The European Football Transfer Market: A Network Analysis

Chukwubueze Hosea Ogeleka, Rohit Bagda

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1. Abstract

The European Football Transfer Market is one of the biggest industries in the world of professional sports. In this project, we analyze the transfer market transactions since the beginning of the 21st century, using a network approach. We explore how our results validate what is known about the industry and how it compares to existing research in the field. The paper concludes that English teams generally dominate financially, while Italy is generally the busiest country with player transfers. We highlight particular clubs like Chelsea, Manchester United, and Liverpool which have bought some of the biggest talents over the years, while observing FC Porto, Internazionale, and Benfica as exporters of some of the most expensive talents. We explore PageRank and Eigenvector Centrality measures and their meanings in the transfer market. We conclude that teams are more likely to trade players within the same country; however, much of the big spending happens from trades between different countries. While this paper focuses on painting a general picture of the 21st century transfer market, the ideas conveyed in this paper could be further extended to include a time component, in order to analyze particular trends over time.

2. Introduction

The commercialisation of human talent, in the form of transfers, are an important component of professional team sports. For athletes, a transfer could be a significant step in the right or wrong direction for their career trajectory; for the fans, transfers could represent the arrival or departure, of a hero or villain, to their favourite teams; and for the teams, transfers play an important role in the commercial, athletic, and professional development of a sports team. Transfers can lead to huge commercial success in the form of improvements in team performance, jersey sales, stocks, ticket prices, and more. In the world of European football, transfers are most certainly an essential ingredient to how fans, teams, and other professionals engage in the sport.

In this paper, we use concepts from Network Science to analyze the European Football Transfer Market. We make use of Centrality Measures to gain insights on key members of the transfer market over the last two decades. Furthermore, we investigate how these metrics relate to one another, and corroborate our findings with specific references to events in the transfer market and some already established research in the field. We also introduce new metrics which help us understand the trading tendencies domestically within different countries. The level of impact that a team has on the transfer market is a broad, subjective question. Is a team important because they spend a lot of money? Is it important because they sell a lot of players? Do certain teams rely more on loans due to their relatively low cost? Are teams more likely to trade within the same league? Are there teams spending significantly more money on younger players? Our paper provides some understanding on how to approach these questions, and highlights the various answers we can arrive at, with the help of Network Science.

3. Background

There is ongoing network-oriented research on the European transfer market. In the paper “A Network Approach to the Transfer Market of European Football Leagues” written by Lee et. al*,* the authors constructed a weighted network of the teams in the Spanish La Liga, English Premier League, and German Bundesliga. The teams were nodes and the weight of an edge is the aggregation of the google search popularity (number of search results) of all the players transferred between the two teams in the 2014 July-September Transfer Window. The paper validated this methodology by showing a positive correlation between number of google search results for a player and the transfer value of the player.

Some of the results this paper highlights is important to our work. For instance, the paper found that there was random assortative mixing, with an assortativity coefficient of about -0.07, between the teams in the individual leagues, i.e, it invalidates the general idea that teams in the same league are less likely to trade between each other (i.e it assortativity is not close to -1). We speculate that our results might show something similar. Furthermore, the paper studied betweenness centrality of teams, and showed how it correlated with the "strength" of the teams.

While this paper uses transfer data to carry out a network analysis of big football leagues, we do not believe that a single transfer window would give sufficient information to make conclusive insights about the general trends in the transfer market. Furthermore, during the summer of 2014, the summer for which the work of Lee et al is based, there was a FIFA world cup. With the world cup being such a global spectacle, transfer activity for such a summer generally does not paint an accurate picture of what transfer activities typically look like.

Furthermore, we would like to take a different approach with the weights and directions of the edges. We believe it is important to make the edges directed (an arc/edge from team A to team B means A sold at least one player to B). In the work of Lee et al, the "strength" of a team is proportional to its inbound and outbound transfers. In our work, the distinction between inbound and outbound transfers is important. This is because selling players (weighted out-degree) and buying players (weighted in-degree) tell us different things about teams and the general structure of the market. Our weights are based on monetary value of the actual transfers and the number of players sold between teams. We intend to compare what the market activity is like, with and without the component of money. With directed edges, pagerank and centrality measures, and others, we can develop a slightly different perspective on the "strength" of a team.

Another interesting paper we looked at was "The Anatomy of the Global Football Player Transfer Network: Club Functionalities versus Network Properties" by Liu et al. The work of Liu et al largely performs research similar to what we would like to do in our work. It carries out network analyses on the teams and transfers, with clubs being nodes and edges being transfers between clubs. However, their emphasis is more on how player transfers affect team performance. The paper focuses on grouping large teams together. It studies leagues but does not carry out extensive (interpretative) analysis on the centrality measures and other properties which we will be studying. We intend to see how some of the conclusions of this paper on how involvement in the transfer market affects team performance, corresponds with our research.

The data in this paper only studies 2011-2015 transfers, which, again, is a small subset of the 21st century. In addition, as stated earlier, we intend to do an analysis that also considers number of players sold between teams, as this provides different kinds of insight in the level of trade activity which has occured. Team A buying one player for 80 million Euros, and team B buying 10 players for 8 million Euros each, mean different things both when we factor cost of transfer or when we simply consider the number of players involved. In our work, we would like to study the results from all seasons in the 21st century, because it will help paint a more holistic picture of what the networks say about the transfer market.

Lastly we looked at “Transfer market activities and sportive performance in European first football leagues: A dynamic network approach” authored by Matesanz et al. This paper uses a dynamic network to analyze the growth of the transfer market. It uses transfer data from TransferMarkt website to observe how more and more teams are involved in the European Transfer Market since 1996. It uses clubs as nodes and the total transfer fees paid for all players that transferred from one club to another. They analyze change in indegree and outdegree over the years and try and correlate a club’s UEFA coefficient (uefa.com) with their involvement in the transfer market. Our goal in this research is to analyze a static network, and observe which teams are more involved in the transfer market rather than how many teams are getting more involved in the transfer market over time. Moreover, we use a different metric for the edge weight in our monetary network. Matesanz et al. in their paper do not account for the inflation of the transfer market over the years. In our work we will normalize the transfer amounts for each transfer so as to avoid transfers from recent years dominating the entire network. Our paper also looks at new metrics to study specific patterns within leagues, in order to develop a broader understanding of the dynamics involved in domestic and international transfers in Europe.

