beautiful game" as they say. However, in the modern era it is just as much a global business attracting billions of euros every year as it is a sport where competing teams aim to score one more time than the opponent. And for businesses, as the stakes became higher in terms of financials, efficiency and smart strategies for maximized sport performance at lowest cost came forward as clear goals. But how are teams built up in the first place to achieve sport success?

Professional football teams compete in their respective domestic championships with a squad of approximately 24 players. There are basically two main sources for the teams to get these players: They can either operate with a youth academy where coaches of the club train the young football players from an early age and the best and most persistent ones can simply go up the latter all the way to the first team. Then there is also a second way in which clubs can acquire players for their professional first team that gets much more spotlight. Players can be purchased, sold and loaned out on the international transfer market. It is important to note that players tend to have careers ranging over 15 to 20 years and are to service for a club only for couple of years. Thus, the number of transfers can be very high, and activities on the transfer market became more and more prominent over the past years. Gross transfer spending reached a record total of €6.5 billion by European top-league clubs in the summer of 2019 (UEFA 2022).

Football clubs follow various strategies on the transfer market based on their priorities. Some clubs concentrate more on maximizing value for the owners by making smart deals (trying to buy cheap, sell high). Their choice of approach in this labor market is thus to to achieve financial success. But some other clubs sell players in an effort to buy better ones (Rossetti and Caproni 2016). Strategies and management on the transfer market affects both sportive and financial performance of football club.

The aim of this study is twofold. The first question it aims to answer relates to the temporal evolution of the structure of the entire transfer networks that get built each time the transfer window opens. The question is how the transfer network of all deals conducted by the European top 5 leagues evolved over the past 30 years, and whether it moved towards a less random and more small-world structure?

The second question this research paper puts forward relates rather to the relationship between the positions of the football clubs in these networks and their immediate subsequent performance. In detail, the question is whether and to what extent local network metrics capturing the activity and strategy of football clubs in the respective transfer networks built for each window impact the ranking of the teams in their domestic league tables. The main data used for this analysis consist of all the transfers conducted by the first-tier teams of the top 5 European football leagues

(England, Spain, Italy, France, Germany) from 1992 to 2021. From these, transfer networks are conducted for each transfer window where the nodes are the football clubs and the transfers between them constitute the edges. For the description of the global structure of these networks, besides the classical average degree, average path length and clustering coefficients, a more sophisticated small-worldiness index is also calculated. For the analysis of sportive performance, all final-, and mid-league tables are used. Its relationship with the local network metrics (in-, and out-degree, betweenness and in-, and out-coreness) is investigated via linear regressions where the ranking of teams on these tables is the target variable. Finally, further information on the squads of the teams (estimated value, age and height of players) are also collected to be used as control variables.

Regarding the first research question, findings suggest that there was a general increasing trend in the average degree of the transfer networks (both summer and winter), but in the past couple of years it started to decline. As for the small-worldiness, we find a great deal of heterogeneity and no clear trend for the summer windows, and a similar trend to the degree in case of the winter windows.

As for the second research question, the effect of the summer transfer window strategies and that of the winter windows has been analyzed separately. We find that in the summer window, higher betweenness seems to have a negative effect on expected ranking, while in the specification with less control variables, in-degree is positively related to performance and out-degree is negatively correlated. In the case of the winter window, only the in-degree has a significant positive effect. Coreness is not significant in any of the models.

The rest of the paper is structured as follows: Section two presents a thorough review of the prior literature on the objectives of teams on transfer markets in general and studies that portrayed and investigated transfer markets from a network perspective. Next, in section 3, the data used is introduced in fine detail along with the methods, technical approach and some descriptive statistics. Section 4 then turns to the investigation of the temporal evolution of the transfer network. Finally, section 5 looks at the relationship between local network metrics and sportive performance. Section 6 concludes the findings.

2 Literature review

In order for professional football teams to achieve sportive success, they tend to rely more and more often on the acquisition of players on the international transfer market. Every club has different resources, strategies and approaches, but the aim to improve on their respective squads and out-perform them in the subsequent period in their championships is common. In the literature review section, first, the main types of objectives of clubs on the transfer markets are presented. Second, prior works on the representation of the transfer market as a complex system i.e. a network are introduced.

2.1 Football transfer market objectives

Clubs are essentially football companies that operate with a double objective that often oppose each other. Efficiency is required both in the sport and the economic side of the business at the same time, though they have different measures. It is the job of the management to find the right balance (András 2003). According to Chikán (2003), the same duality is also present for the football clubs in the creation of value, as it should be created for the client and the owner at the same time. If the company is unable to react and reflect on the demands of its clients, which are in case of a football club the fans who pay for the tickets, merchandise, television etc., it seizes to be profitable in longer run as fans will churn away. This way, football clubs are not able to stay alive on a self-financing basis. If the owner(s) or investor(s) can not see any return on his investment, then they will not keep the company alive. Thus there is an ongoing debate over the types of transfer strategy the club should follow: Primary goal can be either win maximization or financial performance maximization (Coates, Naidenova, and Parshakov 2020).

Football players are not only the scarce resources of the football companies, but also the foundation of their future performance (András 2003). In connection with the second goal of targeting win maximization, it is not a surprise that the majority of the budget of football clubs is spent on players. This is what makes it a strategically important question how big of a budget clubs can work with when putting together their respective squads(Havran 2016). Notably, there is a rich-get-richer phenomena in place, since more successful clubs get more wealthy, which allow them to build even better teams by buying the best players. As a result, they are in favor of keeping the inequality between themselves and less wealthy clubs as big as possible (Havran 2016).

The Union of European Football Associations (UEFA) puts together a each year a document called The European Club Footballing Landscape, in which they publish all sorts of economic data of the European football clubs. Interestingly already in the first edition (UEFA 2008), they show a clear positive correlation between sport success and revenue. But in the 2009 edition (UEFA 2009), they further outline that the relationship between financials and sportive success is not linear, but rather exponential. For a unit higher sport performance much higher financial resources need to be invested (Havran 2016). However, if football clubs realise that the most significant part of their revenue is from selling players, they may rather opt for a transfer-strategy. For such clubs, much bigger emphasis and resources are put on the quality of youth academy and training. Being embedded into the global transfer network is an an intangible, but very much valuable asset for such clubs (Fűrész and Havran 2021).

Rossetti and Caproni (2016) analyze the transfer market history from 1990 to 2015 and cluster clubs into certain profiles. They find that regardless of the clubs' budgets, transfer market strategies affect sportive performance greatly. The authors argue that clubs that trade globally in the transfer market tend to dominate their domestic league, thus it is worth to be part of the network these companies establish through repeated transactions.

There are at least two well-identifiable ways how player movement can affect team performance on the pitch. The first one is that player transfers enhance diversity, which in turn enhance the effectiveness of organizations (Richard et al. 2004). The authors argue that people with different cultural and personal backgrounds and characteristics have different skill sets. When all these are put together inside of a team, it produces positive synergies, which increase productivity. Sources of diversity can be gender, nationality, age, experience etc. Getting back to the application of these theories in football, Ingersoll, Malesky, and Saiegh (2014) find that cultural diversity of football players in the UEFA Champions League had a positive impact on group performance.