4. Methodology

To obtain the networks, we created Python scripts to scrape the TransferMarkt website to obtain transfer data for the top 15 leagues (uefa.com) in Europe. We disregarded all internal club transfers, and retirement transfers because these do not contribute meaningful information to our networks; they do not tell us anything about how teams interact with other teams. After obtaining the data, we generated weighted, directed networks. In our network, a node represents a Football team, and an edge implies that within the last 19 years, at least one transfer has occurred between two teams. An arc going from team A to team B tells us that team A has sold or loaned players to team B since the year 2000. The weights of the edge represent different two different values:

1. **Type 1**: The weight of an edge from node A to node B represents the aggregation of all the transfer fees for transfers from team A to team B. In order to account for how the market prices have generally changed since the year 2000, we normalised the monetary values of the transfers. If we do not do this, our data skews way too heavily towards more recent transfers and does not accurately reflect the entirety of the 21st century. To set the transfers to be balanced among the years, we set the transfer cost of each transfer to be a fraction of the most expensive transfer for that given year. This way, a $40m transfer in the year 2002, when the most expensive transfer was about $50m(TransferMarkt.us), gets considered as a more valuable transfer than a $50m transfer fee in 2017, when the most expensive transfer was about $250m(TransferMarkt.us). Furthermore, we multiplied this fraction by 10 in order to have a good scale of weights for Gephi to visualize the network. There are three categories of networks of this type which we consider:
    a. All non-loan transfers
    b. All non-loan transfers for players under the age of 25
    c. All non-Transfers for players over the age of 29.
2. **Type 2**: The weight of an edge from node A to node B represents the total number of players that team A has sold or loaned out to team B. In this, there are two categories of networks:
    a. All loan transfers
    b. All non-loan transfers

After generating the networks, which consisted of over 6000 nodes (teams) and 60,000 edges, we imported the data into Gephi to generate the network visualisations. We obtained statistics for PageRank, Weighted In-degree, Weighted Out-degree, and Eigenvector Centrality. The edge thickness is proportional to the weight of an edge. The edges have a clockwise orientation to indicate their directions and have the same color as the source node. A legend for the country colors is shown on the right.

Furthermore, we imported the statistics into R and Python3, which we used to further extend our analyses; we observe the relationships between these metrics and investigate other properties of the network.

Some of the network properties we studied are extensions to the concept of Assortativity. In Network Science, Assortativity gives an understanding on how strong the connections are between nodes of the same type. In the context of the European Transfer Market, Assortativity tells us whether the football teams, in Europe, are more likely to trade within their own country. Assortativity values range from -1 to 1. An Assortativity value of 1 tells us that all the teams in Europe trade only within the leagues of their own country, while a value of -1 implies that teams only trade with teams that are not in the their own country. However, Assortativity does not give us any insights about trading tendency of teams within individual countries. Furthermore, the software limitations of the NetworkX library in Python does not factor in the weights. In order to develop a stronger perspective on community-like behaviour, we introduced two new metrics: *Relative Internal Trade Activity* (RITA) and *Intra-National Trading Coefficient* (INTC).

Relative Internal Trade Activity, or RITA, tells us the proportion of internal trade activity which occurs within a country, relative to the overall network. We define the RITA value, σ, of a country C in in a network G the following way:

$$\sigma_c = \frac{\sum_{i,j \in C} A_{i,j}}{\sum_{i,j \in G} A_{i,j}}$$

where $A_{i,j}$ is the i,jth entry of the Adjacency Matrix A of the network. In simpler terms, what proportion of the monetary transaction or number of transfers of the European transfer market occurs within in a specific country? An summation of the RITA values for all 15 countries tell us how much of the transfer market is occuring internally within countries. A value closer to 1 tells us that in this network, most trade occurs among nodes of the same country rather than outside.

In addition to RITA we explored the *Intra-National Trading Coefficient* Φ (INTC). We define the Intra-National Trading Coefficient Φ of a country C in the following way:

$$\Phi_c = \frac{\sum_{i,j \in C} A_{i,j}}{\sum_{i \in C} k^{-}(i)}$$

where $A_{i,j}$ is the i,jth entry of the Adjacency Matrix A of the network, and $k^{-}(i)$ is the weighted in-degree of node i. The Intra-National Trading Coefficient gives a more specific idea of how much trading is going on within a country, relative to the overall aggregate trading activity of the individual teams of a certain country. It is the proportion of domestic purchases by the teams of a country relative to all purchases by teams of that country.

The RITA and INTC values of the graph tell us two different, but interesting stories. While assortativity gives us some understanding of how much internal trade is occuring, RITA and INTC help us identify how, if at all, this varies from country to country in the network.

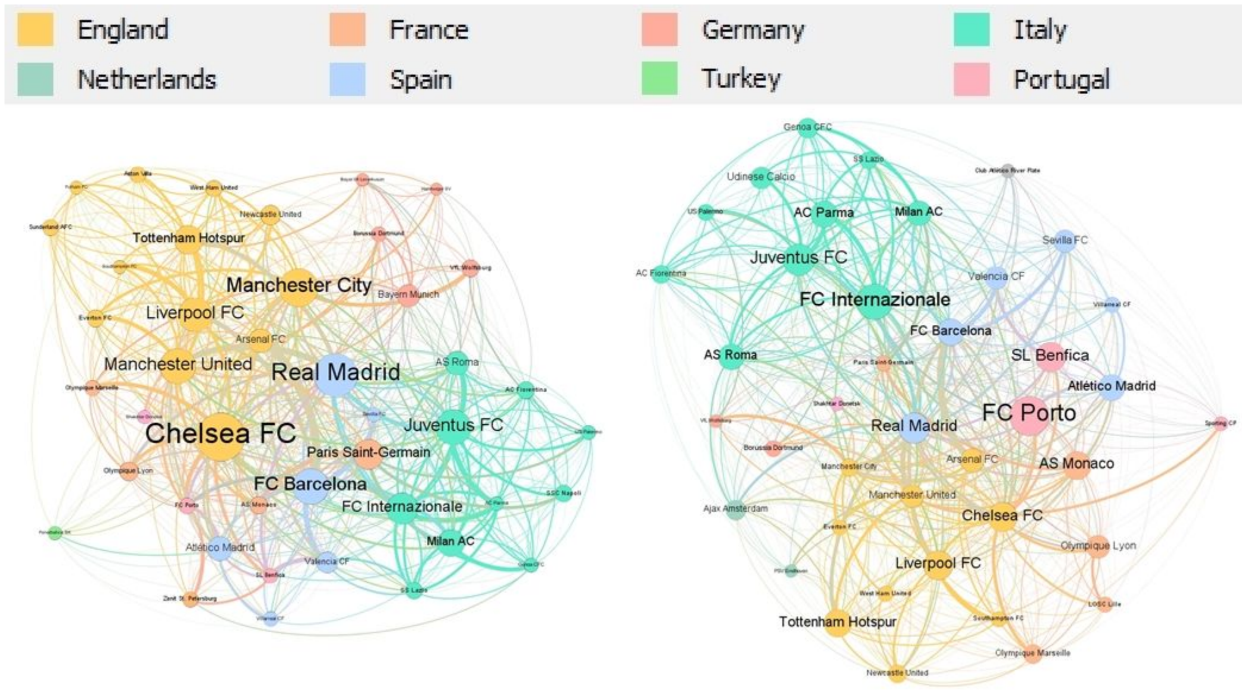
In our work, we scraped transfers for which at least one of the involved teams (selling or buying team) belonged to one of the 15 biggest leagues in Europe. This paper uses leagues/countries interchangeably, because although the top division league for each country dominates the market (especially financially), it is important to consider trading activity within the same country. Transfers occurring between lower and higher division teams in the same country are important in our understanding of the level of trade activity.