It is also worth to note that diversity can also have negative or mixed effects. Potential problems include that buying a player from a significantly different club or even league often lead to a long period of integration and adaptation which takes away time and energy from proper training and the team may perform poorly on the field as a consequence. According to Franck and Nüesch (2011), a diverse set of players in terms of talent has mixed effects on team performance based on the scope. If there is huge disparity among those selected to play (the starting eleven), the team performs worse. But if there is wide disparity in talent within the entire squad, the team performs better. There can also be language difficulties for teammates from different countries (Brandes, Franck, and Theiler 2009), leading to a reduction in team cohesion (Caruso, Carlo, and Marco 2016).

Another way how player movement can affect team performance on the pitch is transfer of knowledge. Thanks to the mobility of workers, different technologies and important information get transmitted from firm to firm (Gupta and Govindarajan 2000), which increases firm performance (Mostafa and Klepper 2018) and the productivity of the workers (Markusen and Trofimenko 2009). Importantly, these articles considered employee transfers going from advanced, pioneering (often multinational) companies, to rather domestic firms. But it is true in general that the greater the difference in knowledge, the higher the potential effect on performance from the transfer. Furthermore, though these papers dealt with other businesses than sports, the lessons are applicable.

According to Frick and Simmons (2014) players can share to their new teammates good practices and information about their diet or other types of training routines and teach new playing skills. On the same subject, Yamamura (2009) finds that players from developing nations who played in leagues of developed country gained from the technology transfers substantially, which in turn improved the performance of their home countries.

2.2 Network perspective

Though the application of a network perspective on sports is relatively new, there are increasing number of papers that take this approach. The first articles on using network analysis in sports were rather focused on in-game networks where players are nodes and passes between them are edges(e.g. (Pena and Touchette 2012)). But the kind of networks we are interested in consider the transfer market of football teams as a complex system represented by a network where the clubs are nodes and transfers between them are edges.

The network approach allows a systematic overview of the football transfer market (Liu et al. 2016). In the talent management literature, the importance of recruiting, retaining, and investing in human resources in organizations is emphasized. However, for most businesses, it is impossible to track a person's places of employment outside one workplace. In football, however, we can actually see how employee transfers between firms influence the performance of the organizations (Coates, Naidenova, and Parshakov 2020).

One of the prominent papers on transfer market networks was written by Liu et al. (2016), who analyze a total of 24 top football leagues from 2011 to 2015. They claim that football can be considered a 'money game' because the money invested in buying players is reflected in sporting performance. In a bit more detail, the authors identify different league categories based on the relationship between investments and sportive team performance. Categories include 'money', 'farm', and 'outlier' leagues. 'Money' leagues reveal a negative correlation between annual transfer balance and average league game points obtained. Hence, the more the clubs within this league type spend on transfers, the more their match performance increases. In contrast, this correlation is found to be positive in case of 'farm' leagues, i.e. the higher the clubs' transfer market profits, the better match performance becomes. The remaining leagues are classified as 'outlier' leagues. Remarkably, the authors identify a large and increasing inequality within the transfer market.

Matesanz et al. (2018) also take a network perspective and analyse transfers in 21 countries between 1997 and 2016. They first look at the evolution of the transfer network over time and find that at around the time of the global financial crisis of 2008, the number of clubs involved in the market and the number of players transferred both stopped growing and the network became more connected and dense. But overall, the whole transfer network evolved towards a small-world network over the examined period. Next, the authors also employ machine learning algorithms (Kohonen SOMs and PCA) to reveal similarities among clubs and cluster them in terms of their transfer market activities. Their results show that English clubs dominate the transfer market, followed by Spanish, Italian and Portuguese ones, but a French and German club are also key participants.

The structure and characteristics of the transfer networks have also been investigated already through numerous centrality indicators. Li et al. (2018) examine 470,792 transfer records among 23,605 football clubs in 206 countries and regions to construct a mutual transfer network and determine that the in-degree, out-degree, in-strength and out-strength values of clubs follow bimodal distributions and the distribution of link-weights has a power-law tail. Bond et al. (2018) also look at a wide variety of metrics including degree, closeness, betweenness and eigenvector centralities as well as brokerage (capturing structural holes). The authors are especially interested in the role of emerging markets in the structure of the global transfer network. They find that the network has a core-periphery structure with European countries at the core, developing countries at the semi-periphery and countries where football is less developed on the periphery. Turkey and Brazil are found to occupy structural holes acting as brokers (central participants in each region). Finally, Fűrész and Havran (2021) investigate around 20,000 transfers between 2005 and 2019 on the European transfer market. They take a regional level approach and calculate small-world indicators for the resulting subnetworks. The authors find that the network structure of Western and Eastern European top clubs with significant losses and the Western and Eastern European non-top leagues with significant profits are remarkably different.

To sum up, according to the literature, football clubs face a double challange of satisfying their customers, the fans by building a strong team and achieving sportive success and the investors who want high returns. But both goals require transfers, the magnitude of the spending on them is a clear signal of that. Other studies look at different ways acquiring players can impact sportive performance, enhancing knowledge and diversity are highlighted. Then, several studies are introduced that looked at the transfer market as a network already. There are however two aspects in which this research can bring novelty. First is the timescope of the study (from 1992 to 2021), which constitutes a longer time period than any prior study before. Second is the perspective of looking at all the windows as separate networks and measuring immediate (half-year and year) impact on sportive performance.

3 Data and technical approach

3.1 Sources and shape of data

There are various sources of data be combined in this research. But all of it was scraped from transfermarkt.com (2022), the leading portal on football transfer data, using the worldfootballR package developed by Jason Zivkovic (2019). The most important one contains all transfers, both loans and permanent deals, that were conducted by the first-tier teams of the top 5 European championships (England, Germany, France, Italy, Spain) from 1992 to 2021. This dataset contains a total of 94,423 transfers and multiple information besides the name of the player and the two clubs involved in the deal. We know the transfer fee paid, the age of the player, the number of minutes he played in the subsequent season (or half season if winter transfer), the number of goals scored, and the type of transfer as well, whether it is a loan or a permanent transfer.

The football transfer market is open for two periods over one year: there is a summer transfer period and a winter transfer period. Each period, all teams have the opportunity to engage in transfer activity in an effort to restructure the composition of their team and improve their chances for a better sportive performance. The movement of players can take the form of either a transfer or a loan deal. The difference is that during a transfer, the player terminates his contract with the former club and signs a contract with the new club. In case of a loan, on the other hand, the player is sent by the club temporarily to play for another one. Though the loan network and transfer network show different characteristics (Liu et al. 2016), we treat loan and transfer links between clubs in the same way. However, we do introduce the share of loans as a control variable later in the regression settings.