5. Results

5.1 Type 1 networks - Money as edge weights.

5.1.1 Weighted Degree Analysis

As stated earlier in this paper, in these networks, an edge pointed from node A to node B has a weight which is an aggregation of the transfer fees of all player transfers from team A to team B. We account for the differences in the market by setting each transfer fee as a proportion of the most expensive transfer in a given year. The following networks below give us some interesting insights into the level of financial activities within the transfer market.



(a) (b)

Fig 1: Type 1 weighted networks. Nodes are sized by a) Weighted In-degree b) Weighted Out-degree.

In Fig. 1a) and 1b) above, the nodes are sized by their weighted in-degrees and weighted-out degrees respectively. From Fig. 1a), we can see that Chelsea, Real Madrid, Barcelona, Manchester United, Manchester City, Juventus, Liverpool, and Paris Saint-Germain are some of the biggest spenders in the transfer market. These correspond to arguably the biggest names in European Football, and the network demonstrates their financial dominance over the rest of the market. It is well known that the English Premier League is the richest football league in the world (List of Professional Sports Leagues by Revenue) and our in-degree network shows that the English teams (yellow nodes) dominate the market financially as they tend to spend a lot of money in the transfer market. Our results correlate well with already existing research (Liu et al 2016, Lee et al 2015, Matesanz et al 2018)

Another worthy observation is that some of the thickest edges correspond to money flowing between countries. We see this in the Liverpool to Barcelona, Manchester United to Real Madrid, and Arsenal to Barcelona edges. This demonstrates that some of the biggest purchases in the 21st century represent player movements between countries. Furthermore, teams such as Chelsea, Barcelona, Real Madrid, and Manchester City, appear in between multiple countries, implying that they make the big purchases from different leagues, operating in a hub-like manner.

The thickness of the Arc from Southampton to Liverpool is worth mentioning. This is in line with what football enthusiasts already know, in terms of the quality of players who have gone from Southampton to Liverpool, especially in recent years (Kleebauer 2017, Coleman 2019, Phillips 2017). When we look at Fig. 1b) , we observe some of the biggest exporters of the most expensive football talent in the transfer markets. We see that Porto, Internazionale, Juventus, and Benfica dominate this more. Some of the biggest legends, and most remarkable transfers in the 21st century are of players who have left these teams and gone somewhere else. Ronaldo Delima and Zinedine Zidane are some of the biggest names known to have left Internazionale and Juventus. Furthermore, our results demonstrate the dominance of SL Benfica (Watts 2017) and Porto (Newman 2015) when it comes to how much money these clubs earn from selling their biggest stars. In 2013, FC Porto sold two of their best talents James Rodriguez and João Moutinho for massive total of $80 million dollars to AS Monaco. Few of the many famous talents that were exported from SL Benfica are Angel Di Maria, Ederson, and David Luiz, were sold to big teams like Real Madrid, Manchester City and Chelsea respectively.

We further carried out weighted in-degree analysis to see which teams spend the most money for players age 24 or younger, and for players age 30 or older.

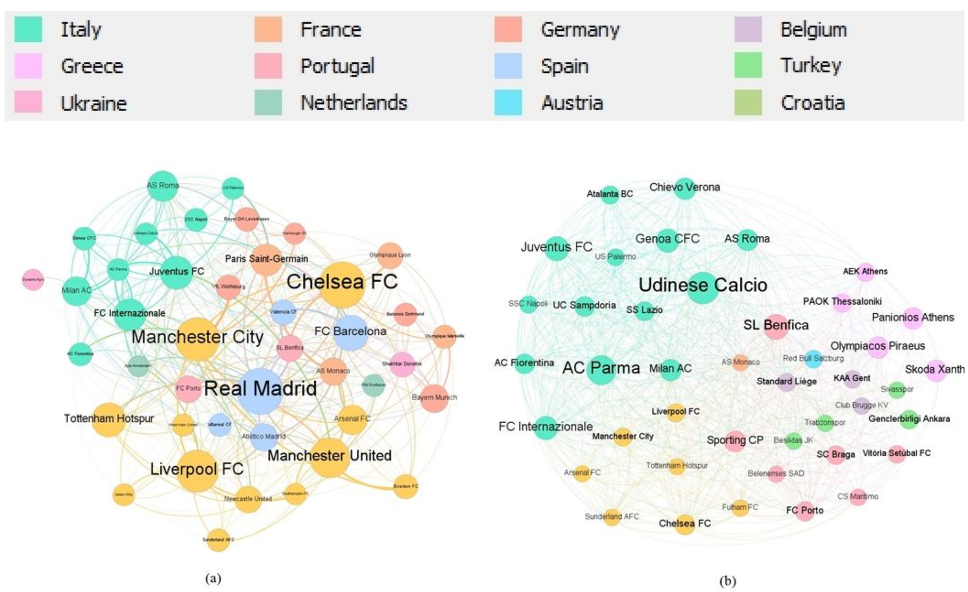


Fig 2: Type 1 networks of transfers for players. a) age 24 or younger b) age 30 or older. In both figures, nodes are sized by weighted in-degree, and edge thickness correlates to weight of edge

According to the results in figure 2 above, we notice that the big spending clubs, spend significantly on young players. When we look at the networks for transfers of players over the age of 30, we notice that there is a level of balance across Europe, and the top-spenders are obviously not spending money to buy old players. This makes sense, because as we would expect, the top teams buy young talent, so that these young talents can spend their prime years with them, before these players move on to smaller teams as their careers begin to decline. There are a few exceptions, such as Juventus, and this is explained by the large transfer fee of over $130 million which Juventus paid to Real Madrid for the then 33-year-old Cristiano Ronaldo in 2018. Another interesting observation is that Barcelona and Real Madrid, two of the biggest spenders in world football, do not spend money on old players, as their weighted in-degree values are not even significant enough for them to be shown in the network.

5.1.2 Eigenvector Centrality and PageRank Analysis

In the field of Network Science, Eigenvector Centrality and PageRank are two measures we can use to understand the level of importance of a node. Eigenvector Centrality recursively defines the importance of a node as an accumulation of the importance of all other nodes pointing towards it; thus, a node is important if it is connected to other important nodes in the network. In our project, a club is important because it is buying players from other important teams. Figure 2 below shows the type 1, subtype a network with the nodes sized by Eigenvector Centrality.

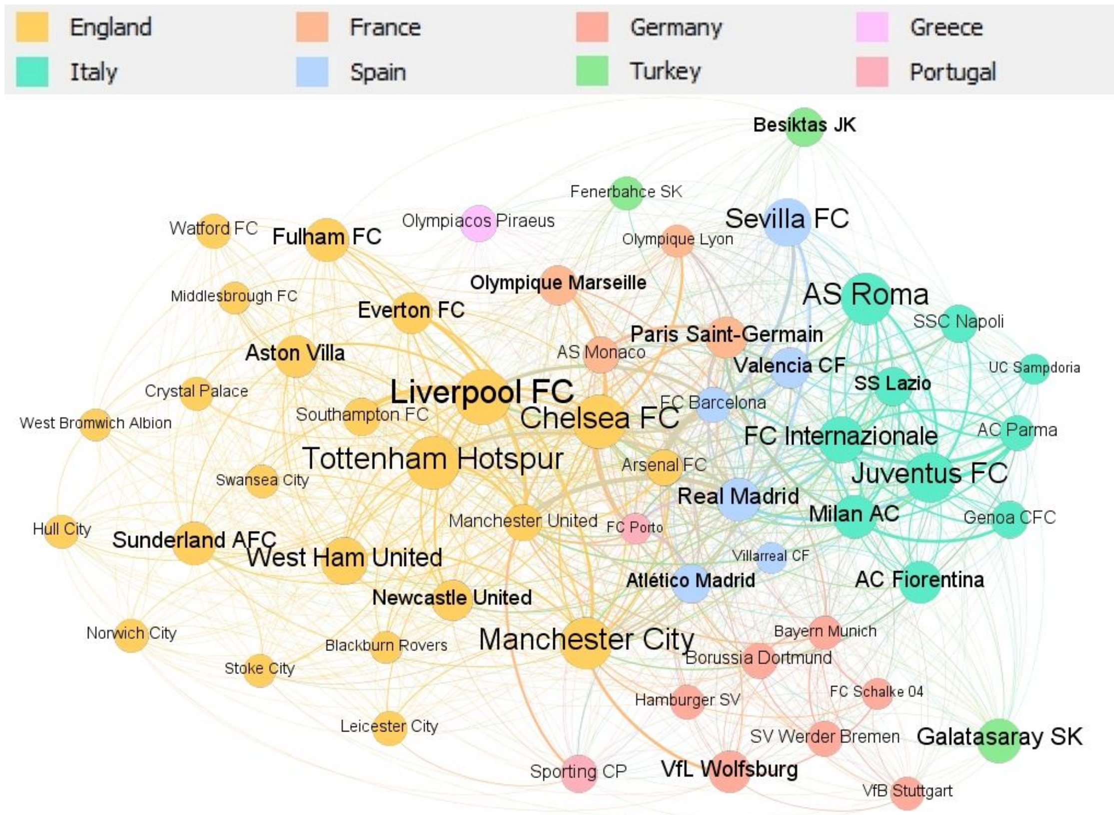


Fig. 2: Nodes as Clubs ranked by Eigenvector Centrality.

Similar to Eigenvector Centrality, PageRank also defines the importance of a node as a property which depends on its neighbours. The way this differs from Eigenvector Centrality is that each node j pointing to node i, contributes a fraction proportional to the out-degree of node j, to the pagerank of node i. For example, if an edge goes from node j to node i, with a weight of 30, and node i is the only neighbour of node j, the contribution from node j to the pagerank of node i is larger, than if there were an edge from node j to node i, still with a weight of 30, but node i was one of 20 neighbours of node j.   In our network, every small club j which sells players to big club i contributes a decent proportion to the pagerank of club i, because the money that club i spends to buy players from club j is a relatively large proportion of money that club j earns from selling players. In this case, a club has a high pageRank because all its purchases are relatively significant to both the buying club ad selling club. Figure 3 below shows the network of type 1, subtype a, with the nodes sized by PageRank.