Furthermore, in contrary with various prior literature that looked at aggregate transfer network over multiple years, we take a different approach and construct transfer networks at each of these transfer periods. In the resulting networks, the teams are nodes and the transfers between them constitute the edges. The main reason behind building networks each transfer window is that in this paper, the second research question centers around immediate impact of transfer activity on sport success for which this approach appears most appropriate.

When calculating the various local metrics calculated capturing different characteristics of the teams (to be introduced in detail in the next subsection), the resulting dataset will already be on the team level. Here we only keep those teams that are in the first-tier of the top 5 leagues, so the characteristics of the teams that only sold to these teams are disregarded. This allows us to merge it to our second important source of information, the domestic league tables of the teams. Not only all final league tables were downloaded, but also the detailed information on the position and performance of teams at exactly halfway. These tables were merged to the tables containing the teams' network characteristics for each window in the following way. First, to each teams' summer window characteristics, the performance (points, position etc.) from the end of last season is joined in order to get an idea of the situation of the club before the market opened. Next, to the same rows, the performance (points, position etc.) of the teams at the halfway and full season following the transfer window are merged. Similarly to the network metrics of teams in the winter window, the previous, current and final performance are joined.

As the scope turned to team level, all the additional information available at the transfer level needed to be aggregated as well. For the age of the players, the average value is taken for both the outgoing and the incoming players and in case no information was available, the mean value is imputed. For the transfer fees, minutes spent on the pitch and goals scored by the player transferred, also the mean values are taken. But in this case, 0 value was iputed in place of the missing observations. We also calculate the share of loans of all the in-, and out-transfers as a further variable. Finally, as a further complementary information, the valuation of teams was also collected as a further potential confounder in the later analysis.

3.2 Network metrics

As we have seen in the Literature Review section, various network metrics can be used to analyze the structural characteristics of the football transfer market in general and locally, the positions of clubs in it.

In this paper, we use two kinds of metrics. We use rather global metrics that describe the entire network to analyze the temporal evolution of the network structure of the transfer market. This way we hope to pick up on some characteristic trends and get a holistic picture.

3.2.1 Global metrics

One of the basic metrics in this regard is the average degree, which is just the arithmetic mean of the number of edges linked to all nodes constituting the network. It is calculated by considering the network undirected and the total number of links, L can be expressed as the sum of the node degrees. (Barabási and Pósfai 2016) The average degree formula is given simply by:

$$AD = \frac{1}{N}\sum_{i=1}^{N} k_i = \frac{2L}{N} \tag{1}$$

Another important network metric is the average path length, which is the arithmetic mean of the shortest paths between all pairs of nodes (Barabási and Pósfai 2016). Its formula is given by

$$APL = \frac{\sum_{i=1}^{N} \sum j = 1^N d_i j}{N(N-1)} \tag{2}$$

In this formula $d_i j$ stands for the general element of the distance matrix, which is the shortest path between nodes (i.e. clubs) i and j.

Next, we also consider the clustering coefficient, which can be calculated for each node. It measures the extent to which neighbours of a given node are also connected to each other (Cowan 2005). Its formula again from the Barabási book (2016) is given by:

$$C_i = \frac{2L_i}{k_i(k_i - 1)}, \tag{3}$$

where L_i stands for the number of links between the k_i neighbors of node i. Notably, C_i is always a number between 0 and 1.

Then, the global clustering coefficient can be easily obtained from the local clustering coefficient by taking the mean of all values. The global metric then measures how closed the structure of the networks is overall.The formula is then given by:

$$AC = \frac{\sum_{i=1}^{N} C_i}{N}, \tag{4}$$

Following on the footsteps of Fűrész and Havran (2021), a small-world index is also constructed from the combination of the clustering coefficient and the average path length. As networks change over time, they can have different density and size, thus these metrics were normalised by Erdös-Rényi random graphs (Erdös and Rényi 1959). As a result, clustering coefficients and average path lengths are compared from within networks of equivalent degree on average. The formula is thus given by:

$$SW = \frac{AC}{AC_r} \div \frac{AD}{AD_r}, \tag{5}$$

As described by Watts and Strogatz (1998), there is a difference in how random and local-structured networks look like. Based on randomness, they can be either regular (all the nodes have the same links), small-world (there are local clusters), or completely random networks. For the European football transfer market, it is evident that it is not a regular network, as the nodes (which are the clubs) have different numbers of links (that is transfers). But the investigation of the extent of small-worldiness is a relevant question (Fűrész and Havran 2021). Random networks are characterised by low average clustering and short paths, while small-world networks are characterised by high clustering and short average paths (Cowan 2005; Watts and Strogatz 1998). Thus, using this metric, we can look at the extent to which the networks are small-world type.

3.2.2 Local metrics

For the investigation of the relationship between clubs performance and their transfer market strategy and activity, instead of the introduced global metrics, we consider node-level, local network metrics. With the help of these we hope to catch upon some kinds of characteristics in the transfer network that help teams perform better immediately than some others.

The first such local network measure is a simple one, and can be familiar as a constituent of the average degree in case of the global networks. The degree (or connectivity) of a node is defined as the number of links of the node (Barabási and Pósfai 2016). However, since we have a directed network, we distinguish between the in-, and out-degree of the nodes, which are simply the counts of the incoming and outgoing links. They are in our case great measures for how many different business partners the football clubs have from which they buy, and how many from which they sell. A node with high degree implies a high synchronization of the node with other nodes. It is an important centrality measure of a network because nodes with high degree play a central role in the network dynamics.

Next, we have the in-, and out-coreness of the nodes. The k-core of graph is a maximal subgraph in which each vertex has at least degree k. The coreness of a vertex is k if it belongs to the k-core but not to the (k+1)-core. Since the k-core allows nodes to be involved in a clique even though they may not have to connections to every other node, a high out-coreness shows great involvement in hubs, but low involvement otherwise. Similarly, if a given club has a high in-coreness metric, it shows that the football clubs he buys players from constitute a closed, small community.

Finally, we also consider betweenness centrality. It is an indicator of prestige, referring to the extent to which node i is involved in the geodesic distance of two unconnected nodes, j and k. Thus, it is essential to the indirect link between j and k. This centrality has important strategic implications that can be exploited and leveraged. For the club i, it represents the proportion of geodesic distances it is involved in indirectly by connecting clubs j and k (Vega-Redondo 2007). The standardised formula based on Freeman's (1977) work on betweenness centrality is given by:

$$B_i = \frac{\sum_{j \neq k} \frac{D^i_{jk}}{D_{jk}}}{(n-1)(n-2)}, \tag{6}$$

where D_{jk} stands for the sum of geodesic distance between nodes j and k, and D^i_{jk} is the geodesic distances between j and k involving i. Thus, a high betweenness measure suggests that the club i conducts trade with more unconnected trade partners. This can provide a strategic role within the network (by filling a structural hole).

3.3 Descriptive statistics

Finally, as part of this section, let us look at some useful descriptive statistics on the transfer market data utilised for this research.

First of all, Figure 1 shows the aggregate spending of transfers by the teams. First of all, it is apparent that there was an increasing trend from 1992 to 2001 in which period the spending on both summer and winter windows depicted an upward sloping trend. Then, there was a smaller setback from 2002 to 2006, but 2007 to 2009 were again strong years when overall transfer fees exceeded 3 billion euros. After yet another bit of decrease in 2009 to 2012 compared to these years, from 2013 onwards there seemed to be no turning back. By 2016, the sum of the money paid on the market neared 6 billion euros and in the record breaking year of 2019, it reached a whopping 9.6 billion euros. Afterwards, the covid-19 pandemic caused severe harms in the intake of the clubs and such heights became unreachable. But the fact that even so, the 2020 and 2021 numbers only decreased to the 2015-16 levels shows the incredible amount of money football clubs still spend on improving their squads. Looking more closely also on the distinction between winter and summer transfer windows, we can see that there is a strong correlation, they mostly move together. However, for example in 2019 when the summer window broke all records, the winter window did not get near the peak of 2017.

Next, Figure 2 depicts the overall number of incoming (arrivals) and outgoing (departures)

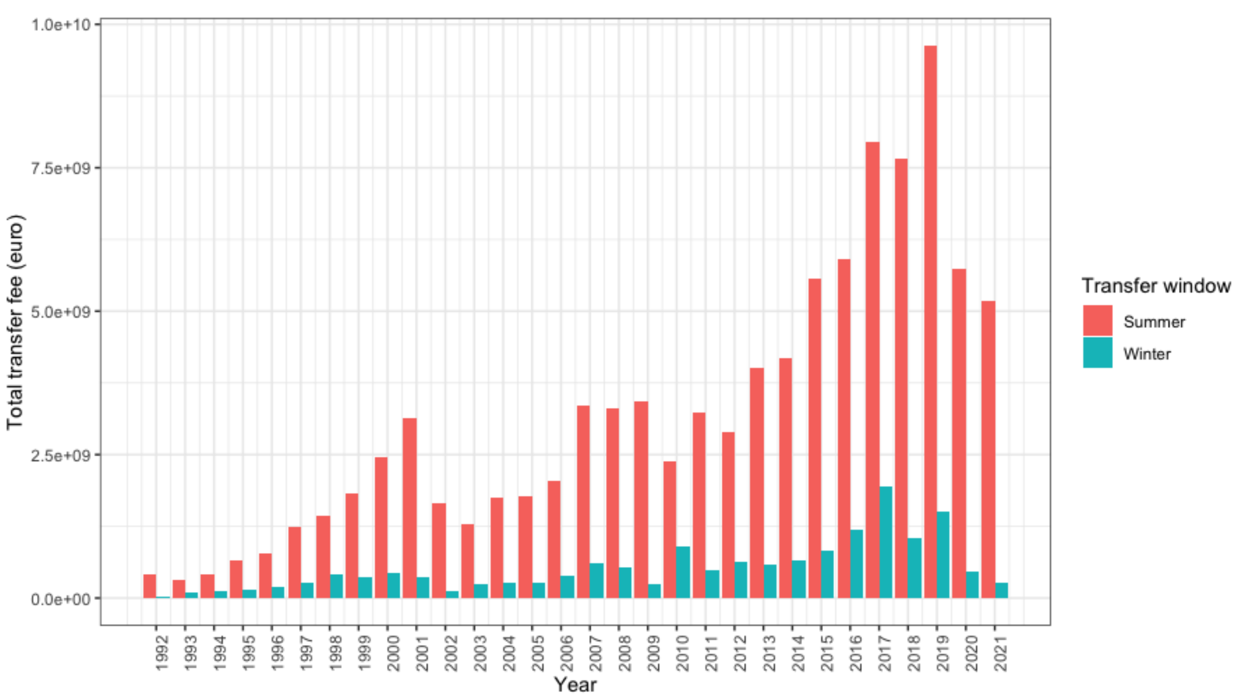

Figure 1 Total amount of transfer fee spent by the teams in my database over the examined period.

transfers in the dataset. First of all, it is no surprise that the two sides of the coin follow similar trends. The difference comes from the fact that the first-tier clubs of the top 5 European clubs do not only buy players from clubs that are also in these leagues, but also acquire from and sell them to other leagues. Though the trends are very similar, the number of arrivals always tend to outweigh the departures. This is rather unsurprising, the clubs of the best leagues tend to rather buy players from lower-level leagues than sell players to them. Another important observation, especially considering the trends we saw regarding aggregate transfer fees, is that there is a steady increase in the number of transfers, but only until 2014. From then on, the number of transfers rather declined. Also, in this regard, the covid-19 affected two past years do not seem to be out of trend for the summer windows. For the winter transfer windows on the other hand, a much clearer decline is observable.

Finally, we also look at the share of loan transfers and the average age of the players transferred on the market in our database. On Figure 3A, we can see first of all that loan transfers are by a magnitude more prevalent in the winter transfer windows. This can be explained by the fact that during the season, teams look for short-term solutions that do not cost a lot of money, but can potentially make an impact. This way, such investments are not too risky, but offer some potential, and loan deals can be turned into permanent deals later on, which is not the case in the opposite case. The only exception is the last transfer window of 2021. It is also apparent that there is an increasing trend in the share of transfers that are loan deals rather than permanent transfers. This is attributable to the fact that wealthier teams realized that they need a big squad with a lot of players,