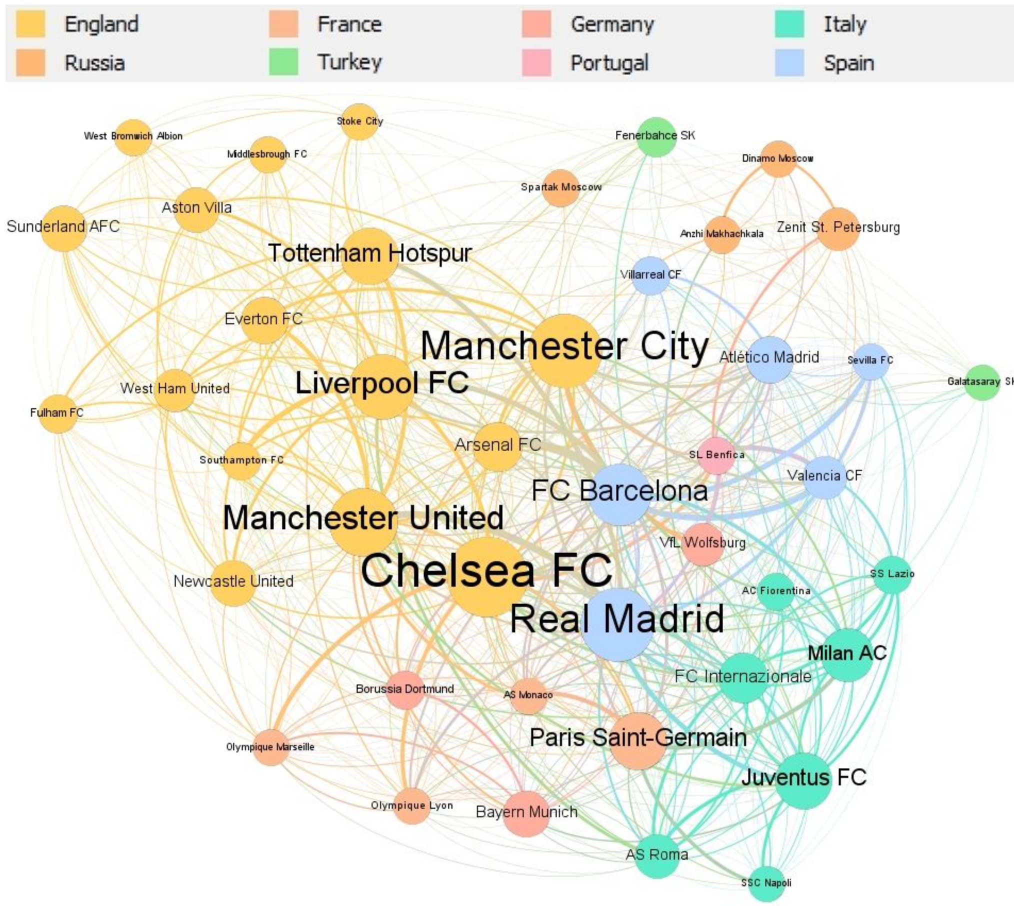


Fig 3: Nodes as Clubs ranked by PageRank.

In our study, we decided to investigate the relationship between PageRank, Weighted In-degree, and Eigenvector Centrality, as shown below in Fig 4.

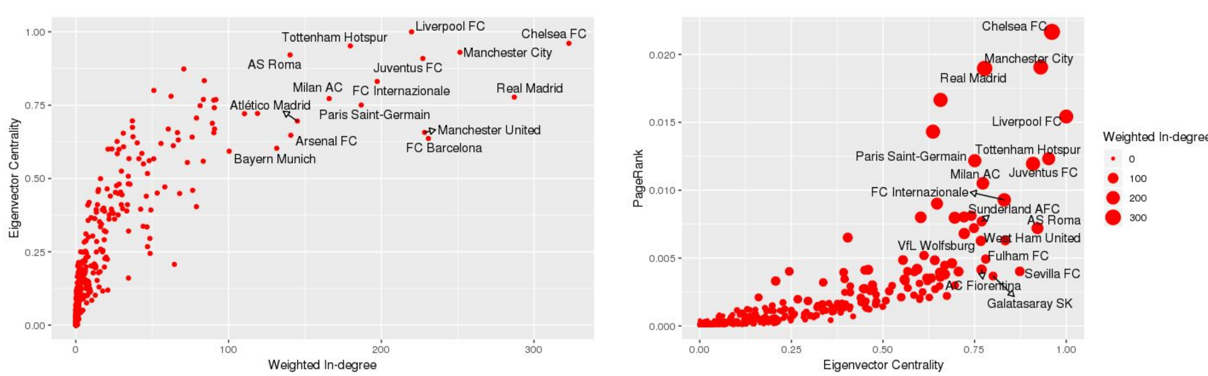


Fig. 4: a) Eigenvector Centrality vs Weighted Indegree b) PageRank vs Eigenvector Centrality

From the figures above, we observe that there is higher variation in PageRank and Weighted In-degree for higher Eigenvector centrality values. This means that for the teams which buy from important clubs, these transactions could represent very large or very small sales proportions from the selling teams. In other words, when a “small” team buys from a big team, it contributes only a small amount to the PageRank of the small team, because the sale only represents a small proportion of the sales made by the big teams. When a big team buys from another big team, it contributes a higher value to the PageRank of the buying team. Furthermore, we notice that with Eigenvector Centrality, when the weighted In-degree of a team gets high up to a certain value, any further increase in weighted-indegree has effectively no effect on Eigenvector Centrality. This is because a team’s importance depends on trading with other important teams. Therefore trading more (with other important or less important teams) does not raise the Eigenvector Centrality any more. With regards to PageRank, we see that there are teams with low PageRank values which still have high Eigenvector Centrality values; these are teams which buy from big teams, but do not generally spend a significant amount of money, such as Galatasaray and Sevilla. A key observation from this study is that there are top teams, such as Arsenal and Bayern Munich, that do not spend as much money as some of their counterparts in the same league (like Chelsea, Manchester United), or other leagues (Internazionale, Milan, Juventus, Barcelona). This corresponds well with what is generally known in the world of football about the relative frugality of Arsenal (Kuper 2013), and Bayern (Cohle 2018) over the years. We see that relatively small teams have high Eigenvector Centrality values. A flaw in using Eigenvector Centrality as a measure of importance, is that when a small team trades with a more important club, it contributes to how important the small team is. However, we consider PageRank to be a better reflection of team status, as it signifies engaging in important trade with other (important) teams. As we would expect, there is a positive correlation between weighted in-degree (how much money is spent buying players), and pagerank (how important are a team’s transactions), as shown in Fig. 5:

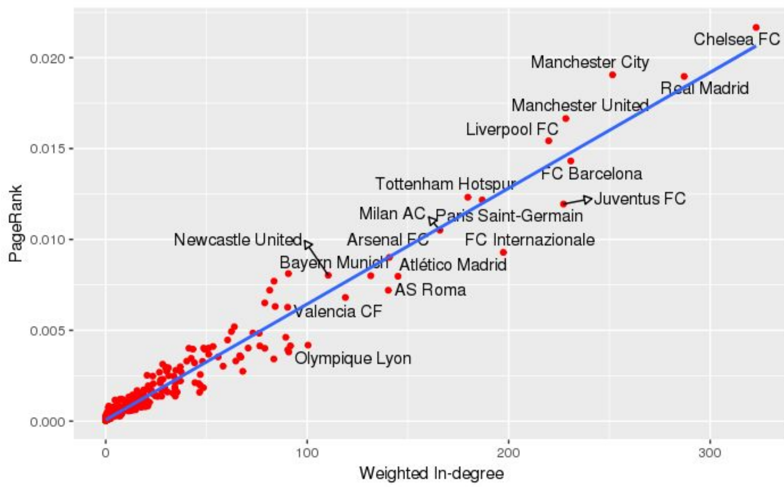


Fig. 5: PageRank vs Weighted In-degree

5.2 Type 2 networks - number of players as edge weights.

5.2.1 Weighted Degree Analysis

Recall that, in type 2 networks we use the total number of players transferred from club A to Club B as the edge weights. In the Fig. 6a) and 6b) below, the nodes are sized by weighted in-degree and weighted out-degree respectively.

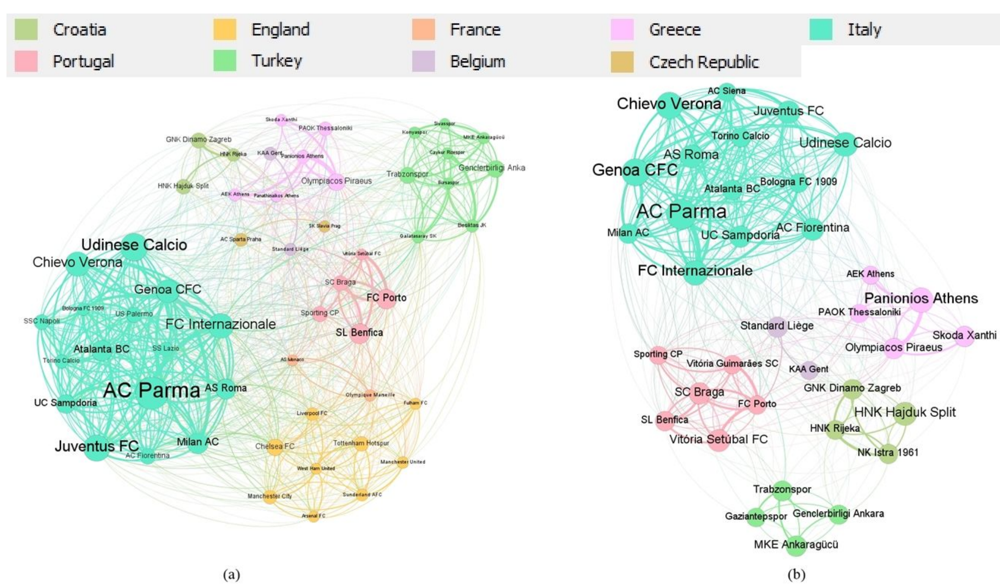


Fig 6: Type 2 Non-Loan weighted networks. Nodes are sized by a)Weighted In-degree b) Weighted Out-degree.

In these set of networks, we observe a change in the network leaders. We see that the teams which are actually buying and selling the most amount of players are no longer the premier league teams. We see heavy involvement of Italian clubs, such as AC Parma, Internazionale, Udinese Calcio, and Juventus. FC Porto and Benfica, two Portuguese teams, have also been very busy over the years. When we create the networks using loan transfers, we also observe similar results as shown in Fig. 7 below. A 2015 article (Greene 2015) validates some of the results of our analysis; we observe that Chelsea, Udinese Calcio, AC Parma, Benfica being the teams that loan out large numbers of players.

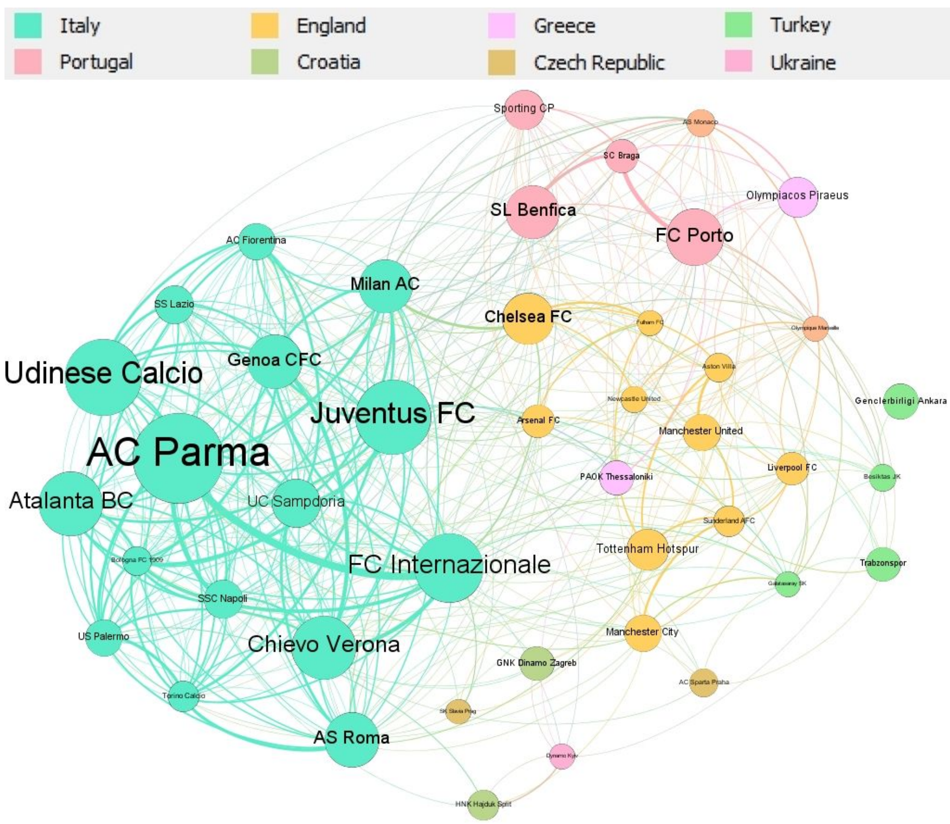


Fig 7: Type 2: Network of loan transfers. Nodes are sized by Weighted Out-degree.

5.3 Comparing Type 1 & Type 2 Networks

5.3.1 Weighted Degree Comparison by Country

The bar plots below show the aggregate weighted in-degree and weighted out-degree of teams belonging to all 15 countries, for type 1 and type 2 networks.

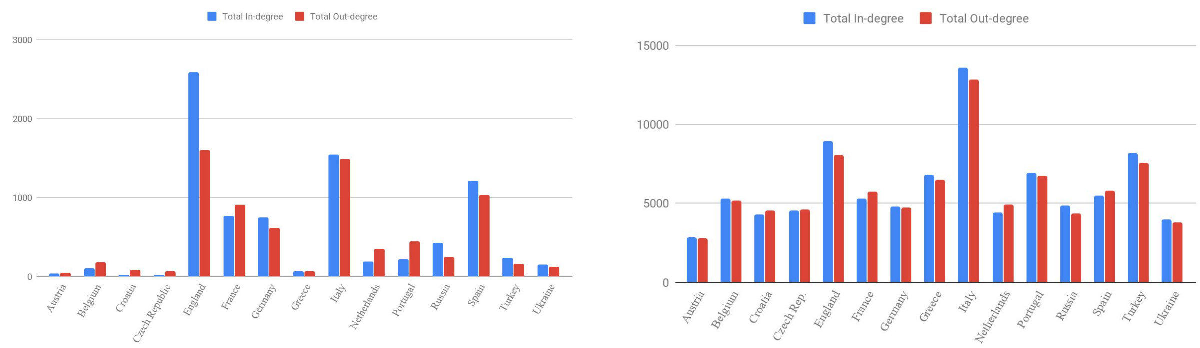


Fig 8: Total In-degree & Out-degree of all nodes, grouped by country for a) Type 1 b) Type 2

From the diagrams above, we observe a significant difference in the level of trade activity of the different countries. We can see that the top 5 leagues - England, Spain, France, Italy, and Germany have obvious financial domination in the market. These are the most popular leagues in European football, and it is unsurprising that their financial domination correlates with how well their teams perform in UEFA competitions (uefa.com). This is in line with previous research (Liu et al 2016, Lee et al 2015, Matesanz et al 2018) which shows the obvious correlation between clubs expenditure and team performance.

When we observe the number of players, the networks seem generally more balanced. With the exception of Italy, there are no obvious dominators, i.e, for each league, the teams are buying and selling players at similar levels. England has a relatively high out-degree for type-2 networks. However, in Fig. 6b), English teams do not appear. This is perhaps because all the teams in England are selling players at a relatively similarly levels, and so their aggregated weighted out-degree seem high enough. But, for smaller leagues there are specific teams which sell a significantly larger number of players causing these teams to out-perform English teams in the network shown in Fig. 6b).

We further study the relationship between number of players bought and amount of money spent. Theoretically, one would expect that the more players a team buys, the more money they spend; however, the plot in Fig. 9 below demonstrates that there is a little to no correlation between those.

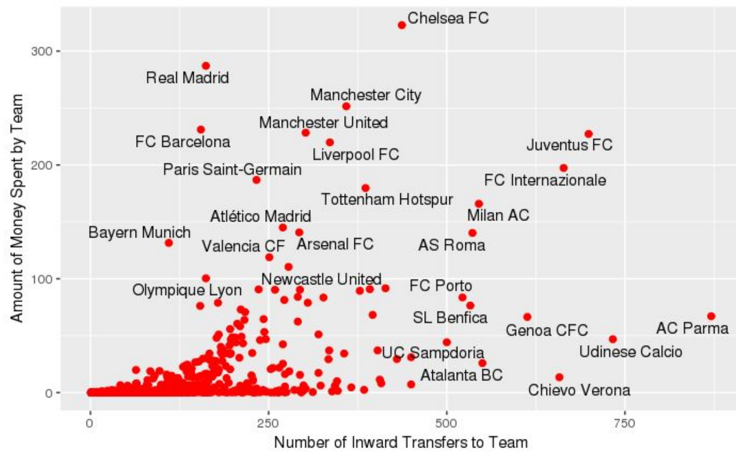
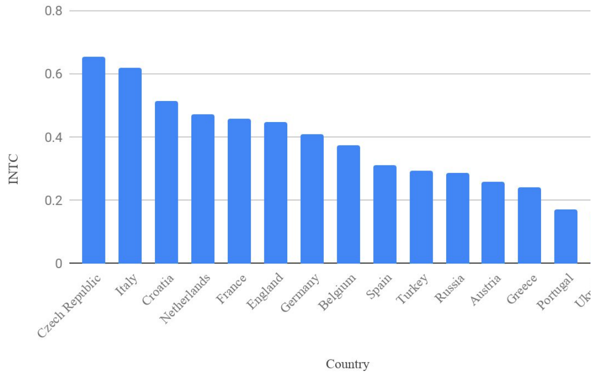


Fig 9: Normalized amount of money spent vs Numbers of players bought.

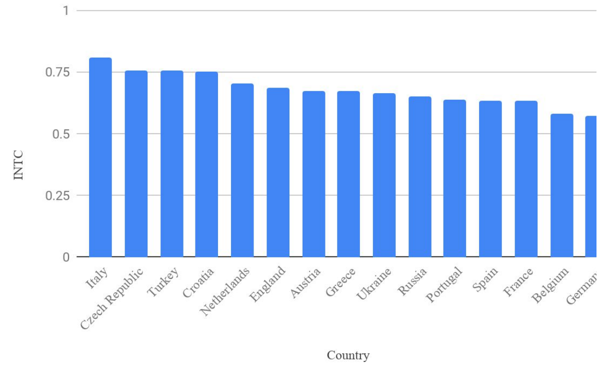
This is unsurprising, as the range of talent amongst professional footballers varies a lot, since all players do not have equal talent or industry relevance. Consequently, if a team buys more players, they are not necessarily spending more money, and conversely, if a team spends a lot of money, they are not necessarily buying more players. We calculate a pearson correlation coefficient of about 0.52, indicating the weak correlation. Furthermore, we speculate that for teams that spend very little money, there might be a slightly stronger correlation; however, after a club gets "rich enough", then the relationship between players bought and money spent is less prevalent.

5.3.2 Intra-National Trading Coefficient & Relative Internal Trade Activity

We move our analysis further to study other properties of the network. Recall that we defined the Intra-National Trading Coefficient of a country as a measure of the proportion of financial activity of all teams belonging to a country, that occur within that country. The figures below show the INTC values for the different countries for both type 1 and type 2 networks.