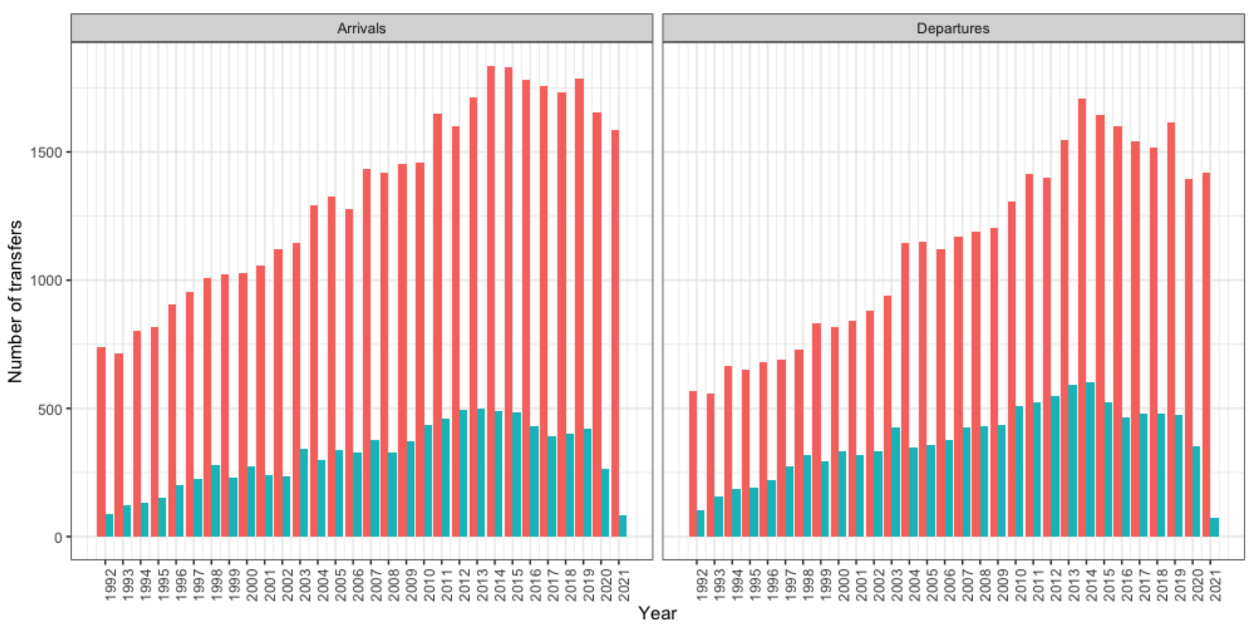

Figure 2 Average age of players transferred in the dataset over the examined period.

but since only 11 can make the pitch, they cannot make everyone happy. And without playing time, the benched players also do not develop. As a result, they more and more often outsource the development of their young, promising players to other clubs in the form of loan deals.

On Figure 3B, we also look at the average age of the players transferred. Here there is also some difference based on the transfer window, but it is less clear as in the case of loans. In the earlier years until 2002, players transferred in the winter were older, but from then on they are rather younger. In general, it can be said that the age of players on the market decreases over time. The introduction of the Bosman-ruling is naturally an important milestone in this regard (Frick and Simmons 2014).

Figure 3 (A) shows the share of loan transfers in the networks from 1992 to 2021 and **(B)** depicts the average age of players transferred in the dataset over the examined period

4 Temporal evolution of transfer network

In order to get a holistic picture of the evolution of structural characteristics of the transfer network of the European top 5 leagues, we first look at the evolution of global metrics. Transfer networks may have a different structure over time due to the different roles and changing market strategies of the clubs.

Figure 4A depicts the average clustering coefficient, the average path length and the average degree of all the summer transfer networks from 1992 to 2021. Notably, the clustering coefficient and the average path length are both normalized as described in the Network metrics subsection. Firstly, we can see that the mean of the shortest paths between all pairs of nodes is relatively stable over time, in the early years before the Bosman-ruling, it used to be higher around 1.5, but from then on it remained around 1.2. The average degree on the other hand has been steadily increasing over time. This is in line with what we saw on Figure 2 about the the overall number of transfers. In the same way, the drop in the number of transfers is also visible in the past two years attributable to the pandemic. Finally regarding the clustering coefficient, it shows by far the greatest volatility among our metrics considered.

Figure 4B depicts the same measures for all winter transfer networks over the examined time period. By comparing it with the summer windows, we can see first of all on the y axis that the values are in general much smaller. The average degree only starts from around 2 in the 1990s (compared to around 4 in the summer), and also the average clustering coefficient is much smaller,

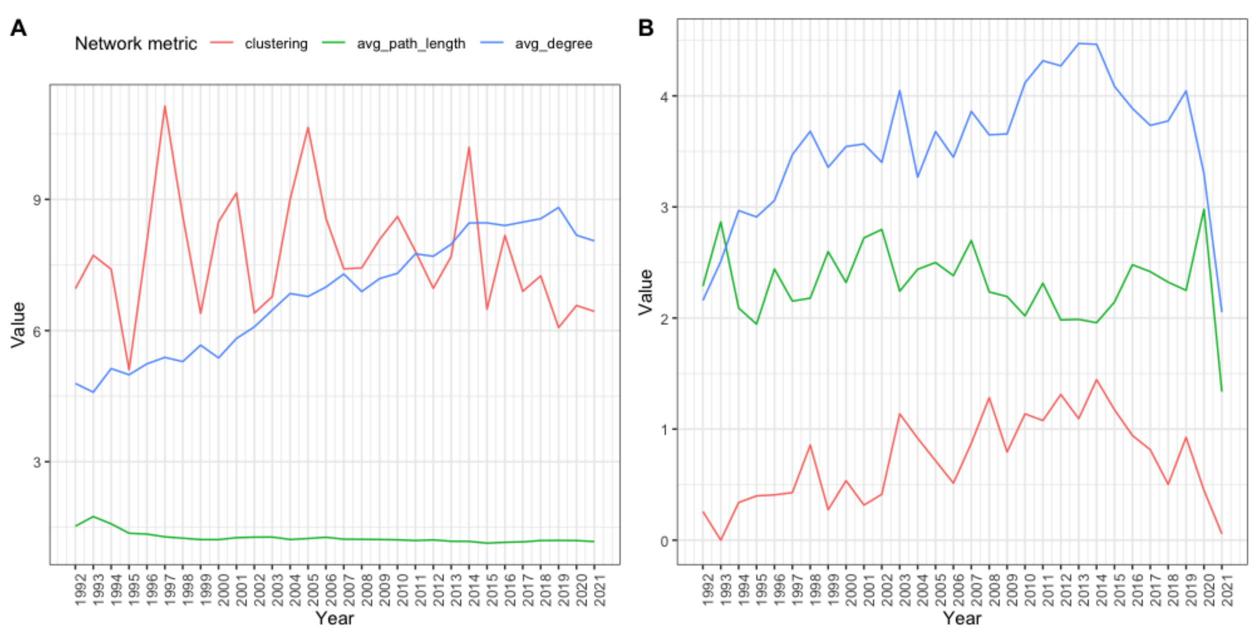

Figure 4 Temporal evolution of basic network metrics: average path length, global clustering coefficient and average degree

mostly between 0 and 1 (compared to between 6 and 10 in the summer networks). As for the average path length on the other hand, it remained roughly similar to that of the summer networks, both in magnitude and trend (it is roughly steady). As for the trends of the other metrics, the average degree also tended to increase from the 1990s to the 2010s, but since 2014, it is rather declining (again in line with Figure 2). Regarding the clustering coefficient, it has a very similar trend to that of the average degree, which is seemingly different to that of the summer networks that do not show a deterministic trend.

Next, we turn to the more sophisticated metric combining two of these measures, but providing a more meaningful interpretation in our context. If networks have central actors as profit-oriented clubs try to trade with players, this can easily lead to hubs, resulting in a more small-world type of network (Barabási and Albert 1999). However, if in a network, players can be acquired from pretty much anywhere, as most clubs tend to have almost identical roles in the transfer network, the network may behave like a random network. With no key participants players may be obtained in ’random’ ways.