(a)



(b)

Fig 10: INTC values for each country in Network of a) Type 1 b) Type 2

From the plots above, we see that - with the exception of Italy, Croatia, and Czech Republic, most countries have an INTC value less than 0.5. This essentially means that teams spend a higher proportion of their money buying players from other countries. With an average value of about 0.377 and a median of 0.374, we can see that in the European transfer market, less than 40% of each team's expenditures occur domestically. 4 out of the top 5 leagues - England, Spain, Germany, and France do not particularly stand out in anyway, thus we can infer that spending relatively more money to import talent from other countries is not just unique to the top leagues..

When we consider type 2 networks, we see that the INTC values are generally much higher. This implies that there is heavy trade activity, in terms of the movement of players, within each country. With an average value of 0.678 and median of 0.672, we can conclude that there is more movement of players domestically, than internationally. The two networks effectively tell us that in Europe, there is a much larger movement of players domestically within each league, but a much more flow of money among leagues.

Recall that the Relative Internal Trade Activity (RITA) of a country is a metric we use to measure what proportion of the transfers in the overall network, occur domestically within said country. The plots below show the RITA values for the 15 different countries we studied.

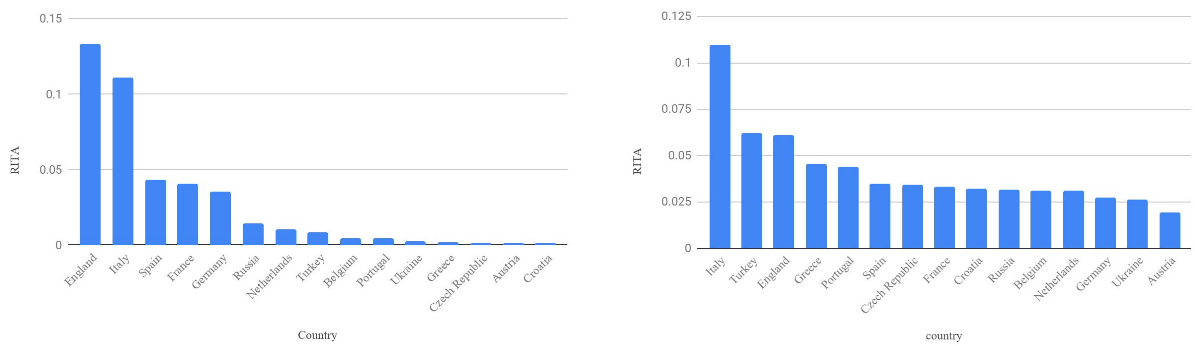


Fig 12: RITA values for each country in Network of a) Type 1 b) Type 2

With respect to type 1 networks, we see that financially, England and Italy dominate. With RITA values greater than 0.1, it means that over 10% of the total flow of money occurs within England, or within Italy. When we observe type 2 networks, we see that with Italy, there is an RITA value over 0.1, implying that more than 10% of the total movement of players occurs between Italian teams.

Summing up all the RITA values, we get a clearer idea of how what fraction of the transfer market occurs within teams of the same country. For type 1 networks, we calculated the aggregate RITA value to be about 0.411. We infer that over 40% of the financial activity occurs amongst teams of the same country. For type 2 networks, we calculated the aggregate RITA value to be about 0.62, implying that over 60% of the movement of players occurs between teams of the same country.

We would expect the average INTC value and the aggregate RITA value to be similar, as we use them both as metrics to understand how well teams the same country are likely to buy/sell players to/from one another. Our metrics correlate with previous research (Lee et al 2015) which suggests that the trading network of the transfer market is not strongly disassortative. We conclude that financial activity is more likely to occur internationally, but player movement is more likely to occur domestically.

6. Conclusion

In this paper, we have analyzed transfer networks of over 6000 nodes and 60000 edges, with transfer data from the top 15 leagues in Europe since 2000. We have methodically highlighted the top “importers” of talents, like Chelsea, Real Madrid, Liverpool, FC Barca, and the top exporters of talents, like Benfica, Juventus, Internazionale, Monaco, and Porto. Furthermore, we have explored the differences in the results that Eigenvector Centrality and PageRank provides for us, showing wide variation in pagerank for high-eigenvector centrality teams. We conclude that PageRank is a better indicator of importance than Eigenvector Centrality. We observe that there is little to no correlation between how many players a team buys and how much money is spent, as player talents (and consequently, market value), vary significantly. Furthermore, our results show that financially, England, Spain, Italy, Germany, and France, dominate the market; however, in terms of of number of players, the level of activity is relatively balanced amongst the 15 countries. We go on to study INTC and RITA values, to see how much trade activity occurs between nodes of the same country. For these, we observed that there is a larger flow of money between teams of different countries, but more players being transferred between teams in the same country. We corroborate our findings with previous existing research and the impact of certain real-life transfer activities.

This sort of work could be extended to include teams in other continents like the Americas, Asia, and Africa. For example, Brazil is one of the biggest exporters of talents to Europe, with some prominent figures like Ronaldo De Lima, Ronaldinho, and Neymar. Additionally, the MLS (Ranking the 15 Most Famous Soccer Players to Play in MLS 2018), Japanese (Joseph 2018), and Chinese (Joseph 2018) leagues are known for taking stars from Europe, who are in the decline of their careers, into their leagues. It would be interesting to see how these foreign transfers impact the transfer market in those continents.

A limitation of our study is that we do not factor in a component of time, in order to observe how, if at all, these patterns change over the years. In our paper, we aggregate all the activities in order to get a fuller picture of the 21st century European transfer market. For future work, it would certainly be interesting to see how these networks change with time, or what they look like for specific years, such as 2006 or 2010 when the FIFA world cup occured. Furthermore, we only took data from the top 15 leagues in Europe. While there might be differences if other leagues in other European countries are considered, we speculate that the results will largely remain the same: financial domination of certain English, French, Spanish, German, and Italian teams, relatively equal movement of players, more money spent importing talent from other leagues, and more players moving around domestically.

With the tools of Network Science, we have demonstrated how Mathematics can give us fresh, objective insights into professional Football. Additionally, it is a great way for enthusiasts to validate or debunk certain myths, opinions, or general intuition about the industry.

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8. Appendix

The source code, data sets, implementation of methodology and results for our analysis can be found in this Github Repository.