Looking at Figure 5A, which shows the evolution of the small-worldiness index of the summer transfer networks, we can make two general observations. First of all, there is no general trend, there are huge spikes and overall the volatility of the metric is high throughout the period investigated. Secondly, the first three years are definitely outliers. Before the Bosman-ruling was

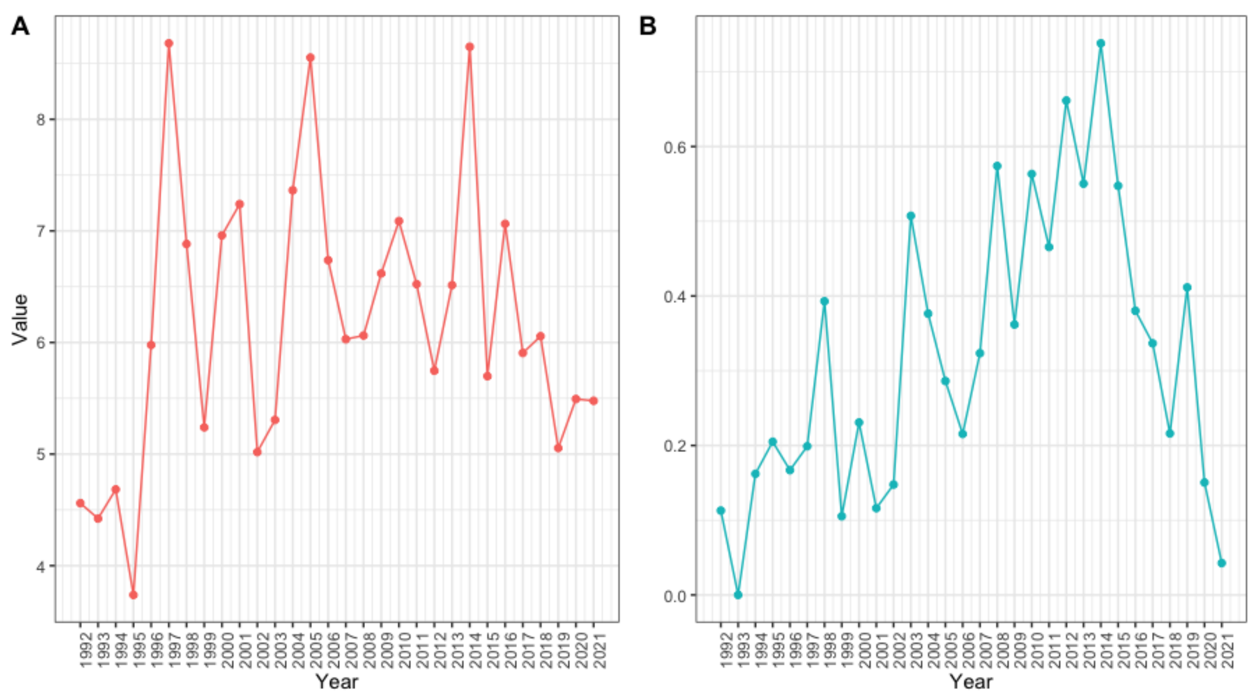

Figure 5 Small-worldiness of transfer network in the summer **(A)** and the winter **(B)** transfer networks from 1992 to 2021.

introduced, the networks were much more random, since then the networks consist of definitive hubs that are more or less prevelant from year to year, but such randomness as before did not happen since.

Turning on to Figure 5B depicting the evolution of the same metric, but this time for the winter transfer networks, we can see a much different picture. Two obvious trends can be detected over the time period. From the 90s up until 2014 there is a generally increasing small-worldiness. Over time, the these networks seem to be less random and more clearly hubs started to form among the clubs. But there is also a very well-visible trend after 2014 that goes in the exact opposite direction. By the winter of 2021, the random character of these networks basically returned to those of the beginning of the 1990s.

Overall, there are certainly hubs in the network, but the increase in the small-worldiness over time is much less obvious than we would have expected.

5 Network characteristics and performance

After the analysis of the transfer networks in general, it is time to dig deep to the level of the nodes of these networks. This means turning our attention at the level of football teams, and specifically whether and to what extent their position and activity in the transfer network relate to their immediate subsequent sportive performance.

As an indicator of success in sportive performance, we use the ranking of the domestic league table. Researchers commonly use win percentage (Espitia-Escuer and Garcia-CebriAn 2004), but as draws are frequent in football,it may give biased impressions of performance (Dawson, Dobson, and Gerrard 2000). Another approach could be looking at the points per game of the teams, like Coates et al. (2020). But since our database starts in 1992 when not all leagues have introduced the 3 points for win system, it would give somewhat biased estimates. For the analysis of the summer transfer activity, both the mid table ranking and the final table ranking is used in order to look at a bit longer-term impact of transfer activity as well.

Reagarding the main explanatory variables, we use the preceding performance, measured by the ranking on the final table in the preceding season in case of summer transfer windows and the ranking halfway through the season in case of the winter transfer windows. Furthermore, all the network measures introduced in section 3.2.2, namely in- and out-degrees, betweenness centrality and in-, and out-coreness are analyzed.

It is also important to control for determinants of team performance that are not attributable to team building activities or prior performance in order to capture the immediate effect of transfer strategy without contaminating it with the influence of omitted variables. Thus, numerous control variables are used. First of all, we use league and year dummies to get the effect of the immediate transfer market strategy and within the reins of the domestic soil (as also for the target variable domestic performance is used). This is all that is included in the rather uncontrolled regression setting. Thus, to analyze the impact of transfer strategy on team performance, the following simpler regression is estimated:

$$RANK_{it} = \beta_0 + \beta_1 RANK_{i,t-1} + \beta_2 NETW_{it} + \theta_i + \sigma_i + \varepsilon_{it}, \tag{7}$$

where θ and σ stand for the fixed effects to control for year and league.

Then we also have a lot of further controls that we use to account for potential confounders of our analysis. Squad characteristics are captured by the estimated market value, the average age and height of the squad. Further transfer information include the mean age and transfer fee of both the arriving and departing players, as well as the share of these deals that are loans in both direction. Finally, the subsequent player performance of the traded players is also controlled for by the average number of minutes spent on the pitch and number of goals scored. Thus, the formula of the controlled regression looks like this:

$$\begin{aligned} RANK_{it} = \beta_0 + \beta_1 RANK_{i,t-1} + \beta_2 NETW_{it} + \beta_3 SQUAD_{it} \\ + \beta_4 TRANSFER_{it} + \beta_5 PLAYER_{it} + \theta_i + \sigma_i + \varepsilon_{it}, \end{aligned} \tag{8}$$

5.1 Summer transfer network

First, we look into the relationship between the transfer activity of football clubs during the summer transfer window and the performance in the subsequent season and half-season.

Table 1 presents the results of four linear regressions that capture the relationship. In columns 1 and 2, the target variable is the ranking of the teams on the final table in the season after the summer transfer window, while in columns 3 and 4, it is the position of the teams in the table halfway through the season. In all of our models, we are interested in the local network metrics of the first-tier teams of the top 5 European leagues. In the first model, besides the ranking from last season, the in-, and out-degrees as well as the betweenness is statistically significantly related to the final table ranking. The positive relationship between in-degree and final table ranking indicates that those teams that have a unit more connection to other clubs in terms of incoming players are on average expected to rank higher in the table on average by 0.19 places. As rankings are integers, this should be interpreted as being connected to 5 more goes together on average with 1 higher ranking, keeping everything else constant. On the contrary, out-degree is negatively related to the ranking of the teams, meaning that those teams that offload players to a wider variety of other clubs are on average likely to rank lower than than others with the same attributes. Betweenness is also negatively correlated with the league table ranking, its influence is very mild however. Its effect remains the same for all specifications (in all 4 models) In-, and out-coreness measures on the other hand are not even statistically significantly related to final table ranking.

In the second model, by including a wide arsenal of control variables as described earlier, the effect of network metrics was expected to fall. On this longer run, not only did the effect of both the in-, and out-degrees smaller, but became statistically insignificant. Only betweenness remained significant with its mild negative effect.

In the third and fourth model, we concentrate on really short impact by looking at whether the strategy of the football clubs on the market has an effect immediately in the next half-season. Using only league and year fixed effects, we can see that interestingly the effect is even greater than it was for the case of the effect on the final league table. The direction of the relationships is the same, but the coefficients are higher.

Finally, in the fourth model specification, the effect of in-degree becomes insignificant just as in the case of the second model. However, the negative impact of higher out-degree on the ranking at mid-season remains statistically significant at 10% significance level.

Appendix 7.1 contains further models where each type of network metric (degree, betweenness and coreness) is used as explanatory variables by themselves to check for effects without multicollinearity.

	Dependent variable:			
	Final table ranking		Mid table ranking	
	(1)	(2)	(3)	(4)
Ranking last season	0.643***	0.469***	0.603***	0.453***
	(0.020)	(0.022)	(0.021)	(0.023)
In-degree	0.187***	0.041	0.194***	0.045
	(0.034)	(0.034)	(0.036)	(0.035)
Out-degree	−0.201***	−0.061	−0.202***	−0.075*
	(0.039)	(0.038)	(0.041)	(0.040)
Betweenness	−0.0001***	−0.0001***	−0.0001***	−0.0001***
	(0.00003)	(0.00003)	(0.00003)	(0.00003)
In-coreness	−0.152	0.192	−0.202	0.208
	(0.153)	(0.149)	(0.161)	(0.154)
Out-coreness	−0.081	−0.001	0.139	0.178
	(0.160)	(0.153)	(0.167)	(0.162)
League and year control	Yes	Yes	Yes	Yes
Squad characteristics	No	Yes	No	Yes
Transfer info	No	Yes	No	Yes
Player performance	No	Yes	No	Yes
Observations	2,296	2,296	2,296	2,296
R^2	0.377	0.457	0.325	0.396
Adjusted R^2	0.367	0.445	0.314	0.383
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 1 Linear regression models to uncover relation between final and mid table ranking and network characteristics of summer transfer market

5.2 Winter transfer network

Next, let us turn to the same analysis of transfer activity of football clubs and performance in the subsequent half-season, but this time considering only the winter transfer windows. Since during the middle of the season, significantly less transfers are being made as we saw and less money is moving around as well, we may see different patterns in terms of the relationship as well.

Table 2 presents two linear regressions to uncover this relationship, both in columns 1 and 2, the target variable is the ranking of the teams at the end of the season.

In the first model, we only use league and year fixed effects besides the current ranking of the teams (mid-table ranking). Obviously, the latter is a very significant predictor of the final ranking of the teams, a unit higher position is attributable on average to a roughly 0.8 higher position at the end of the season as well, keeping all other variables constant. Regarding the network indicators, however, there is only two that are statistically significantly related to the subsequent immediate performance at 10% significance level, in-, and out-degree. Interestingly, in contrary with what we saw for the summer networks, both are positively correlated with the subsequent performance. However, it is worth noting that the out-degree is only significant on the 10% level, while the in-degree is also significant on the 1% level. Finally, it is also interesting to look at the overall performance of our model: based on the R-squared value, our model explains more than 70% of the variance in the final table rankings of the teams.

In the second model, when we control for a variety of further important covariates, the effect of the current ranking drops unsurprisingly. The statistical significance of the impact of out-degree also disappears. However, what is really interesting is that the effect of in-degree even increases. One more node from which the club acquires players is attributable on average with a 0.15 higher league position (again it is important to keep in mind that rankings are integers, the coefficient is a conditional mean). Finally, the overall performance of the model now even exceeds 75%.

	Dependent variable:	
	Final table ranking	
	(1)	(2)
Current ranking	0.835^{***}	0.717^{***}
	(0.012)	(0.014)
In-degree	0.067^{***}	0.156^{***}
	(0.015)	(0.017)
Out-degree	0.068^{*}	0.046
	(0.037)	(0.036)
Betweenness	−0.027	−0.007
	(0.034)	(0.033)
In-coreness	0.00003	0.00003
	(0.00004)	(0.00004)
Out-coreness	0.056	0.075
	(0.109)	(0.107)
League and year control	Yes	Yes
Squad characteristics	No	Yes
Transfer info	No	Yes
Player performance	No	Yes
Observations	2,069	2,069
R^2	0.732	0.761
Adjusted R^2	0.727	0.755
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 2 Linear regression models to uncover relation between final league table ranking and network characteristics of winter transfer market

6 Conclusion

While there are a lot of components to being successful in football, it is hard to question the importance of building and improving upon the squad of players. Football teams engage in transfer activities on the global market for footballers in the hope of better sportive (and to differing degree financial) performance. This work contributed to the literature on the study of the transfer market of footballers from a network perspective.

First, a concise literature review was conducted on prior works in the subject matter. Regarding the objectives of the teams in the market, several studies highlighted the double goal of satisfying the clients i.e. the fans by building a strong team and achieving sportive success and satisfying the owners i.e. the investors who would like to see financial return on their investments. Studies also showed multiple ways in which transfers can impact sportive performance. Besides the evident quality of the players, enhancing knowledge and diversity can also play a big role. Then, studies on the transfer market as a network were sampled and introduced. The research gap this paper intended to fill compared to them lies in both the scope of the study (from 1992 to 2021), which constitutes a longer time period than any other before and the perspective of looking at all the windows as separate networks and using them to measure immediate (half-year and year) effect on sportive performance.

Before diving into the main analysis, some useful descriptive statistics were also presented. The aggregate spending on the transfer network depicted a generally increasing trend reaching its peak in 2019, but suffered substantial decline due to the pandemic in recent years. The number of incoming and outgoing transfers also showed similar trends, but they started to decline earlier in the middle of the 2010s. Finally, the share of loan transfers and the age of players traded were also examined. The former had a clearly increasing trend, while the latter showed a rather decreasing trend. This showed that the preference of the market leans more and more towards outsourcing player development with loan deals essentially bringing down the average age of players transferred as well.

Then, the study showed the evolution of global structural characteristics of the transfer networks, which were constructed from all deals conducted by the first-tier teams of the top 5 European leagues for all transfer windows between 1992 and 2021. The increasing trend in the average degree of of both summer and winter transfer networks from the 90s until recent years suggests that over time clubs moved towards more and more heavy involvement in the market. This could signal less emphasis on in-house youth development, but also the tendency of football teams to attract more financial resources by owners that require success as soon as possible. However, we also found a declining trend in the past couple of years, which is mostly attributable to the coronavirus pandemic that affected the revenues of the clubs greatly. Regarding the extent to which these transfer networks possess small-world character, no clear trend in case of summer windows was found. For winter windows, on the other hand, an increasing, but recently decreasing trend was found, similar to that of the average degree.

Finally, the paper looked at the network characteristics of football clubs in the summer and winter transfer networks and how they relate to their performance measured by their ranking on the league table in the next half-season (and season in case of summer windows). The findings suggest that higher in-degree is associated with higher ranking on average in expectation (though only in the rather uncontrolled setting for the summer windows), while higher out-degree is associated with lower ranking (again significant at 5% level only without all the controls). Higher betweenness in the summer window is found to be negatively correlated with subsequent performance, but is shown not to have significant effect in the winter. Coreness is deemed insignificant in all of the model specifications.

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7 Appendix

7.1 Robustness checks

In the following section further linear regressions are shown for a robustness check on the results presented in section 5.1 and 5.2.

On Table A.1 we can see similar regressions as in Table 1 of the main text, but only the in-, and out-degrees are the main explanatory variables. The results are essentially similar, which increases the robustness of the findings.

	Dependent variable:			
	Final table points		Mid table points	
	(1)	(2)	(3)	(4)
Rank last season	0.643***	0.467***	0.601***	0.429***
	(0.020)	(0.022)	(0.021)	(0.023)
In-degree	0.147***	0.033	0.153***	0.045
	(0.031)	(0.030)	(0.032)	(0.032)
Out-degree	−0.250***	−0.084***	−0.225***	−0.076**
	(0.032)	(0.032)	(0.034)	(0.034)
League and year control	Yes	Yes	Yes	Yes
Squad characteristics	No	Yes	No	Yes
Transfer info	No	Yes	No	Yes
Player performance	No	Yes	No	Yes
Observations	2,296	2,296	2,296	2,296
R^2	0.374	0.455	0.322	0.397
Adjusted R^2	0.364	0.443	0.312	0.385
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A.1 Linear regression models to uncover relation between final and mid league table rank and degree characteristics of summer transfer market

On Table A.2 we can see again similar regressions as in Table 1 of the main text, but the only network characteristic as explanatory variable is the betweenness. The results are again essentially similar.

	Dependent variable:			
	Final table points		Mid table points	
	(1)	(2)	(3)	(4)
Rank last season	0.685***	0.472***	0.640***	0.435***
	(0.019)	(0.022)	(0.020)	(0.023)
Betweenness	−0.0001***	−0.0001***	−0.0001***	−0.0001***
	(0.00002)	(0.00002)	(0.00002)	(0.00002)
League and year control	Yes	Yes	Yes	Yes
Squad characteristics	No	Yes	No	Yes
Transfer info	No	Yes	No	Yes
Player performance	No	Yes	No	Yes
Observations	2,296	2,296	2,296	2,296
R^2	0.363	0.456	0.313	0.399
Adjusted R^2	0.354	0.445	0.303	0.386
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A.2 Linear regression models to uncover relation between final and mid league table rank and betweenness characteristics of summer transfer market

On Table A.3 we can see again similar regressions as in Table 1 of the main text, but the only network characteristic as explanatory variable are in-, and out-coreness. The results are again very similar, which shows that it was not multicollinearity that took away the significance of this measure.

	Dependent variable:			
	Final table points		Mid table points	
	(1)	(2)	(3)	(4)
Rank last season	0.671***	0.469***	0.632***	0.433***
	(0.020)	(0.022)	(0.021)	(0.023)
In-coreness	−0.053	0.141	−0.088	0.105
	(0.139)	(0.133)	(0.146)	(0.141)
Out-coreness	−0.483***	−0.210	−0.255*	−0.038
	(0.136)	(0.132)	(0.143)	(0.139)
League and year control	Yes	Yes	Yes	Yes
Squad characteristics	No	Yes	No	Yes
Transfer info	No	Yes	No	Yes
Player performance	No	Yes	No	Yes
Observations	2,296	2,296	2,296	2,296
R^2	0.362	0.454	0.310	0.396
Adjusted R^2	0.352	0.442	0.300	0.384
Note:			*p<0.1; **p<0.05; ***p<0.01	

Table A.3 Linear regression models to uncover relation between final and mid league table rank and coreness characteristics of summer transfer market

Table A.4 contains similar regressions as in Table 2 of the main text, but only the in-, and out-degrees are the main explanatory variables. The results are essentially similar, which increases the robustness of the findings.

	Dependent variable:	
	Final table rank	
	(1)	(2)
Current rank	0.837***	0.726***
	(0.012)	(0.014)
In-degree	0.083***	0.066**
	(0.031)	(0.031)
Out-degree	−0.047*	−0.018
	(0.028)	(0.028)
League and year control	Yes	Yes
Squad characteristics	No	Yes
Transfer info	No	Yes
Player performance	No	Yes
Observations	2,069	2,069
R^2	0.732	0.759
Adjusted R^2	0.727	0.753
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table A.4 Linear regression models to uncover relation between final league table rank and degree characteristics of winter transfer market

Table A.5 contains similar regressions as in Table 2 of the main text, but only the betweenness is the main explanatory variables. The coefficients are higher, but still insignificant, thus essentially similar, which increases the robustness of the findings.

	Dependent variable:	
	Final table rank	
	(1)	(2)
Current rank	0.846***	0.731***
	(0.011)	(0.014)
Betweenness	0.00004	0.00005
	(0.00003)	(0.00003)
League and year control	Yes	Yes
Squad characteristics	No	Yes
Transfer info	No	Yes
Player performance	No	Yes
Observations	2,069	2,069
R^2	0.731	0.759
Adjusted R^2	0.726	0.753
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table A.5 Linear regression models to uncover relation between final league table rank and betweenness characteristics of winter transfer market

Table A.6 contains similar regressions as in Table 2 of the main text, but only the in-, and out-coreness are the main explanatory variables. Interestingly, in this case both in-, and out-coreness are statistically significantly related to the subsequent sportive performance, in the less controlled stting, but at 10% level, in-coreness is still positively related in the more controlled regression.

	Dependent variable:	
	Final table rank	
	(1)	(2)
Points last season	0.841***	0.730***
	(0.012)	(0.014)
In-coreness	0.182**	0.174*
	(0.092)	(0.092)
Out-coreness	−0.194**	−0.100
	(0.094)	(0.095)
League and year control	Yes	Yes
Squad characteristics	No	Yes
Transfer info	No	Yes
Player performance	No	Yes
Observations	2,069	2,069
R^2	0.731	0.759
Adjusted R^2	0.727	0.753
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table A.6 Linear regression models to uncover relation between final league table rank and coreness characteristics of winter transfer market